THE MINIMUM WAGE, INCOME, AND HEALTH: EVIDENCE FROM THE UNITED STATES

by

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ABSTRACT

Interest in the noneconomic impact of minimum wage laws have led to a growing literature examining how population health measures respond to state minimum wage increases in the US. These studies rely on the canonical two-way fixed effect estimator, which is an unreliable method to infer causal effects with spatially heterogeneous populations. In this Dissertation, I make three contributions to the minimum wage, income, and health literature. First, I study the impact of minimum wage differences across states and within-state ordinances on infant mortality rates in Chapter 1. I isolate the causal effect of the minimum wage by employing a spatial regression discontinuity design using neighboring counties in different states that are contiguous to a common state border as local treatment and control populations. I find that a 10 % higher cost-of-living adjusted minimum wage is linked with lower infant mortality rates by 3.2 % among lower-educated mothers—a group more likely affected by minimum wage changes. I find that reductions in infant mortality is concentrated in the post-neonatal period. I also demonstrate that the traditional empirical approach employed in this literature will produce lower estimates of the health impact of the minimum wage. My findings in Chapter 1 provide robust evidence that higher minimum wages are causally linked with improved infant survival rates.

In Chapter 2, I investigate the relationship between the minimum wage and a set of maternal healthcare inputs and measures of adverse health behavior during pregnancy at the county level among lower-educated and mothers without a high school diploma or equivalent. The aim is to discover possible pathways between minimum wage policies and infant health outcomes. Specifically, I study the timing and total number of prenatal visits, the utilization of prenatal care services in general, the average weekly alcohol beverage consumption during pregnancy, and average tobacco use (cigarettes per day) during pregnancy. I find that higher local minimum wage levels as measured by fair-market-rents are associated with improved prenatal healthcare utilization among lower educated mothers.

However, no effect was found between the minimum wage and adverse health behavior like tobacco and alcohol use. My empirical strategy followed closely what was learned about credible and efficient empirical strategies of the minimum wage effect on population health variables in Chapter 1. I addressed some empirical shortcoming of Chapter 1 by not just differentiated by education level, but also by age, race, and ethnicity. However, all the effect estimates where found to be quite modest as shown by standardized coefficients. I also argue, by way of elimination, that unobserved psychosocial determinants of health that were not empirically evaluated in Chapter 2 may play a large role in maternal and infant health outcomes.

In the final chapter, I provide a more theoretical treatment of the social determinants of health literature by proposing a new choice-theoretic channel mediating the impact of the minimum wage and income policies on population health, with empirical evidence to support the main assumption used in the model. The chapter examines to what extent these socioeconomic factors, specifically income, impact subjective life expectancy (SLE) measured as an individual's belief in surviving to a certain age. I first develop a model to describe how SLE may play an important role in linking wage increases to favorable health behavior by making future time costs of adverse health events binding. The model is based on the familiar Grossman demand for health model. I then estimate a heterogeneous choice proportional odds model, as well as a generalized ordered logistic model to study the income and SLE relationship. The main finding is that income and higher education is positively associated with SLE. I also find that periods of unemployment, disability, divorce, negative life events associated with the great recession were negatively associated with SLE. The chapter contributes to the health disparities literature by providing evidence in support a new channel connecting socioeconomic factors and health outcomes with a theoretical explanation of this channel. The chapter aims to provide additional insight to the relationship between minimum wages and health outcomes.

To my sister, Mahya

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CHAPTER 1

THE MINIMUM WAGE AND INFANT MORTALITY

1.1 Introduction

Empirical research on the impact of minimum wage laws on population health have received scant attention compared to the extensive and more traditional minimum wage literature (Leigh, 2016). Studies in this literature have predominantly focused on the employment and income effects of the minimum wage (Allegretto, Dube, & Reich, 2011; Card & Krueger, 1993; Dube, Lester, & Reich, 2010; Neumark, Schweitzer, & Wascher, 2004; Neumark & Wascher, 1992). Similarly, both proponents and opponents of minimum wage laws outside of academia confine debate within the same lines.[1] As political discussion around national and local proposals of a $15 dollar minimum wage intensify, it is necessary to understand the full scope of minimum wage increases.

Recent contributions in both the public health and economic literature have sparked a debate on the effects of minimum wage increases on population health (Averett, Smith, & Wang, 2017; Bullinger, 2017; Du & Leigh, 2017; Komro, Livingston, Markowitz, & Wagenaar, 2016; Lenhart, 2017a, 2017b; Reeves, McKee, Mackenbach, Whitehead, & Stuckler, 2017). While some studies have found empirical evidence to suggest that a minimum wage is associated with improvements in health, other studies have found the opposite or have found no relationship between the two (Adams, Blackburn, & Cotti, 2012; Cotti & Tefft, 2013; Hoke & Cotti, 2016; Horn, Maclean, & Strain, 2017; Kronenberg, Jacobs, & Zucchelli, 2017). Interests in studying the minimum wage as a potential public health policy tool is based on three factors. First, minimum wage laws have been shown to

[1] http://bostonreview.net/class-inequality/brishen-rogers-what-minimum-wage-debate-gets-wrong

exhibit higher compliance rates than other labor market regulations (Rani, Belser, Oelz, & Ranjbar, 2013; Ye, Gindling, & Li, 2015). Second, minimum wage increases have spillover effects on higher wage earners outside the scope of minimum wage mandates (Engbom & Moser, 2017). Third, minimum wage changes are enacted through legislation and do not require administrated public health interventions. Therefore, the health impact of minimum wage increases, if beneficial, provide an effective and potentially cost-effective legislative channel for improving public health.

However, previous estimates of the minimum wage effects on health have ignored local time varying heterogeneity and the presence of spatial correlation in health data. A review of identification strategies of minimum wage studies by Allegretto, Dube, Reich, and Zipperer (2013) argue for the use of control and treatment populations based on proximity as opposed to standard methods. Majority of the econometric models employed in the minimum wage and health literature have failed to account for such correlation or heterogeneous trends. In addition, little is known about the net impact of the minimum wage on population health. Consequently, new insights on the empirical relationship between the minimum wage and health can be gained with improved identification strategies.

In this chapter, I add to this new and growing literature by studying the effect of minimum wage increases on infant health—specifically, infant mortality rates at the county level. I do this using a spatial regression discontinuity design (Spatial RD) that generalizes a local case study approach for the entire contiguous continental United States based on the seminal work by Card and Krueger (1993). I find that minimum wage increases are associated with declines in infant mortality rates among lower educated mothers. My estimates show that the effect is concentrated in the post-neonatal period. I control for income, poverty, and a set of state level welfare and tax policies and run multiple robustness checks of my estimates. I further compare my estimation results with those attained by standard methods and conduct a falsification test by examining the effect of minimum wage increases on infant mortality rates among college educated mothers. I find no evidence that minimum wage increases are associated with improved infant survival for this subgroup. To my knowledge, this is the first analysis that estimates the minimum wage and health relationship using contiguous counties across state borders as local control populations and first to demonstrate the heterogeneous effect of the minimum wage on infant mortality by educational attainment of mothers.

The chapter proceeds as follows: Section 1.2 discusses the scientific plausibility connecting minimum wage increases and infant health within the context of the standard production of health model. Section 1.3 reviews the minimum wage and health literature. Section 1.4 describes the data sets in detail and how I calculate my main regression variables. I then outline my identification strategy and construction of the county pair sample in Section 1.5. Section 1.6 reports the results. Section 1.7 discusses limitations. Finally, Section 1.8 concludes with a summary and provides some possible extensions.

1.2 Scientific Understanding

Health economics provides one basis of understanding the relationship between minimum wage increases and health. The Grossman (1972) model has become the dominant framework for investigating the relationship between income, wages and health (Bolin, Jacobson, & Lindgren, 2001; Galama & Van Kippersluis, 2018; Grossman, 1972, 2017; Jacobson, 2000). In this framework, health is modeled as a stock variable that depreciates over time. Individuals can invest in their health stock by purchasing healthcare goods and services, or forgo income by investing in their health via rest and exercise. Additionally, wage increases raise the effective opportunity cost of missed work in the future through sick days as a result of adverse health behavior or low investment in health (Du & Leigh, 2017). Consequently, the Grossman model predicts that wage increases will induce individuals to consume higher levels of healthcare services.

Empirical evidence supports the Grossman model for prenatal healthcare services. Mocan, Raschke, and Unel (2015) examined the relationship between mother's weekly earnings with utilization of prenatal care services, and timing of prenatal care. The authors found that among low skilled mothers, increases in weekly earnings were associated with a rise in prenatal care visits and reduced average delay in initiating prenatal care. Inadequate prenatal care utilization has been associated with increased risk of prematurity and late neonatal death (Partridge, Balayla, Holcroft, & Abenhaim, 2012). It is plausible, therefore, that minimum wage increases are casually linked with improved health outcomes of newborns and decreases the likelihood of infant death through this channel. However, income effects may also reduce health investment through increases in unhealthy consumption, for example, tobacco, alcohol, and foods that contribute to obesity (Galama & Van Kippersluis, 2018). Prenatal smoking, alcohol consumption, and obesity have been linked to adverse birth characteristics and infant death in the perinatology literature (Baird, Friedman, & Schady, 2011; Dietz et al., 2010; Djelantik, Kunst, van der Wal, Smit, & Vrijkotte, 2012; Fertig & Watson, 2009; Morgan et al., 2015). Still, knowledge of adverse health behavior leading to adverse health outcomes is not necessarily transmitted equally among social classes and therefore income increases among the poor may not lead to health improvements (Link & Phelan, 2009). Estimating the effect of minimum wage increases may shed light on which of the above income channels will outweigh the other or if there is not effect at all.

A separate social epidemiological model of health exists that explains how factors such as maternal stress, hypertension, access to adequate nutrition and others can have a significant and lasting impact on infant health and decrease the probability of infant survival (Apter-Levy, Feldman, Vakart, Ebstein, & Feldman, 2013; Buchbinder et al., 2002; Cook et al., 2013; Dowd, 2007). Working conditions and low wages have been associated with these factors as well (J. Leigh & De Vogli, 2016; J. P. Leigh & Du, 2012; McLellan, 2017; Morris, Donkin, Wonderling, Wilkinson, & Dowler, 2000; Rusli, Edimansyah, & Naing, 2008). It has been shown that increases in the minimum wage in developing economies is correlated with better working conditions for certain industries (Harrison & Scorse, 2006). It is plausible that minimum wage increases in the United States may reduce infant mortality rates by increasing incomes and improving working conditions.

The relationship between minimum wage increases and working hours is an additional concern for the direction of the health impact. If adjustments in working hours outweigh wage increases with respect to income, the Grossman model would predict decreased consumption of healthcare services which would then adversely affect health. Little evidence exists for significant reductions in working hours after minimum wage increases (Connolly & Gregory, 2002; Stewart & Swaffield, 2008; Zavodny, 2000). In fact, Connolly and Gregory (2002) found no impact of minimum wages changes on total working hours of low paid women. Even if significant adjustments are associated with minimum wage increases, reduced working hours may also improve health via increased rest and exercise as discussed earlier. Additionally, if work is a source of stress for employed mothers, then minimum wage increases could plausibly improve health outcomes even with modest reductions in hours or short-term unemployment of working mothers.

The minimum wage effect on infant health, whether positive or negative, may influence a broader population of newborns than those whose households are directly affected by the wage mandate. A growing number of studies have examined how minimum wage increases change the distribution of earnings for workers in general (David, Manning, & Smith, 2016; DiNardo, Fortin, & Lemieux, 1995; Engbom & Moser, 2017). These studies have confirmed upward spillover effects on higher earners after minimum wage increases. Work by DiNardo et al. (1995); Engbom and Moser (2017) have shown that minimum wage increases explain a significant portion of decreased earnings inequality while others find modest effects at the tail end of the wage distribution. Socioeconomic status is an important and significant determinant of population health as demonstrated by a large volume of work in the economic and public health literature (Adler & Newman, 2002; Kawachi & Kennedy, 1999; Lynch, Smith, Kaplan, & House, 2000; Wagstaff & Van Doorslaer, 2000; Waitzman, Smith, & Stroup, 1999). This suggests that higher minimum wage may be casually linked with infant mortality through reductions in inequality leading to improvements in socioeconomic status of portions of the population.

The social ecology of a community is another factor in determining population health. Living in an unsafe community where individuals cannot be active, have limited outdoor activity, and experience the daily stressors associated with their social environment is known to be detrimental to health outcomes (Doyle, Kelly-Schwartz, Schlossberg, & Stockard, 2006; Ross & Mirowsky, 2001). Low wages and employment are associated with community crime levels (Hansen & Machin, 2002). Hansen and Machin (2002) have found that communities with relatively higher proportion of low wage workers saw decreases in crime rates after the introduction of the United Kingdom minimum wage compared to areas with fewer low wage workers. However, Beauchamp and Chan (2014) found the opposite result in the United States among youth crime rates. Beauchamp and Chan (2014) argue that negative employment effects of minimum wage policies is a possible driver of their results. Consequently, the minimum wage and employment relationship is a potential driver in affecting the social ecology of a community through higher unemployment that could increase crime rates. As mentioned earlier, the voluminous literature on the minimum wage, employment, and income is still in contention (Allegretto et al., 2011; Card & Krueger, 1993; Dube et al., 2010; Neumark et al., 2004; Neumark & Wascher, 1992). Though more recent empirical studies suggest little to no disemployment effects among low wage workers after minimum wage increases (Cengiz, Dube, Lindner, & Zipperer, 2019; Giuliano, 2013). It is unclear whether the minimum wage could harm or promote health outcomes through the social ecology channel mediated through employment and income levels.

It is plausible that minimum wage increases are linked with infant mortality rates through the channels described above. Figure 1.1 summarizes the basic conceptualization of some of these pathways in a simple diagram. The direction and magnitude of the relationship, however, is not obvious. Establishing an empirical relationship is the aim of this first chapter. In the proceeding chapter, we empirically test a number of healthcare variables along with two adverse health behavior variables.

1.3 Minimum Wage and Health Literature

At the national level, Lenhart (2017b) studied the impact of the generosity of the minimum wage as measured by the *Kaitz Index*[2] in 24 OECD countries. He found that higher levels of the minimum wage is associated with declines in death rates from several causes including, diabetes-related mortality, deaths due to circulatory disease, diseases of the digestive system, stroke and heart attacks. He also found that a higher *Kaitz index* in a country was associated with increased life expectancy. Focusing on Infant health, Komro et al. (2016) studied the effects of state minimum wage changes on infant mortality and birth weight at the state level. The authors found that state minimum wages above the federal minimum level was associated with a mild decrease in incidence of low birth weight births and post-neonatal mortality. Similarly, a recent working paper by Wehby, Dave, and Kaestner (2016) found that minimum wage increases were associated with increased birth weights among lower educated mothers, in addition to increased gestational length, and a decline in smoking during pregnancy.

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[2]The Kaitz index is measured by the ratio of a country's nominal minimum wage and the mean wage of full-time workers adjusted for the percent of workers earning the minimum wage.

Some studies have examined the relationship of the minimum wage and health indirectly using simulation models to conduct health impact assessments of wage increases. Bhatia and Katz (2001); Cole et al. (2005) estimated the potential health impacts of proposed city living wage ordinances in Los Angeles and San Francisco, respectively. These authors relied predominantly upon published research on the relationship between income, poverty and health. Both found considerable evidence supporting hypothetical health gains from such wage mandates. A more recent simulation based study by Tsao et al. (2016) estimated the potential impact of raising the minimum wage to $15 per hour on premature mortality in New York City and found that if the minimum wage would have been $15 from 2008 through 2012, then 4 to 8 % of premature deaths would have been averted. Some doubt has been raised on the study design and validity of such projected simulation based health impact assessments (Mindell & Joffe, 2005). The living wage and health relationship therefore requires direct statistical analysis that may produce more reliable estimates.

Some researchers have examined wage mandates and their effect on psychological well-being. The first of these studies was Flint, Cummins, and Wills (2013) in which the authors investigated the impact of the 2011 London Living Wage. Flint et al. (2013) conducted workplace interviews of workers being remunerated at a living wage level and compared them to other low income workers.[3] After controlling for a large set of covariates, the authors found that the London living wage improved self-reported psychological well-being by 3.9 units on the *Warwick-Edinburgh Mental Wellbeing Scale*.[4] A more recent study, Reeves et al. (2017) estimated the mental health impact of the 1999 United Kingdom national minimum wage using longitudinal data from the British Household Panel Survey. Their analysis tied the introduction of the national minimum wage to significant reductions in depressive symptoms for workers who were affected by the wage increase. The importance of financial stress and hardship was highlighted as a potential

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[3]The London Living Wage was set at £8.30, £2.22 above the United Kingdom national minimum.

[4]The Warwick-Edinburgh Mental Well-being Scale (WEMWBS) was developed by Warwick and Edinburgh Universities commissioned by the NHS in 2006 and is used in primarily United Kingdom population health studies.

factor in the health improvements observed in the Reeves et al. (2017) study. The authors found that workers in the intervention group reported experiencing less current financial strain compared to two control groups in the study. Despite this, using a larger sample size and alternative control groups, Kronenberg et al. (2017) did not find a statistical association between the introduction of a national minimum wage and improvements in mental health.

Other studies have pointed to potential negative health consequences of minimum wage increases. Horn et al. (2017) found that increases in the minimum wage worsened self-reported health outcomes among men, and found mixed evidence for health improvements among women. Hoke and Cotti (2016) have shown that increases in the minimum wage is associated with increased alcohol consumption among teenagers. Similarly, Adams et al. (2012) concluded that increases in the minimum wage raises the incidence of alcohol related traffic accidents among younger adults. In addition, Cotti and Tefft (2013) suggest that raising the minimum wage increases the probability of obesity instead of promoting reductions in obesity rates as was previously found by Meltzer and Chen (2011). These negative associations between minimum wage and health introduce serious uncertainty on minimum wage increases as a health policy tool. The empirical relationship is yet unresolved and therefore further empirical work is needed to clarify this relationship.

1.4 Data Setup

I construct two main data samples for my analysis. The first consists of all counties (AC) in the United States, and the second consists of those counties that border a state line and can be paired with a contiguous county in the opposing state (contiguous county pair (CCP) sample hereafter). The latter sample is used for my primary analysis. County boundaries of the CCP sample remained unchanged from 1995 to 2013. Therefore, our county pairs remain consistent for the sample period. I now describe my datasets in detail.

1.4.1 Datasets

Infant mortality rates per 1,000 live births were calculated using data from the National Center for Health Statistics' (NCHS) Linked Birth/Infant Death Records for all counties provided through a data agreement with NCHS and the National Association for Public Health Statistics and Information Systems (NAPHSIS). This data set contains birth and death records occurring within the US to residents and nonresidents. I estimate county mortality rates with an intent-to-treat approach using the Mother's county of residence reported on the birth certificate. Infant mortality rates were calculated by birth year and imputed conception year using date of birth and gestational age of the infant. The timing of the minimum wage treatment is captured for both birth and conception year mortality estimates. Komro et al. (2016) reported contemporaneous and lagged minimum wage effects on infant mortality to adjust for those births that occur at the beginning of the calendar year in which the prior year's minimum wage was the primary treatment. I use imputed conception year to represent a more accurate timing of minimum wage treatment. Regression analysis was conducted on both rate calculations. Post-neonatal mortality rates were then calculated based on infant age at the time of death. County mortality rates, birth and mother's characteristics are summarized in Tables 1.1 - 1.3 for both AC and CCP samples. Average county estimates of infant mortality rates are greater than national estimates since county estimates are right skewed. It is important to note that the study period, 1995 to 2013, exhibits relatively stable fertility rates in the general female population compared to downward secular trends prior to 1995 and more recent changes to the age composition of new mothers (Livingston, 2018; Ventura, Mosher, Curtin, Abma, & Henshaw, 2001; Whelpton, Campbell, & Patterson, 2015). This reduces potentially confounding effects of fertility changes in my analysis.

Annual state and federal minimum wages for nonfarm employment were collected from the US Department of Labor's Wage and Hour Division (WHD) from 1995 to 2013. Data on San Francisco County minimum wage ordinance was collected from the San Francisco Office of Labor Standards and Enforcement (LSE).[5] I define the effective minimum

[5] San Francisco County raised the minimum wage above California's minimum wage in 2004 by $1.75 and continuously raised the minimum wage every year until 2013 where the minimum wage was $10.55 per hour. Since then, a total of 39 municipal and county

wage as the higher of the state and federal minimum wage level observed at the beginning of the calendar year. Changes in the effective minimum wage per county originate from four sources: federal legislation, state legislation, state inflation trends, and local cost-of-living changes. Absent either federal or state legislative increases in the minimum wage, the inflation-adjusted minimum wage will decline over time due to state level price trends. State annual inflation data was collected from the US Bureau of Economic Analysis (BEA) for years 1997 to 2013. Cost-of-living (COL) adjusted minimum wage at the county level will vary over time based on changes to median rent prices. I used estimated county level changes in rent prices from the US Department of Housing and Urban Development's (HUD) annual estimates of Fair Market Rents, which is used by the agency to determine benefits under the Housing Choice Voucher Program (commonly known as Section 8). HUD data was used to calculate the ratio of full-time nominal minimum wage earnings per month before taxes to fair market rents. Both the real state minimum wage level (adjusted for 2009 state dollars) and full time minimum wage earnings to fair market rents on infant mortality rates are modeled. This is the first paper to use median rent price at the county level to measure the purchasing power of the minimum wage in this literature.

The unadjusted minimum wage ranged from $4.25 to $10.55, while the state inflation-adjusted minimum wage ranged from $5.23 to $9.74 throughout the sample. Full-time minimum wage earnings to fair market rents ranged from 0.64 to 2.66. Figures 1.2 and 1.3 show the county mean and median trends in both minimum wage measures. From 1995 to 2013, two significant increases in mean county minimum wage are due to federally legislated wage hikes. The average state minimum wage decreased between 1998 to 2006, and 2010 to 2013 due to inflation and local COL trends. The number of states (including District of Columbia) with minimum wage laws set above the federal level increased from 8 at the beginning of the period to 21 at the end of the period. The federal minimum wage increased six times during the sample period but affected only a subset of states. Affected states had state minimum wage laws below the new federal mandates or never enacted their own state minimum wage. This included 42 states in 1996, 47 states in 1997, 44 states in 1998, 21 states in 2008, 27 states in 2009, and 32 states in 2010. All counties in the data set

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ordinances have been enacted to raise local minimum wages above state levels, but these increases occurred after my sample period.

experienced both an increase and decreases in the minimum wage for both the real state minimum wage level and local COL adjusted minimum wage.

1.4.2 Covariates

Covariates in my statistical analysis included income, poverty, and state welfare and tax policies. County level data on median household income and percent of related children in families in poverty was collected from the US Census Bureau Small Area Income and Poverty Estimates (SAIPE). I adjusted median household income to 2009 state dollars. State level welfare and tax policies include, the Supplemental Nutrition Assistance Program (SNAP), Temporary Assistance for Needy Families (TANF), and the Earned Income Tax Credit (EITC) from the University of Kentucky's Center for Poverty Research (UKCPR) National Welfare Data. SNAP and TANF are measured using maximum benefits for a family of four and adjusted for 2009 state dollars. EITC is measured using both benefits and whether the credit is refundable. Table 1.4 summarizes these variables for both the AC and CCP sample.

1.5 Identification Strategy

I now turn to the issues surrounding identification in the model and how they are addressed in this analysis. Limitations in the traditional approach to identification are addressed first. I then describe my preferred regression model and how I construct counterfactual observations based on proximity.

1.5.1 Background

The empirical challenge in this study, or in any study attempting to identify the relationship between an economic policy variable and population health, is that I cannot directly control the treatment intensity or observe the counterfactual outcome absent the treatment. It is impossible for econometric identification strategies of observational data to meet the standards expected in the medical literature—that is, results of randomized control trials (RCTs). For natural reasons, there are barriers in conducting an RCT to estimate the causal effect of the minimum wage on infant mortality rates. Therefore, I rely on other methodologies to approximate a causal framework.

The canonical two-way fixed effect estimator (TFE hereafter) has been employed by previous authors in this literature to identify the causal effect of the minimum wage on a variety of population health variables in the United States. The specification of this type of model is described by the following equation:

$$Y_{it} = \beta \log(MW_{it}) + \delta_i + \zeta_t + X_{it}\Lambda + \varepsilon_{it} \tag{1.1}$$

where Y_{it} is the population health outcome variable of interest for county, state, or province i at time t. δ_i are county fixed effects that capture unobserved county level characteristics that are consistent over time. Year fixed effects, ζ_t capture unobserved changes in Y at the national level that vary over time but remain constant across all i. X_{it} is a matrix of time varying county characteristics and relevant state policy variables. ε_{it} is the disturbance term.

Equation 1.1 allows for the estimation of intermittent and variable treatment effects. Naturally, it has been the preferred model for minimum wage studies in the United States. For studying single and continuous minimum wage treatments such as the introduction of the 1999 national minimum wage in the United Kingdom, the standard Difference-in-Difference (DID) model has been used (Kronenberg et al., 2017; Lenhart, 2017a; Reeves et al., 2017). In a balanced panel setting with a single treatment, the TFE and DID are identical.

The TFE estimator described above has a number of potential limitations. The estimation may be biased if there exist systematic relationships between the policy variable and other factors that may affect the outcome variables of interest in a given time period. Therefore, the econometric model assumes contemporaneous exogeneity, $E(\varepsilon_t|MW_t) = 0$ for all t in the data set. This potential problem can be addressed by including a rich set of observed time varying covariates, as well as a full set of state and year fixed effects. In addition, the TFE approach designates the treatment and control groups not based on random assignment, but based on whether the state's minimum wage increased or remained unchanged for a given period. For valid causal inferences to hold, Equation 1.1 assumes that the treatment assignment for each county is ignorable conditional on the set of covariates included in the model. Conditional ignorability of treatment assignment is a particularly strong assumption when analyzing health outcomes. Moreover, the TFE approach is known to be a "quasi-experimental" research design in that it constructs counterfactual observations based on average national trends. Consequently, a potential limitation in this framework is that controlling for covariates and absent the minimum wage treatment, differences in Y_{it} is fully captured by the county and year fixed effects—this is often referred to as the parallel lines assumption.

1.5.2 Time Varying Heterogeneity

A constant ζ_t for all counties excludes the possibility of time varying heterogeneity in the outcome variable. There are a number of reasons to believe that such heterogeneity exist with respect to infant mortality rates in the United States. For instance, there are large variations in total births across counties (Simpson, 2011). Infant mortality rates will exhibit a high level of instability due to small changes in death counts in low birth counties while remaining relatively stable in highly populated counties. Consequently, ζ_t will be less meaningful for a subset of observations. Further, it is well known in the epidemiology literature that population health outcomes are not randomly distributed across space (Pfeiffer et al., 2008). Factors associated with birth outcomes such as prenatal stress, nutritional and lifestyle habits, healthcare utilization, environmental conditions and high pollution periods vary greatly by region (Bhargavan & Sunshine, 2005; Currie, Neidell, & Schmieder, 2009; King, Dube, & Tynan, 2012; Obisesan, Vargas, & Gillum, 2000; Pope III, Ezzati, & Dockery, 2009; Willett, 2012). Additionally, in a recent large-scale study published in *Nature*, Leslie et al. (2015) found that there is significant local clustering of the genetic composition of the population in the United Kingdom. It is plausible that a similar phenomenon may exist in the United States—though such a study has not yet been conducted to the knowledge of the author. Genetic clustering implies that variations in Y between spatially distant counties with different treatment intensities are not appropriate comparators since these populations are genetically different and may face different health risks. Not surprisingly, infant mortality rates in the United States have been shown to be spatially correlated at the county level (Banerjee, Wall, & Carlin, 2003). Moreover, determinants of infant health are broad and there may be numerous additional unobserved variables that vary by region and time that cannot be fully accounted for. It is thus unlikely that the parallel lines assumption of the TFE is valid for this study.

Accounting for heterogeneous trends in health outcomes have been shown to be non-trivial. Meltzer and Chen (2011) found that minimum wage increases were negatively associated with obesity using the canonical TFE estimator. Cotti and Tefft (2013) reexamined this relationship using the same data set and found the opposite result after modifying Equation 1.1 to include county specific time trends such that,

$$Y_{it} = \beta \log(MW_{it}) + \delta_i + \zeta_t + \gamma_i(t) + X_{it}\Lambda + \varepsilon_{it} \tag{1.2}$$

However, there is no reason to assume that within-county time varying heterogeneity, $\gamma_i(t)$ should follow a linear pattern for all counties as shown in Equation 1.2. In fact, many studies have shown that population health variables follow business cycle fluctuations, so a nonlinear trend may be preferred if the data spans multiple years (Gordon & Sommers, 2016; Ruhm, 2000; Toffolutti & Suhrcke, 2014). Similar to the minimum wage and obesity studies, Chou, Grossman, and Saffer (2004); Gruber and Frakes (2006) also report contradictory results in separate estimations of the effect of smoking on obesity. The main difference in these two studies was the inclusion of quadratic time trends in the estimation equation in Chou et al. (2004), where $\gamma_i(t) = \gamma_{i0}t + \gamma_{i1}^2 t$ in Equation 1.2 without ζ_t, while Gruber and Frakes (2006) estimated the canonical TFE estimator—Equation 1.1.

The above-mentioned reporting of opposite-signed coefficients using the same data sets with small regression modifications is not surprising, since the inclusion of even a single functional time element in Equation 1.1 changes the counterfactual outcome for all the treated observations in the sample. The sensitivity of the coefficients observed in these studies highlights the need for an alternative research design.

1.5.3 Spatial Discontinuity

An estimation method that allows for local time varying heterogeneity has been proposed as a credible research design for minimum wage studies by Allegretto et al. (2013) and a recent review of the minimum wage and health literature explicitly suggested this methodology (J. P. Leigh, Leigh, & Du, 2018). Indeed, a number of recent studies have used neighboring counties near state borders with policy discontinuities as local treatment and control populations to account for time varying heterogeneity and to mimic a randomized experiment (Dube, Goodman, Kaplan, & Boone, 2016; Dube et al., 2010; Holmes, 1998; Rohlin, 2011). The highly cited Card and Krueger (1993) was one of the first to use counterfactual observations based on proximity. Card and Krueger (1993) compared employment changes in fast food restaurants in New Jersey before and after a minimum wage increase using employment trends in fast food restaurants in Eastern Pennsylvania as local controls.

I generalize the Card and Krueger (1993) study for the entire contiguous continental United States. Specifically, I follow closely the estimation strategy presented by Dube et al. (2010), which is similar to a regression discontinuity design where treatment is determined by state boundaries instead of a threshold predictor variable. To do this, I examine a subsample of US counties that are contiguous to a state border and use neighboring counties in the opposing state with a lower minimum wage as local control populations—CCP sample described above. Figure 1.4 illustrates the CCP sample in our study. I estimate the following regression specification for both infant and post-neonatal mortality rates among different groups of mothers based on education:

$$Y_{ipt} = \beta \log(MW_{it}) + \delta_i + \zeta_{pt} + X_{it}\Lambda + \varepsilon_{it} \tag{1.3}$$

Y_{ipt} is the natural log of infant mortality rates for county i at time t in county pair p. The above model is equivalent to Equation 1.1 except that I replace the constant year effects with a county pair specific year effects, ζ_{pt}. My preferred regression model allows for time varying heterogeneity, does not impose a specific functional form of the time trends, and does not assume conditional ignorability of the treatment assignment. Equation 1.3 relies on two identifying assumptions: (1) state boundaries between two contiguous counties are "as-good-as" random assignment, and (2) unobserved determinants of health are similar between county pairs.

In addition, each county will be observed in our model as many times as it can be paired with a cross-border county. Figure 1.4 displays a heat map indicating how many instances a county is paired with a cross-border county. Each pair represents a single case study where the treatment variable is the observed minimum wage. Multiple pairings are due to the disproportionate size of counties, wherein a large county will share a contiguous border with multiple cross-state counties of a smaller size. Also, counties at the corners of a state boundary will be paired with counties from multiple states. As noted by Dube et al. (2010), multiple pairings of counties may introduce multidimensional correlation in the disturbance term. To account for this source of second-order bias, I cluster the standard errors in the CCP sample regressions by county and the state border segment (See Cameron, Gelbach, and Miller (2011) for a discussion of multiway clustering).

I first regress the log of infant mortality rates measured by birth and imputed conception year on the log of the effective real state minimum wage (adjusted for 2009 state specific dollars) and full-time minimum wage earnings to county fair market rents (COL adjusted) in Equation 1.3. These results are then compared to estimates from regression Equation 1.1 using the all county sample. This procedure is then repeated for infant mortality rates among a subsample of lower educated mothers, in other words, less than or equal to a high school education. Results from the lower educated subsample in Equation 1.3 are then compared to estimates of the minimum wage effect on infant mortality rates among infants born to college educated mothers. This serves as a falsification test, since I do not expect a significant relationship between minimum wage increases and infant health among the highly educated mothers group. An insignificant relationship will validate a causal effect in my identification strategy by ruling out unobserved factors driving my results. I also estimate Equation 1.1 and 1.3 for post-neonatal mortality rates for all and lower educated mothers. I do not estimate Equation 1.2 or its quadratic time trend equivalent because it is a special case of Equation 1.3.

An unadjusted model of the relationship between infant mortality rates and my two measures of the minimum wage was run first, and then adjusted for income, poverty, state welfare, cash transfer, and tax policies. Median household income in the regressions control for heterogeneous macroeconomic fluctuations across counties that may impact infant mortality rates over time. Related children in families in poverty will account for absolute disparities in infant health that persist in each county that may vary over time. Relevant state policies that may affect infant health similar to the minimum wage included, SNAP, TANF, and the EITC. Previous contributions on the link between the minimum wage and infant mortality did not account for such confounding policies (Komro et al., 2016).

1.6 Results

Results from the CCP sample estimates with local controls strongly link COL adjusted minimum wage increases to reductions in infant mortality rates among lower educated mothers. I find that a 10 % increase in the COL adjusted minimum wage reduces infant mortality rates by 3.2 % among lower educated mothers. Reductions in infant mortality is concentrated in the post-neonatal period. A 10 % increase in the COL adjusted minimum wage reduces post-neonatal mortality rates among all mothers between 3.2 to 4.4 %. Estimates of the minimum wage effect on post-neonatal mortality reductions is slightly larger and more significant when studying post-neonates born to lower educated mothers—a group more likely affected by minimum wage changes. The COL adjusted minimum wage produces more consistent and stable coefficient results compared to the state level price adjusted minimum wage. Estimates from the AC sample indicate that minimum wage increases are associated with infant mortality rates among all mothers. This finding is less plausible and not found in my preferred CCP sample estimates. My findings provide evidence that minimum wage increases are causally linked with improved infant survival and the magnitude of the effect is similar to prior contributions in this literature (Komro et al., 2016). The concentration of the minimum wage effect in the post-neonatal period is consistent with prior work on the determinant of mortality between neonates and post-neonates in the US (Chen, Oster, & Williams, 2016).

Trends in infant mortality rates are counter cyclical to aggregate income fluctuations. A strong negative association between infant mortality rates among all and lower educated mothers with real median household income at the county level was found. This finding is consistent with the literature (Baird et al., 2011). SNAP is negatively associated with infant mortality rates, but not significant at the 5 % level for the majority of my regressions. This is not surprising since recent quasi-experimental evidence connects nutritional assistance programs to health gains of children in later adolescent years of life and not early childhood (East, 2018). Although prior work has found that the EITC is associated with modest reductions in the incidence of low birth weight, I do not find a consistent association between infant mortality and the EITC (Hoynes, Miller, & Simon, 2015). Overall, my empirical analysis further supports the utility of minimum wage increases as a health policy tool to improve infant health.

1.6.1 All County Sample

Results of the canonical TFE estimator on the AC sample are reported in Tables 1.5 - 1.9 alongside the CCP estimates. In general, the minimum wage effect in the AC analysis is smaller in magnitude than what is estimated using the CCP sample with time varying heterogeneity. In addition, the standard errors in the AC sample are less than those of the CCP analysis throughout each set of regressions. Since two-way clustering was used in the CCP estimates, the higher variance can be attributable to positive correlation on both dimensions of the clustering with minimal correlation on the intersection of the two dimensions.[6] Moreover, the traditional approach indicates that minimum wage increases are associated with infant mortality rates among all mothers regardless of education level. In so far as the CCP sample regression provides more valid controls, my results could indicate that inferences based on the canonical TFE may be less reliable for causal inference.

1.6.2 Robustness Tests

Although the use of county pair time effects in Equation 1.3 provide relatively valid counterfactual outcomes, it unfortunately imposes a large set of parameter constraints on our estimation equations. The degrees of freedom is dramatically reduced by $\frac{N}{2}$. This issue has not been addressed by previous researches that have applied this method. I remedy this restriction on our estimation by replacing ζ_{pt} in Equation 1.3 with state border segment year effects. The proximity of counties that share a state border are sufficiently close so as to remain valid comparators. The degrees of freedom is significantly increased for all such estimates while still allowing for local time varying heterogeneity. We present the results of this approach as a robustness check of the minimum wage effect on infant and post-neonatal mortality rates Table 1.10. I find that the state border segment specific time effect estimates produce similar results as my original regressions.

Previous authors have noted that neighboring counties in the western region of the United States that share a state border cover large geographic areas and may not be valid

[6]Note that $V(\hat{\beta}) = \sum_{g=1}^{2}[(X'X)\Omega_g(X'X)^{-1}] - (X'X)\Omega_{1\cap 2}(X'X)^{-1}$ when clustering by 2 dimensions.

local controls (Dube et al., 2010). For example, San Bernardino County, California and Clark County, Nevada are two pairs in our CCP sample that span a large area. These two pairs cover a distance that stretches 30 miles from the Pacific coastline to the Southwest corner of Utah. The inclusion of distant county pairs undermines our estimation strategy of using local controls. In order to address this issue, I estimate Equation 1.3 with a subsample of county pairs in which the centroid distance between them is less than 136.4 kilometers (95^{th} percentile). Figure 1.5 in the appendix illustrates which county pairs remain in our new sample after dropping distant counties. I find that my main estimation results are robust to this distance restriction.

As noted earlier, infant mortality rates are unstable in counties with low annual birth counts. Consequently, county pair time effects will exhibit high variance and produce unrealistic counterfactual for low birth county pairs. I partially solve this problem by transforming the infant mortality rates by its natural log and reducing the apparent skew in Y. Further, I estimate the minimum wage effect after removing from the CCP sample to those counties with total births below the 5^{th} percentile ($<$ 79 births) for a given year.Estimates in this county pair sample are nearly identical to my original CCP sample.

1.6.3 Falsification Test

A review of the minimum wage and health literature has stressed the importance of conducting falsification tests (J. P. Leigh et al., 2018). If statistically significant effects are estimated for groups likely unaffected by minimum wage increases, then there may be unobserved forces outside the statistical model that are generating our results. For example, state legislatures that raise the minimum wage may also increase community health funding directed at prenatal or pediatric care. I therefore construct a falsification test using infant mortality rates among higher educated mothers (greater than high school education). I estimate Equation 1.3 for both county pair time effects and state border segment time effects. As noted earlier, an insignificant relationship between minimum wage increases and infant mortality rates among a likely unaffected group of infants would further validate a causal relationship.

I find no statistically significant relationship between minimum wage increases and infant mortality among higher educated mothers. Estimates of the minimum wage coefficient in my regressions ranged from -.3 to .089 with an average p value of 0.65. These results are reported in Table 1.7. Moreover, I further analyze the impact of the minimum wage level on infant mortality rates on mothers with some college education but without a degree, and mothers with a college degree or greater. The some college group are more comparable to the lower educated mothers in our main analyses. The college degree holding group would be least comparable. Table 1.8 reports these results. No statistically significant negative relationship (at the 5 % level) is found in either of these two analyses. I do not find evidence that the minimum wage effect on infant mortality rates found in our analysis of lower educated mothers is due to unobserved forces.

1.6.4 Accounting for Zeros

Distribution of biomedical and population health data are often highly skewed. Two classical parametric approaches of dealing with such skew have been regularly employed: (1) the use of nonlinear models, and (2) transforming the outcome variable of interest by taking its natural log. Nonlinear models have been a popular approach in the analysis of healthcare expenditures, while log transformation has been widely used in population health studies. Unfortunately, nonlinear models are not ideal in this study due to the inclusion of two sets of fixed effects in my preferred estimation equation. Nonlinear fixed effect models are known to be inconsistent when the time observation of a panel data set is small relative to the cross-sectional unit—the incidental parameter problem (Greene, 2004). However, the approach employed here, the log transformation of infant mortality rates, excludes any zero observations in my regressions. Twenty-four percent of the observations in the CCP sample consisted of a mortality rate of zero. To deal with this issue, I add a positive epsilon term to infant mortality rates before taking the natural log.

$$Y^{\epsilon}_{ipt} = \log(Y_{ipt} + \epsilon) \tag{1.4}$$

The addition of the epsilon term allows county observations where an infant death was not observed in a given year to be included in the regressions. I estimate Equation 1.3 with Y^{ϵ}_{ipt} as the new outcome variable using imputed conception year mortality estimates. I find that when accounting for these zero mortality observations the minimum wage effect on infant and post-neonatal mortality rates are generally negative, but insignificant at the

5 percent level.[7] The insignificant results were not expected given that the mean state inflation and COL adjusted minimum wage levels are higher for these zero infant mortality counties compared to the CCP sample. I also find that the total birth counts for these counties are significantly less than the CCP sample as a whole. A two-part model may be an interesting extension of my current methodology that could provide further insight on this issue.

1.7 Limitations

Several factors warrant caution in the claim that the CCP approach can be considered a reliable method to isolate the causal effect of the minimum wage. First, there exists within county differences in neighborhood structure that is unaccounted for in my analysis. Studies have continuously found significant neighborhood effects on a variety of health outcomes (Diez Roux, 2001; Diez Roux & Mair, 2010; Meijer, Röhl, Bloomfield, & Grittner, 2012; Smith & Waitzman, 1997; Waitzman & Smith, 1998a, 1998b). It is not possible to control for such neighborhood effects with the data utilized in this paper. Furthermore, the CCP sample consists mainly of rural and low population density counties. This fact prevents the collection of a rich set of relevant covariates from publicly available data sets, such as the Integrated Public Use Microdata Series (IPUMS). Even so, this limitation is partially attenuated in the model since we use local control populations. Allegretto et al. (2013) demonstrated that cross-border counties better reduce potential omitted variable bias than noncontiguous pairs in key labor market covariates. Their findings apply to this paper.

The identification of an appropriate measure of poverty is also potential limitation. While the related children in families in poverty rate is arguably a more relevant measure of poverty than the general poverty rate for the minimum wage effect on infant mortality, it is still a source of limitation. Broad measures of poverty that are based on proportions or headcount index does not reflect the degree of poverty experienced by families. Improved estimates could be attained if measurements of the poverty gap or poverty severity among children were available (Muñoz, Álvarez-Verdejo, & García-Fernández, 2018).

[7] Results not reported, but available from the author upon request.

Treatment intensity of the minimum wage is limited by actual variation in policy and local price trends. Generalizability of my findings is thereby limited to the observed minimum wage variation in the study period and may not predict out-of-sample policy changes. Moreover, my estimates are based on an intent-to-treat approach using county residence of mothers on the birth certificate for the minimum wage treatment. It is possible that minimum wage workers will commute across state lines given minimum wage discontinuities between county pairs. This is a major limitation as I do not have data on the employment location of mothers or members of their household. This issue implies that the treatment effect of the minimum wage found in this paper is conservative since workers will only commute for out of state employment for higher minimum wage jobs. However, I cannot rule out cross-state commuting to access healthcare services related to prenatal care.

Another potential limitation of this study is that minimum wage variation due to legislative changes could be correlated with other state level policies that may also impact health. For example, a state legislature that increases the minimum wage may also increase funding for community health programs that will improve infant health outcomes. This problem is limited since such policies are not systematically introduced for all minimum wage legislative changes across states. Moreover, state welfare and tax policies used as model covariates are likely correlated with such omitted policy variables. Finally, about a third of the educational attainment data of mothers was missing in the Linked Birth/Infant Death records. Missing data reduces the reliability of the estimated minimum wage effect by education of mothers. Consequently, my findings that minimum wage increases have an effect on infant mortality rates among all mothers in the AC sample could be driven by improvements in infant survival of lower educated mothers of which education data is missing. The bias due to data quality is dependent on whether it is correlated with either lower or higher minimum wage states. If such correlation exists, then the generalizability of the effect estimates would be reduced.

1.8 Conclusion

A new model was presented in this chapter of the impact of minimum wage increases on infant and post-neonatal mortality rates using a quasi-experimental identification strategy that generalized local case studies for the entire contiguous continental United States. Shortcomings of the traditional approach in the minimum wage and health literature were addressed using pairs of contiguous counties across state borders to isolate a causal effect. Principally, my approach addressed the well-known parallel lines problem by including time varying heterogeneous year effects by county pairs, as well as shared state border segments. To my knowledge, this is the first paper in this literature to do this.

Using the CCP sample estimates, I find that minimum wage discontinuities across state borders and within-state ordinances reduce infant mortality rates among lower educated mothers. This effect was found to be concentrated in the post-neonatal period. My results were shown to be robust to the exclusion of geographically distant county pairs and for a subsample of counties above the 5^{th} percentile of total births per year. I partially solved the degrees of freedom problem previously unaddressed by also using state border segment year effects instead of county pair year effects. A falsification test negated the possibility of unobserved factors producing the results found in my analysis and bolstered the case for a causal relationship. My preferred estimation strategy suggested that the canonical TFE model may be less reliable as compared to my preferred model. However, both approaches indicated that the minimum wage can be applied as a public health policy tool to improve infant health outcomes.

Recent work by Komro et al. (2016), which also studied the minimum wage effect on infant mortality rates, found similar results to this paper. Komro et al. (2016) used state level data and employed the canonical TFE estimator discussed in section 1.5. They reported a 3.6 to 4.9 % reduction in post-neonatal mortality rates per $1 increase in the nominal minimum wage. My study provides further insight on the minimum wage and infant mortality relationship in several ways. I used disaggregated data in my regressions by examining infant mortality rates at the county level instead of state level aggregates. I estimated county infant mortality rates by both birth and imputed conception year to capture minimum wage treatment during the gestational period. I used both real state minimum wage and local COL adjusted minimum wage rather than nominal minimum wage above the federal level in my regressions. Local counterfactual estimates were employed in my identification strategy and several robustness tests were conducted. I also compared the minimum wage effect among lower educated and highly educated mothers in order to rule out unobserved factors driving the results. Moreover, a parallel literature on the impact of EITC on infant health necessitates controlling for this important policy variable in the statistical analysis (Hoynes et al., 2015; Strully, Rehkopf, & Xuan, 2010). I controlled for EITC, as well as, SNAP, and TANF which are also potential policy confounders. My findings and the previous contribution by Komro and colleagues provide evidence that minimum wage increases improve infant survival.

There are several possible extensions to this analysis. Recent increases in the minimum wage at the county and city levels provide an opportunity to reexamine the minimum wage effect using the CCP approach over a broader range of minimum wage treatments within states. Application of the CCP sample estimation strategy may clarify currently unresolved empirical relationships between economic policy variables and population health. Specifically, the opposite signed results in the effect of minimum wage on obesity rates discussed earlier is a promising extension.

Although I have shown robust evidence that higher minimum wage levels, on net, are associates with lower infant mortality rates among lower educated mothers, little is known about the direct causal link. Using the identification strategy employed in this paper to investigate the effect of the minimum wage on birth weight, gestational length, smoking during gestation, prenatal care services, and initiation of prenatal care would provide a better understanding of how minimum wage increases improve infant health.

In this study, I differentiated mothers by level of education to approximate likely affected and unaffected groups. An alternative approach would be to differentiate by age. Specifically, studying the minimum wage effect on infant mortality rates among teenage mothers and compare them to the older female population. I chose not to do this in this study since there is evidence that minimum wage increases are associated with reductions in adolescent fertility rates (Bullinger, 2017). This would potentially bias our results because age of mothers is an outcome variable. Lastly, studying the minimum wage effect on the health status of mothers during gestation may provide additional insight on the precise channel of the minimum wage effect on infant mortality rates.

The debate around the minimum wage and its efficacy on raising household incomes, disemployment effects on less skilled workers, and reducing poverty is still a contentious issue. The evidence I present in this chapter expands the ongoing debate in the literature by providing insight on the noneconomic impact of minimum wage increases. In the following chapter, I analyze possible pathways on maternal healthcare inputs (prenatal care visits, timing of initiation of care) and health behavior (alcohol and tobacco consumption during pregnancy). It is important to note that the detailed identification strategy presented here aimed to isolate the minimum wage effect from other confounding policy changes. For policy makers, however, the minimum wage should not be considered as necessarily a stand-alone policy. The minimum wage was historically part of a broader set of labor market reforms that aim to protect workers from the negative effects of labor markets. It was introduced as part of the Fair Labor Standards Act Of 1938. The Act and its later amendments included other worker protections, such as right to overtime pay, prohibition of minors participating in the labor force, and made discrimination by sex or age illegal. Conceptualizing the minimum wage as part broader set of labor market policies that can improve incomes of low income families and protect vulnerable workers from the labor market should remain the goal of labor market reforms.

Table 1.1: Mother's Characteristics: All County Versus County Pairs

	AC Sample			CCP Sample		
	Mean	Median	Std. Dev	Mean	Median	Std. Dev
No High School	15.0%	15.2%	.120	14.3%	14.3%	.110
High School	25.0%	29.9%	.166	24.9%	28.8%	.159
Greater than High School	26.1%	27.7%	.195	25.9%	26.6%	.185
No Education Data	33.9%	19.5%	.403	34.9%	22.2%	.381
Married	63.1%	64.2%	.126	62.4%	63.7%	.128
Black non-Hispanic	11.7%	2.8%	.177	11.6%	2.6%	.180
Hispanic	11.1%	4.5%	.162	9.35%	4.2%	.134

Table 1.2: Birth Characteristics (1995-2013): All County Versus County Pairs

	AC Sample			CCP Sample		
	Mean	Median	Std. Dev	Mean	Median	Std. Dev
Premature Birth	11.2%	10.8%	.040	11.6%	11.1%	.039
Low Birthweight	8.1%	7.7%	.030	8.3%	8.0%	.027
Very Low Birthweight	1.5%	1.3%	.012	1.6%	1.4%	.011
Male	51.2%	51.2%	.033	51.2%	51.2%	.031

Table 1.3: Level and First Difference of Main Regression Variables

	Level		First Difference	
	Mean	Std. Dev	Mean	Std. Dev
	AC Sample			
Real Effective MW	6.50	.63	.03	.33
MW Earnings to Fair Market Rents	1.79	.34	-.01	.12
Infant Mortality	9.43	10.77	-.26	14.65
Post-neonatal Mortality	4.62	6.01	-.40	15.21
	CCP Sample			
Real Effective MW	6.52	.64	.03	.33
MW Earning to Fair Market Rents	1.75	.35	-.01	.11
Infant Mortality	9.64	8.06	.18	6.62
Post-neonatal Mortality	5.74	6.51	.86	4.62

Table 1.4: Economic Characteristics: All County Versus County Pairs

	AC Sample			CCP Sample		
	Mean	Median	Std. Dev	Mean	Median	Std. Dev
Real Median Income	$44,370	$42,558	11326	$44,423	$42,218	12047
Family Poverty Rate	19.1%	17.9%	.085	18.9%	17.8%	.085
TANF	$1,016	$1,005	150	$1,027	$1,020	164
SNAP	$562	$542	47.9	$561	$541	47.6
Fair Market Rents	$556	$526	176.6	$561	$522	189.4

Table 1.5: Minimum Wage and Infant Mortality

	AC Sample				CCP Sample			
Birth year estimates								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$lnMW_t$	-.121**	-.011			-.135	.004		
	(.049)	(.058)			(.157)	(.225)		
$lnMW_t/Rents_t$			-.075**	-.087**			-.023	-.056
			(.037)	(.039)			(.130)	(.132)
Conception year estimates								
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
$lnMW_t$	-.080*	.087			-.163	-.071		
	(.045)	(.064)			(.132)	(.232)		
$lnMW_t/Rents_t$			-.096**	-.108**			-.155	-.187*
			(.034)	(.037)			(.102)	(.103)
Covariates:								
Income, poverty	N	Y	N	Y	N	Y	N	Y
State policies	N	Y	N	Y	N	Y	N	Y
Time Effects:								
Common time	Y	Y	Y	Y	N	N	N	N
Pair×time	N	N	N	N	Y	Y	Y	Y
Std. Errors								
Cluster-robust	Y	Y	Y	Y	N	N	N	N
Two-way	N	N	N	N	Y	Y	Y	Y
$N_{birth-year}$	40,294	35,102	39,339	35,009	22,800	18,112	20,464	18,098
$N_{conception-year}$	39,249	34,485	38,700	34,398	22,064	17,648	19,926	17,634

Note: $*p < 0.01$; $**p < 0.05$; $\dagger p < 0.001$.

Table 1.6: Minimum Wage and Infant Mortality Among Lower Educated Mothers

	AC Sample				CCP Sample			
Birth year estimates								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$lnMW_t$	-.280**	-.297**			-.564	.112		
	(.099)	(.107)			(.406)	(.570)		
$lnMW_t/Rents_t$			-.332†	-.298†			-.393*	-.402
			(.065)	(.067)			(.225)	(.264)
Conception year estimates								
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
$lnMW_t$	-.129	-.116			.010	-.027		
	(.105)	(.130)			(.384)	(.390)		
$lnMW_t/Rents_t$			-.285†	-.252†			-.326**	-.320*
			(.060)	(.066)			(.158)	(.187)
Covariates:								
Income, poverty	N	Y	N	Y	N	Y	N	Y
State policies	N	Y	N	Y	N	Y	N	Y
2-9 *Time Effects:*								
Common time	Y	Y	Y	Y	N	N	N	N
Pair×time	N	N	N	N	Y	Y	Y	Y
Std. Errors								
Cluster-robust	Y	Y	Y	Y	N	N	N	N
Two-way	N	N	N	N	Y	Y	Y	Y
$N_{birth-year}$	25,060	22,633	26,489	22,571	11,774	9,532	11,516	9,528
$N_{conception-year}$	24,851	22,661	26,471	22,605	11,312	9,182	11,100	9,178

Note: *$p < 0.1$; **$p < 0.05$; †$p < 0.001$.

Table 1.7: Falsification Test: Infant Mortality Rates Among Higher Educated Mothers

	(1)	(2)	(3)	(4)
$lnMW_t$	.089		-.102	
	(.631)		(.604)	
$lnMW_t/Rents_t$		-.146		-.300
		(.390)		(.206)
Time Effects:				
Pair×time	Y	Y	N	N
State border × time	N	N	Y	Y
N	4,600	4,600	11,143	11,129

Note: *$p < 0.1$; **$p < 0.05$; †$p < 0.001$.

Table 1.8: Falsification Test: College Degree and Some College

	Some College		College	
	(1)	(2)	(3)	(4)
$lnMW_t/Rents_t$	.169	.722*	-.224	-.738
	(.382)	(.374)	(.619)	(.718)
Covariates:				
Income, poverty	N	Y	N	Y
State policies	N	Y	N	Y
Time Effects:				
Pair$\times$time $\times$ time	Y	Y	Y	Y
N	4,532	3,716	2,388	2,162

Note: *$p < 0.1$; **$p < 0.05$; †$p < 0.001$.

Table 1.9: Minimum Wage and Post-neonatal Mortality Among Lower Educated Mothers

	AC Sample				CCP Sample			
Birth year estimates								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
2-9 $lnMW_t$	-.264**	-.333**			-.837*	-.171		
	(.105)	(.116)			(.444)	(.680)		
$lnMW_t/Rents_t$			-.372†	-.355†			-.525**	-.606**
			(.074)	(.073)			(.231)	(.238)
Conception year estimates								
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
2-9 $lnMW_t$	-.177*	-.255*			-.321	-.413		
	(.107)	(.133)			(.445)	(.539)		
$lnMW_t/Rents_t$			-.341†	-.343†			-.646**	-.559**
			(.064)	(.071)			(.212)	(.256)
Covariates:								
Income, poverty	N	Y	N	Y	N	Y	N	Y
State policies	N	Y	N	Y	N	Y	N	Y
2-9 *Time Effects:*								
Common time	Y	Y	Y	Y	N	N	N	N
Pair×time	N	N	N	N	Y	Y	Y	Y
2-9 *Std. Errors*								
Cluster-robust	Y	Y	Y	Y	N	N	N	N
Two-way	N	N	N	N	Y	Y	Y	Y
$N_{birth-year}$	19,663	17,718	20,834	17,684	7,672	6,124	7,502	6,120
$N_{conception-year}$	18,836	17,121	20,237	17,090	7,142	5,758	7,038	5,754

Note: $^{**}p < 0.1$; $^{**}p < 0.05$; $\dagger p < 0.001$.

Table 1.10: Robustness Check Using 108 State Border Year Effects

	All Mothers		Lower Educated Mothers	
Infant Mortality				
	(1)	(2)	(3)	(4)
$lnMW_t$	.066		-.209	
	(.215)		(.461)	
$lnMW_t/Rents_t$		-.160*		-.284**
		(.090)		(.126)
N	25,522	25,490	16,895	16,871
Post-neonatal Mortality				
	(5)	(6)	(7)	(8)
$lnMW_t$	-.513**		-.306	
	(.221)		(.582)	
$lnMW_t/Rents_t$		-.266**		-.415**
		(.099)		(.160)
N	18,286	18,258	12,882	12,860

Note: $^{**}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.001$.

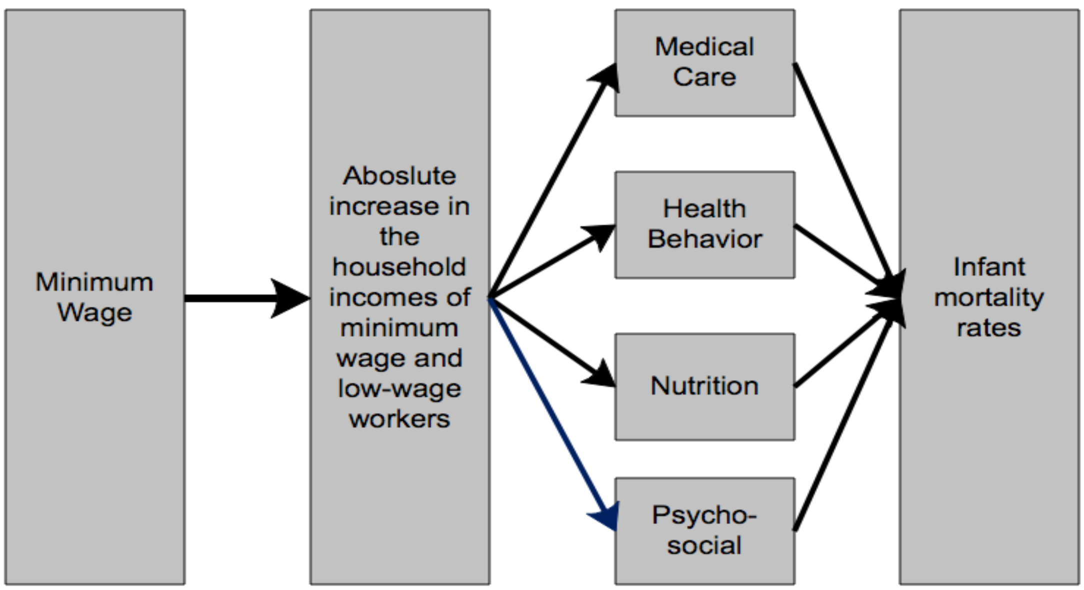

Figure 1.1: Diagram of the Minimum Wage Effect on Infant Mortality

Figure 1.2: Real Effective Minimum Wage (2009 State Specific Dollars): 1997 - 2013

Figure 1.3: Nominal Minimum Wage Earnings to County Fair Market Rents: 1995 - 2013

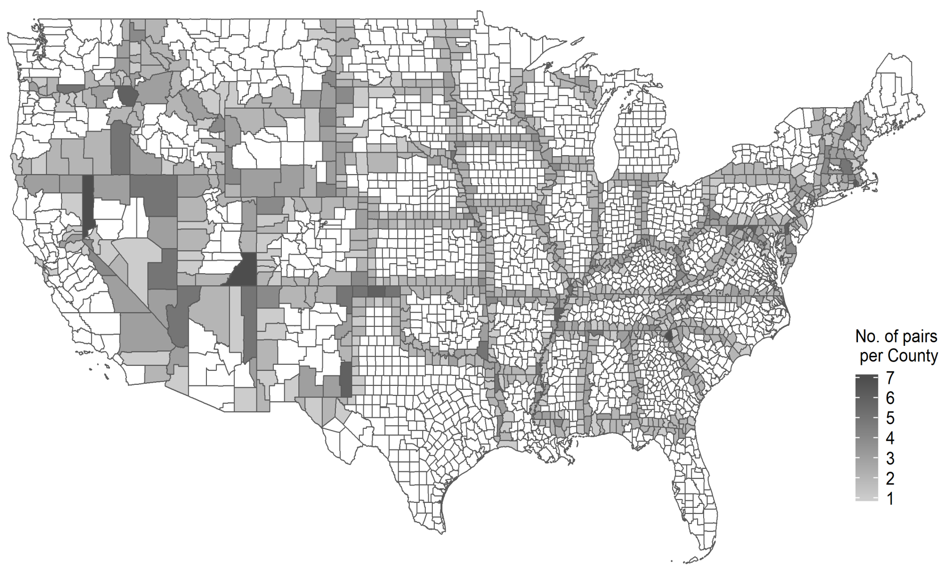

Figure 1.4: Map of CCP Sample With Total Number of Pairs Per County

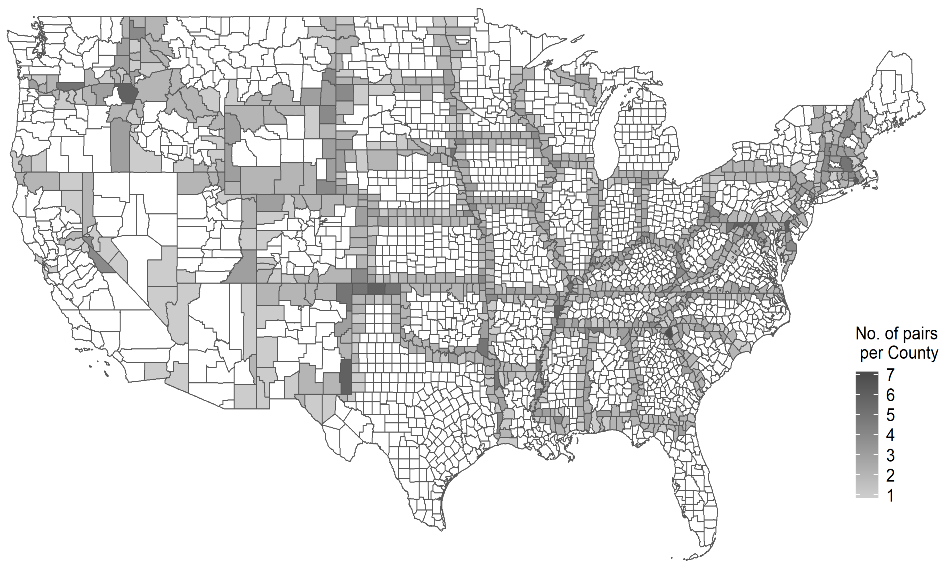

Figure 1.5: Map of 95^{th} Percentile CCP Sample by Centroid Distance ($<$ 136.4 km.)

CHAPTER 2

HOW DOES THE MINIMUM WAGE IMPROVE INFANT HEALTH?

2.1 Introduction

The impact of minimum wage increases on infant and post-neonatal mortality rates among lower educated mothers using a spatial identification strategy (regression discontinuity design/contiguous counties) was established in the preceding chapter. Similarly, detailed analysis of other infant birth outcomes, such as birth weight and gestational length among lower educated mothers have been shown by Wehby et al. (2016). Wehby et al. (2016) employed quasi-experimental methods, mainly triple-differences approach, to study the relationship between minimum wages and infant health. Imputed conception year estimates were also used in their analysis to serve as a better timing of minimum wage treatment effects. Thus, there is emerging evidence to suggest that minimum wage policies and infant health are linked, though little is known about the actual pathway of this linkage.

In this chapter, I study the relationship between local cost-of-living adjusted minimum wages based on fair market rents on a set of maternal healthcare inputs and measures of adverse health behavior at the county level among less educated mothers. The goal is to illuminate possible pathways between minimum wage policies and infant health outcomes. The empirical strategy employed provides evidence in support of a plausible channel mediating the minimum wage effect. I do not estimate the effect of maternal inputs and health behavior during pregnancy on infant mortality. Rather, the aim of this chapter is to examine whether minimum wages, controlling for confounding state policy variables and maternal characteristics at the county level, is associated with improvements in maternal healthcare utilization and reductions in adverse health behavior during pregnancy that have been prior linked to infant health.

Specifically, I study the timing and total number of prenatal visits, the utilization of prenatal care services in general, the average weekly alcohol beverage consumption during pregnancy, and average tobacco use (cigarettes per day) during pregnancy. These outcomes will be studied within multiple subpopulations and age groups. The main limitation of the data set used in this chapter is that we will not be able to empirically test the psychosocial dimensions of the minimum wage treatment effect on pregnant mothers, which is a significant source of variations in birth outcomes (Hobel, Goldstein, & Barrett, 2008). The results of this chapter contribute new insights to the minimum wage and infant health literature with respect to potential mechanisms.

This chapter proceeds as follows: Section 2.2 discusses the maternal healthcare services and health behaviors studied and their connection to infant health outcomes. Section 2.3 describes the data sets and my main regression variables. I then outline my empirical strategy in Section 2.4. Section 2.5 reports the results. Finally, Section 2.6 concludes with a summary and limitation of our analysis.

2.2 Pathways

A broad set of possible pathways between income and health was discussed in Section 1.2 of Chapter 1 and presented in Figure 1.1. In this section, I highlight two particular pathways of which I will directly test for a statistical relationship with local minimum wage levels. These include the timing, intensity and utilization of prenatal care services, along with adverse health behavior during pregnancy, such as tobacco and alcohol consumption.

2.2.1 Prenatal Care

Inadequate prenatal care utilization is associated with higher risk of premature birth and infant death (Alexander & Kotelchuck, 2001; Partridge et al., 2012). While the effectiveness of prenatal care continues to be debated, it is widely recognized that early and adequate access to prenatal care is an important public policy goal and continues to be a source of healthcare disparity among pregnant women in the United States (Alexander &

Kotelchuck, 2001; Healy et al., 2006). Moreover, prenatal care in group settings has been shown to improve perinatal outcomes, suggesting important social considerations of the provision of prenatal care services in improving infant health (Ickovics et al., 2007). Racial disparities in the timing of prenatal care initiation has remained a facet of the United States healthcare system, and younger mothers are more likely than their older counterparts to delay prenatal care during the first trimester (Alexander, Kogan, & Nabukera, 2002; Hueston, Geesey, & Diaz, 2008). While our previous empirical analyses have focused on educational attainment of mothers, it is crucial that the estimation of the minimum wage effect on prenatal care utilization patterns focus on racial, ethnic, and younger age subgroups.

I hypothesize that higher minimum wages will be positively associated with average total prenatal care visits and negatively associated with timing of prenatal care initiation. This hypothesis is bolstered in part by Mocan et al. (2015), where the relationship between mother's weekly earnings were associated with increased prenatal care visits and reduced average delay in initiating prenatal care. Since minimum wage increases are an absolute income increase for less educated working families, the mechanism should apply here. If higher minimum wages is found to be associated with early initiation of prenatal care, then it is expected that increased utilization of care should also be associate with the minimum wage. A contrary finding would weaken the plausibility of the results of the empirical strategy. To my knowledge, no previous study has specifically tested the minimum wage and prenatal care relationship.

2.2.2 Alcohol and Tobacco

The connection between minimum wage increases and adverse health behavior has been studied and negative consequences of minimum wage increases was discussed in Chapter 1 within this context. Hoke and Cotti (2016) have shown that increases in the minimum wage is associated with increased alcohol consumption among teenagers. Similarly, Adams et al. (2012) concluded that increases in the minimum wage raises the incidence of alcohol related traffic accidents among younger adults. However, it is not clear that alcohol consumption increase during pregnancy when minimum wages are increased. The National Task Force on Fetal Alcohol Syndrome and Fetal Alcohol Effect promote public awareness of fetal alcohol syndrome (FAS) and risks of alcohol consumption on newborns through published recommendations and reports. Nevertheless, prevalence of FAS remain relatively high in the United States (0.5-2.0 cases per 1000 births), varying significantly cross-nationally and among different racial and ethnic background of mothers (Bhuvaneswar, Chang, Epstein, & Stern, 2007; Popova, Lange, Probst, Gmel, & Rehm, 2017).

Unlike alcohol consumption, little is known on the potential relationship between minimum wages and tobacco use during pregnancy. **?** analysis of the Earned Income Tax Credit (EITC) reported that improvements in infant health was mediated by reductions in smoking during pregnancy. A similar relationship may exist between the minimum wage and tobacco use during pregnancy. However, a study by Matone, O'Reilly, Luan, Localio, and Rubin (2012) found that existing prevalence of smoking in a community is the main predictor of the probability of women smoking during pregnancy than targeted interventions—their results may extend to a limited impact of marginal tax and wage policies. Although contributions by **?** indicate an expected decrease in smoking during pregnancy, the standard Grossman model allows for minimum wage increases to have an adverse effect on smoking patterns among pregnant women (**?**). In contrast, given that wage increases raise the cost of future health depreciation and the opportunity cost of future income loss due to caring for a sick infant, the Grossman model also predicts the opposite relationship. It is therefore unclear what direction the minimum wage should have on smoking during pregnancy, and a hypothesis is not established in this chapter.

Though psychosocial factors, access to adequate nutrition, and other significant social determinants of infant health are not directly studied in this chapter, I do not ignore their relevance (Apter-Levy et al., 2013; Buchbinder et al., 2002; Cook et al., 2013; Dowd, 2007; Hobel et al., 2008) If I find no relationship between minimum wages and the above mentioned maternal healthcare inputs and consumption behaviors, then it implies that higher local minimum wages reduce infant mortality rates among lower educated mothers solely through nonhealthcare and adverse health consumption pathways. If a relationship is established using the outcome variables available for my analysis, psychosocial factors mediating the minimum wage and infant health relationship are still not ruled out. On this issue, I refer the readers to the last sentence of Ludwig Wittgenstein's 1922 treatise, *Tractatus Logico-Philosophicus*: "Whereof one cannot speak, thereof one must be silent."

2.3 Data Sources

I utilize much of the same data sets as the prior chapter with a few important additions in the covariates. Similarly, all variables are aggregated at the county level, but partitioned by subsample populations per regression. The outcome variables of interests are collected from the denominator files of the Linked Birth/Infant Death Records from the National Center for Health Statistics' (NCHS). The data set contains birth and death records occurring within the United States to residents and nonresidents.

2.3.1 Data Description

I estimate county average prenatal care timing, intensity, and utilization of prenatal care services, and tobacco and alcohol consumption using the Denominator files of the NCHS's Linked Birth/Infant Death Records. I use an intent-to-treat approach using the mother's county of residence reported on the birth certificate to determine the local minimum wage and rent index. Total prenatal visits, the month prenatal care was initiated, and whether the prenatal care services were utilized during pregnancy were collected and averaged for each county by imputed conception year using date of birth and gestational age of the infant. The average number of cigarettes per day and average number of alcoholic beverages consumed during pregnancy were also estimated for each county using imputed conception year. I use imputed conception year to to be consistent with the methodology employed in the preceding chapter and because it represents a more accurate timing of minimum wage treatment. It is important to note that the quality and content of prenatal care is not observed in the data set.

Given the expectation that minimum wage treatment effects impact lower income families, my analysis in this chapter is restricted to mothers with no more than a high school education or equivalent. This led to the collection of data from 28,689,585 birth records from 1995 to 2013. However, I used all my covariates (described below) in my regression estimates which restricts the observation years to 1997 through 2013. In addition, there are important differences in the utilization of healthcare services and behavior by education level, race, age, and ethnicity. I conduct my analysis on 15 separate within-county population samples to account for possible heterogeneity in the minimum wage effect. The data was differentiated by whether the mother has a high school education or lower at the time of birth, did not have a high school education, young ($\leq$ 24 years), adolescent ($\leq$ 19 years), Black, and Hispanic. All combinations of these indicators were analyzed (e.g., young Hispanic mother without a high school education).

As noted in the preceding chapter, the years studied exhibits relatively stable fertility rates in the general female population compared to downward secular trends prior to 1995 and more recent changes to the age composition of new mothers (Livingston, 2018; Ventura et al., 2001; Whelpton et al., 2015). This reduces potentially confounding effects of fertility changes in my analysis. In addition, my sample does not include years with potentially significant policy introductions such as the expansion of Medicaid in 2014, or the years prior to the passing of the Children's Health Insurance Program.[1]

Annual state and federal minimum wages for nonfarm employment were collected from the US Department of Labor's Wage and Hour Division (WHD) from 1995 to 2013. Data on San Francisco County minimum wage ordinance was collected from the San Francisco Office of Labor Standards and Enforcement (LSE). I define the effective minimum wage as the higher of the state and federal minimum wage level observed at the beginning of the calendar year. State annual inflation data was collected from the US Bureau of Economic Analysis (BEA) for years 1997 to 2013. Cost-of-living (COL) adjusted minimum wage at the county level will vary over time based on changes to median rent prices. I used estimated county level changes in rent prices from the US Department of Housing and Urban Development's (HUD) annual estimates of Fair Market Rents, which is used by the agency to determine benefits under the Housing Choice Voucher Program (commonly known as Section 8). HUD data was used to calculate the ratio of full-time nominal minimum wage earnings per month before taxes to fair market rents. I only study the effect of the full time minimum wage earnings to fair market rents since this adjusted measure was found to be the relevant measure for the infant health effect.

Covariates in my statistical analysis included income, poverty, state welfare and tax

[1]The State Children's Health Insurance Program was enacted in August of 1997 and took affect on September of 1997.

policies, marital status, average age, and prevalence of prepregnancy diabetes to control for underlying factors that influence prenatal care and adverse health behavior. The latter variables relating to mother's characteristics were calculated for each of the 15 subsamples except for average age in the adolescent and young mothers subsamples (see next section for details). County level data on median household income and percent of related children in families in poverty was collected from the US Census Bureau Small Area Income and Poverty Estimates (SAIPE). I adjusted median household income to 2009 state dollars. State level welfare and tax policies include, the Supplemental Nutrition Assistance Program (SNAP), Temporary Assistance for Needy Families (TANF), and the Earned Income Tax Credit (EITC) from the University of Kentucky's Center for Poverty Research (UKCPR) National Welfare Data. SNAP and TANF are measured using maximum benefits for a family of four and adjusted for 2009 state dollars. EITC is measured using both benefits and whether the credit is refundable. Table 1.4 in Chapter 1 summarized the state and county level socioeconomic variables.

2.4 Empirical Strategy

The same estimation method as described in the previous chapter that allows for local time varying heterogeneity via a regression discontinuity design where treatment is determined by state boundaries instead of a threshold predictor variable was adopted here. It addresses issues of local time varying heterogeneity and spatial correlation. The Spatial Regression Discontinuity design (SRD) is applied to a subsample of US counties that are contiguous to a state border and use neighboring counties in the opposing state with a lower minimum wage as local control populations. However, it was outlined that although this methodology was a preferred empirical strategy over traditional approaches, the SRD approach imposes a large set of parameter constraints on our estimation equations. I noted that the degrees of freedom is dramatically reduced by $\frac{N}{2}$. I remedied this restriction on the estimation by replacing ζ_{pt} in Equation 1.3 with state border segment year effects. It was argued that the proximity of counties that share a state border are sufficiently close so as to remain valid controls. Thus, degrees of freedom in the regressions were significantly increased while allowing for local time varying heterogeneity in the models. Moreover, the results in Table 1.10 were similar to results from using Equation 1.3 type estimates. I adopt the following regression specification for all of the maternal input and health behavior variables studied in this chapter based on the multiple subpopulation:

$$Y^s_{ipt} = \beta \log(MW_{it}) + \delta_i + \zeta_{bt} + X_{it}\Lambda + X^s_{it}K_2 + \varepsilon_{it} \tag{2.1}$$

Y^s_{ipt} are the maternal inputs or health behaviors measured for county i at time t in county pair p for subsample s. δ_i are county fixed effects that capture unobserved county level characteristics that are consistent over time among each s. X_{it} is a matrix of time varying county characteristics and relevant state policy variables. X^s_{it} is a matrix of time varying average subsample maternal characteristics for each county i. State border segment year effects, ζ_{bt} capture unobserved changes among contiguous counties on a shared state border line that vary over time. ε_{it} is the disturbance term. The identifying assumptions and limitations of 2.1 was outlined in the preceding chapter, as well as a detailed discussion of the need for multiway clustering of standard errors. Such details apply to the above model.

The empirical strategy is conducted in a two-step manner. I first regress the prenatal care utilization variables and the tobacco and alcohol consumption averages per county by imputed conception year for all mothers with a high school degree or less on the log of full-time minimum wage earnings to county fair market rents (COL adjusted) in Equation 2.1 while controlling for the full set of socioeconomic, policy, and maternal characteristics. When a statistically significant relationship is found, then I proceed to estimate the same model for the rest of the 14 subsample measures. Given the large amount of regressions performed, I only report the results where a statistically significant minimum wage treatment effect (at the 5 % level) is determined. I do not differentiate education levels for adolescent mothers in estimating Equation 2.1 for obvious reasons, but do differentiate adolescent mothers by race and ethnicity. For purposes of evaluating the plausibility of the minimum wage effect, I report semielasticities, standardized coefficients, and the predicted change in the outcome variable of interest by one standard deviation of the minimum wage.

The two-step approach employed in the empirical strategy addresses potential issues of false discovery given that multiple hypothesis tests are run simultaneously (significance level less than 5 %). This is often referred to as multiple comparisons, or the multiple testing problem. The issue is addressed here by only proceeding to further analysis of the various subgroup minimum wage effects, if and only if, the first estimation returns a statistically significant relationship.

2.5 Results

Table 2.1 reports the individual mean and standard deviations of the prenatal care utilization variables, and tobacco and alcohol consumption by mother's race and ethnicity and then separated by education level ($\leq$ high school , $<$ high school). While mean estimates of prenatal care services do not vary widely by race and ethnicity, there is a dramatic difference by education level. Tobacco use is lower among Blacks and Hispanics compared with all mothers, and is dramatically higher for mother's without a high school education. The average number of alcoholic beverages consumed in a week is quite low among all mothers with a high school degree or lower, while mother's without a high school education consume more alcohol on average. These startling differences by whether a high school education was attained supports my empirical strategy of subsample analysis outlined in the previous section.

My first round of regression analysis found that neither smoking nor alcohol consumption of during pregnancy were associated with COL adjusted minimum wages. In contrast, all three prenatal care variables were found to be associated with the minimum wage and statistically significant at the 5 % level or lower. Table 2.2 reports the results for average total number of prenatal visits per county by various subsamples. I find that a one standard deviation increase in the minimum wage is associated with an 11.8 % increase in the standard deviation of average total number of prenatal visits, which translates into .22 more visits. This impact varies by age and ethnicity, but all coefficients indicate a modest relationship.

While I did not find that all subsample estimates were statistically significant at the 5 % level in Table 2.2, the relationship between the minimum wage and the timing of prenatal care initiation in Table 2.3 shows that nearly all of my subsample estimates are statistically significant. I find that a one standard deviation increase in the minimum wage is associated with an 11.6 to 33.8 % decrease in one standard deviation of the timing of prenatal care initiation. The one standard deviation change in the minimum wage thus has the effect of earlier prenatal care initiation by as much as a quarter of a month (approximately 1 week). Similar to the results in Table 2.2, these are very modest effect estimates. Table 2.4 reports the results of whether prenatal care was utilized as a proportion of mothers in a county, and I find similar modest and statistically significant effect of the minimum wage. A one standard deviation change in the COL adjusted minimum wage is associates with 1 to 1.4 % increase in prenatal care use.

The absence of statistically significant relationship between the minimum wage and adverse health behavior is surprising in light of the positive findings on prenatal care. Increased utilization of prenatal care should lead to higher likelihood of in-office interventions by physicians to reduce substance use, for example, tobacco and alcohol (Bailey & Sokol, 2008). One possible explanation of this statistical result is that substance use is more likely to occur before women are aware of pregnancy and prenatal care would then play a protective role on the impact of substance use on perinatal outcomes (El-Mohandes et al., 2003).

There are additional empirical advantages, as well as disadvantages with regard to the power in tests of significance for the results reported in this chapter. Unlike infant mortality, which is a relatively rare event, prenatal care variables and adverse health behavior are measured for all counties and are not log transformed. This means that the maximum variation in the outcome variable is included for each regression. Higher sample size increases the strength of evidence in the statistical tests of the positive prenatal care and minimum wage relationship. However, with respect to mean values, there is larger relative variation (standard deviation > mean) in the adverse health behavior variables than the prenatal care variables. Greater variation means that there is more noise in the outcome variable and this empirical characteristic of the data can potentially drown out the treatment effect of higher minimum wage levels. Therefore, lower power of the test could be a reason why no statistically significant relationship was established and be an additional explanation for why the results are contrary to the prenatal care and substance use literature.

2.6 Conclusion

In this chapter, I tested the hypothesis that the minimum wage would improve prenatal healthcare utilization among lower educated mothers within different subsamples. The hypothesis was confirmed. No effect was found between the minimum wage and adverse health behavior like tobacco and alcohol use. My empirical strategy followed closely what was learned about credible and efficient estimations of the minimum wage effect in Chapter 1. I addressed the shortcoming of Chapter 1 by not just differentiated by education level, but also by age, race, and ethnicity. However, all the effect estimates where found to be quite modest.

While my findings agree with Mocan et al. (2015) and confirm the predictions of the Grossman (1972) model on increased utilization for healthcare services, the other theoretical pathways were not studied. Psychosocial factors and other social determinants of health (by implication of the current results) may play a large role than the healthcare and adverse health behavior pathway for the specific case of maternal and infant health.

As prior mentioned, recent increases in the minimum wage at the county and city levels provide an opportunity to reexamine the minimum wage effect using the CCP approach over a broader range of minimum wage treatments within states. Application of the CCP sample estimation strategy may clarify currently unresolved empirical relationships between economic policy variables and population health.

The evidence I presented in this chapter facilitates further research in the causal pathway from minimum wage increases and infant health. It supports recent contributions by Wehby et al. (2016) and previous estimates of the minimum wage and infant mortality relationship by Komro et al. (2016). In the following chapter, I provide a more theoretical treatment of the social determinants of health literature by by proposing a new choice-theoretic channel mediating the impact of minimum wage and income policies on population health, with evidence to support the main assumption used in my model.

Table 2.1: Summary Statistics of Maternal Inputs by Education, Race, and Ethnicity

	Mean		Std. Dev.	
	≤HS	<HS	≤HS	<HS
Prenat Visits				
All	10.79	3.20	4.22	1.86
Black	10.05	3.31	4.58	1.97
Hispanic	10.47	3.20	4.15	1.87
Prenatal Initiation Month				
All	3.02	3.30	1.68	1.80
Black	3.24	3.48	1.79	1.87
Hispanic	3.16	3.31	1.75	1.81
Tobacco				
All	1.95	2.30	5.27	5.72
Black	0.92	1.23	3.44	3.97
Hispanic	0.34	0.34	2.20	2.18
Alcohol				
All	0.028	0.035	0.677	0.789
Black	0.052	0.073	0.890	1.077
Hispanic	0.012	0.013	0.408	0.433

Table 2.2: The Minimum Wage Impact on Prenatal Care Visits: Using Conception Year Estimates

	Semi-elasticity	Std. Err.	Std. Coef.	Std. Prediction
≤High School (HS)	0.986†	(0.280)	0.118	0.215
<HS	0.813*	(0.319)	0.085	0.177
Adolescent Mothers ≤HS	.708*	(0.291)	0.076	0.153
Young (Y) Mothers ≤HS	0.958†	(0.270)	0.111	0.208
Y Mothers ≤HS	0.883**	(0.269)	0.111	0.191
YHispanic Mothers ≤HS	0.707*	(0.291)	0.101	0.159

Note: $^{**}p < 0.1$; $^{**}p < 0.05$; $\dagger p < 0.001$.

Table 2.3: The Minimum Wage Impact on Month of Prenatal Care Initiation: Using Conception Year Estimates

	Semi-elasticity	Std. Err.	Std. Coef.	Std. Prediction
≤High School (HS)	-1.046†	(.0121)	-0.332	-0.228
<HS	-1.109†	(0.143)	-0.296	-0.204
Black	-0.801†	(0.212)	-0.167	-0.189
Hispanic	-0.878†	(0.178)	-0.180	-0.196
Black <HS	-0.586**	(0.212)	-0.116	-0.139
Hispanic <HS	-0.966†	(0.225)	-0.181	-0.217
Adolescent (A) ≤HS	-0.953†	(0.139)	-0.265	-0.206
Young (Y) ≤HS	-1.082†	(0.14)	-0.338	-0.235
Y <HS	-1.116†	(0.157)	-0.292	-0.240
Y Black ≤HS	-0.773†	(0.204)	-0.161	-0.182
Y Black <HS	-0.493*	(0.231)	-0.097	-0.117
A Hispanic ≤HS	-0.964†	(0.280)	-0.168	-0.221
Y Hispanic ≤HS	-0.863†	(0.215)	-0.164	-0.193
Y Hispanic <HS	-1.135†	(0.270)	-0.200	-0.258

Note: **$p < 0.1$; **$p < 0.05$; †$p < 0.001$.

Table 2.4: The Minimum Wage Impact on Prenatal Utilization: Using Conception Year Estimates

	Semi-elasticity	Std. Err.	Std. Coef.	Std. Prediction
≤High School (HS)	0.0580**	(0.0189)	0.1756	0.0127
<HS	0.0626**	(0.0204)	0.1773	0.0137
Hispanic	0.0524*	(0.0230)	0.1203	0.0117
Young (Y) ≤HS	0.0504**	(0.0191)	0.1592	0.0110
Y <HS	0.0463*	(0.0201)	0.1339	0.0101
Adolescent Hispanic ≤HS	0.0600*	(0.0279)	0.1260	0.0138
Y Hispanic ≤HS	0.0473*	(0.0234)	0.1032	0.0106

Note: $^{**}p < 0.1$; $^{**}p < 0.05$; $\dagger p < 0.001$.

CHAPTER 3

THE IMPACT OF INCOME ON SUBJECTIVE LIFE EXPECTANCY

3.1 Introduction

A large volume of literature links social and economic factors with mortality and life expectancy. This chapter examines to what extent these socioeconomic factors, specifically income, impact subjective life expectancy (SLE) measured as an individual's belief in surviving to a certain age. SLE has been extensively studied, but has so far primarily focused on savings and retirement decisions (Bae, Kim, & Lee, 2017; Distante, 2013; Mirowsky & Ross, 2000; Ross & Mirowsky, 2002). Little is known about the role SLE plays in the demand for health. I first develop a model to describe how SLE can play an important role in linking wage increases to favorable health behavior by making future time costs of adverse health events binding. Endogenous formation of SLE over time with respect to availability of information is not considered. The model is based on the familiar Grossman (1972) demand for health model discussed extensively in the previous two chapters and its later variants (Bolin et al., 2001; Galama & Van Kippersluis, 2018; Grossman, 2017; Jacobson, 2000). I then estimate a heterogeneous choice proportional odds model, as well as a generalized ordered logistic model using previously unexplored data within the SLE literature from the Federal Reserve's 2013 Survey of Household Economics and Decisionmaking (SHED). The main finding is that income and higher education is positively associated with SLE. I also find that periods of unemployment, disability, divorce, negative life event associated with the great recession were negatively associated with SLE. The chapter contributes to the health disparities literature by providing evidence in support of a new channel connecting socioeconomic factors and health outcomes with a theoretical explanation of this channel. The chapter aims to provide additional insight to the relationship between minimum wage increases (or income policies in general) with health outcomes.

Previous contributions in the choice-theoretic modeling of health have studied income effects on curative care, leisure substitution, opportunity costs of sick days, but have not explicitly studied the income and SLE relationship. Studying the SLE dimensions are important for a number of factors. First, evidence exist that linkes SLE with actuarial life expectancy (Mirowsky, 1999; Reid et al., 2006; Siegel, Bradley, & Kasl, 2003). Also, SLE and retirement decisions have been extensively studied and it is understood that SLE plays an significant role in future economic planning (Bloom, Canning, Moore, & Song, 2006; Hurd & McGarry, 1995; Hurd, Smith, & Zissimopoulos, 2004; Van Solinge & Henkens, 2009). Moreover, association between SLE and healthy behavior (e.g., smoking, exercise, and alcohol consumption), psychological stress, happiness and socioeconomic status have been observed (Bae et al., 2017; Mihalopoulos, Chen, Iezzi, Khan, & Richardson, 2014; Wolinsky et al., 2008). The extensive empirical literature on SLE implies that it is a nontrivial factor within economic decision making. The lack of attention within the choice-theoretic literature on SLE is therefore surprising.

One possible explanation of the lack of theoretical treatment of SLE may be due to the difficulty in incorporating SLE in a dynamic optimization model in a non ad hoc manner. SLE is the belief of a decision maker on the terminal date of the optimal control problem and therefore it is unclear how to incorporate SLE in within-cycle dynamics. Hamermesh (1984) was the first to examine the effect of a more distant terminal date on consumption and retirement decisions. Hamermesh (1984) showed that a more distant time horizon in a standard consumption/leisure utility model led to lower consumption levels as people age in order to enjoy greater leisure time in the future. In this chapter, I provide a more detailed theoretical analysis with an explicit solution for how changes in the terminal date impacts demand for health. To my knowledge, no other study has examined this topic.

The chapter proceeds as follows: Section 3.2 describes the basic assumptions of the choice-theoretic model, including the equations of motion and income and time constraints. Section 3.3 presents the optimal control problem, the boundary conditions for the problem, solves the first order conditions, and provides the explicit solutions for determining the optimal time path of investment in health status along with intuition for the results. Then in Section 3.3.1, I incorporate exogenous wage changes within the model. I then argue in Section 3.4 how the model can be used to incorporate SLE. I then outline my statistical methods in Section 3.6. Section 3.7 reports the results. Finally, Section 3.8 concludes with a summary of the main findings.

3.2 Theoretical Model

In this section I present a dynamic model of health investment or demand for healthcare following Case and Deaton (2005); Grossman (1972); Muurinen (1982). I first provide the basic assumptions for the model along with equations of motion for the decision makers assets, health stock, as well as time and income constraint equations.

3.2.1 Assumptions

In the model, it is assumed that individuals derive utility in each period, U_t from contemporaneous level of health, H_t and consumption of nonmedical commodities, C_t such that $\frac{\partial U_t}{\partial H_t} > 0$, $\frac{\partial^2 U_t}{\partial H_t^2} < 0$, $\frac{\partial U_t}{\partial C_t} > 0$, and $\frac{\partial^2 U_t}{\partial C_t^2} < 0$. Health is defined as a capital good that appreciates with investment in health, I_t via the purchase of medical care goods and services, M_t and time spent resting, $T_{t,H}$ such that

$$I_t = I(M_t, T_{t,H}) \tag{3.1}$$

where the health investment function is assumed to be concave in both M_t and $T_{t,h}$ for all t. For simplicity, we assume that time spent resting is only valuable in so far as it improves health and not a source of utility itself. Individuals are endowed with an initial stock of health, H_0 but this initial health stock depreciates over time by a time invariant biological aging factor, $\delta \in (0, 1)$. Absent any investment in health, individuals remain alive so long as $H_0 - \sum_{t_0}^{\mathcal{T}} \delta_t H_t \geq H_{min}$, where H_{min} is a nonnegative minimum health level needed to sustain life. The evolution of an individual's health state can thus be described by the following differential equation:

$$\dot{H}_t = I_t(M_t, T_{t,H}) - \delta H_t \tag{3.2}$$

The equation of motion for assets, W_t is given by

$$\dot{W}_t = rW_t + \omega_t(H_t, E_t)T_{t,l} - P_{t,m}M_t - P_{t,c}C_t \tag{3.3}$$

where r is the return on assets, ω_t is the endogenous wage rate as a function of health and education, E_t with $\frac{\partial \omega_t}{\partial H_t} > 0, \frac{\partial^2 \omega_t}{\partial {H_t}^2} < 0$ and $P_{t,m}$ and $P_{t,c}$ are prices of medical and consumption commodities, respectively.

Time is allocated to three activities: time spent working in the labor market ($T_{t,l}$), time spent resting ($T_{t,H}$) to promote health, and time spent outside the labor market due to illness or sick time. Any residual time is equivalent to $T_{t,H}$. Following Galama and Van Kippersluis (2018), we introduce sick time as a function of an individual's health status, $S_t(H_t)$ where $\frac{\partial S_t}{\partial H_t} < 0$. Letting Ω be the total time available to the individual we arrive at the following time constraint:

$$\Omega = T_{t,l} + T_{t,h} + S_t(H_t) \tag{3.4}$$

Total income, Y_t is then given by the wage rate and time spent in the labor market.

$$Y_t = \omega_t(H_t, E_t)\Big[\Omega - T_{t,h} - S_t(H_t)\Big] \tag{3.5}$$

Notice that a low level of health has an associated opportunity cost for the decision maker, which is equal to the lost income streams due to $S_t(H_t)$.

3.3 Individual's Optimization Problem

The individual's optimization problem in this framework is to determine the optimal time paths of M_t, $T_{t,h}$, and C_t by maximizing the present discounted value of their lifetime utility function, $U(H_t, C_t)$ with an exogenous discount factor, ρ . The dynamic maximization problem can be stated as follows:

$$\begin{aligned}
\max_{U \in \mathcal{R}} \quad & \int_{t_o}^{\mathcal{T}} e^{-\rho t} U_t(H_t, C_t) \\
\text{subject to} \quad & \dot{H}_t = I_t - \delta H_t \\
& \dot{W}_t = rW_t + \omega_t(H_t, E_t)T_{t,l} - P_{t,m}M_t - P_{t,c}C_t \\
& \Omega = T_{t,l} + T_{t,h} + S_t(H_t)
\end{aligned} \tag{3.6}$$

with boundary conditions:

$$H_t(0) = H_0, \; W_t(0) = W_0 \tag{3.7}$$

$$H(\mathcal{T}) = H_{\mathcal{T}} \geq H_{min} \tag{3.8}$$

$$W(\mathcal{T}) = W_{\mathcal{T}} \geq 0 \tag{3.9}$$

$$M_t, T_{t,h}, C_t \geq 0,\ t = 1, \ldots, \mathcal{T} \tag{3.10}$$

The current value Hamiltonian for the above problem is

$$\begin{aligned} \mathcal{H}_c &= U(H_t, C_t) + \lambda_{t,H}(I_t - \delta H_t) \\ &+ \lambda_{t,W}(rW_t + \omega_t(H_t)T_{t,l} - P_{t,m}M_t - P_{t,c}C_t) \end{aligned} \tag{3.11}$$

and the Lagrangian is given by

$$\mathcal{L} = \mathcal{H}_c + \theta_t[\Omega - T_{t,l} - T_{t,H} - S_t(H_t)] \tag{3.12}$$

The first order conditions (FOC) for an interior solution are:

$$\frac{\partial \mathcal{L}}{\partial M_t} = \lambda_{t,H}\frac{\partial I_t}{\partial M_t} - \lambda_{t,W}P_{t,m} = 0 \tag{3.13}$$

$$\frac{\partial \mathcal{L}}{\partial C_t} = \frac{\partial U}{\partial C_t} - \lambda_{t,W}P_{t,c} = 0 \tag{3.14}$$

$$\frac{\partial \mathcal{L}}{\partial T_{t,H}} = \lambda_{t,H}\frac{\partial I_t}{\partial T_{t,h}} - \theta_t = 0 \tag{3.15}$$

$$\frac{\partial \mathcal{L}}{\partial \theta_t} = \Omega - T_{t,l} - T_{t,h} - S_t(H_t) = 0 \tag{3.16}$$

$$\dot{\lambda_{t,H}} = -\frac{\partial U}{\partial H_t} + \delta\lambda_{t,H} - \lambda_{t,W}\frac{\partial \omega_t}{\partial H_t}T_{t,l} + \theta_t\frac{\partial S_t}{\partial H_t} + \rho\lambda_{t,H} \tag{3.17}$$

$$\dot{\lambda_{t,W}} = -r\lambda_{t,W} + \rho\lambda_{t,W} \tag{3.18}$$

$$\frac{\partial \mathcal{L}}{\partial \lambda_{t,H}} = I_t - \delta H_t \tag{3.19}$$

$$\frac{\partial \mathcal{L}}{\partial \lambda_{t,W}} = rW_t + \omega_t(H_t)T_{t,l} - P_{t,m}M_t - P_{t,c}C_t \tag{3.20}$$

The FOCs yield the optimal condition for gross investment in health, I_t and consumption, C_t implicitly by the following three equations:

$$\frac{\partial I_t}{\partial M_t} = \frac{\lambda^{\star}_{t,W}}{\lambda^{\star}_{t,H}}P_{t,M} \tag{3.21}$$

$$\frac{\partial I_t}{\partial T_{t,h}} = \frac{\theta^{\star}_t}{\lambda^{\star}_{t,H}} \tag{3.22}$$

$$\lambda^{\star}_{t,W} = \frac{\partial U_t}{\partial C_t} / P_{t,c} \tag{3.23}$$

where $\lambda_{t,H}$ is the shadow price of health, $\lambda_{t,W}$ is the shadow price of assets, and θ_t is the Lagrange multiplier for the individual's time constraint.

Equation 3.21 shows that the marginal product of medical care goods and services is proportional to the shadow price of the asset constraint, $\lambda_{t,W}$ as well as the price level of medical goods and services $P_{t,M}$. Also note that $\frac{\partial I_t}{\partial M_t}$ is inversely related to the shadow price of health, $\lambda_{t,H}$ at the optimal time path of H_t. Similarly, the shadow price of health is inversely related to the marginal product of time spent resting, $\frac{\partial I_t}{\partial T_{t,h}}$. Equation 3.23 is a familiar result in consumer theory.

The model provides some intuitive results. First, as the shadow price of health, $\lambda_{t,H}$ increases (implying a low level of H_t), individuals will maximize utility by adjusting both consumption of medical care goods and services and time spent resting corresponding to a point in the health investment function where the value of $\frac{\partial I_t}{\partial M_t}$ and $\frac{\partial I_t}{\partial T_{t,h}}$ are low. Since $I(M_t, T_{t,H})$ is concave in both M_t and $T_{t,h}$ for all t, the individual will invest more in their health status and reach a higher level of health stock, H_t. In addition, we see that as prices of medical goods and services rises, the individual reduces purchase of M_t corresponding to a lower point in the investment function and therefore health deteriorates. Conversely, Equations 3.21 and 3.23 show that when prices of consumption goods increases, individuals will invest more in health by purchasing more M_t but not by resting. Moreover, Equations 3.21 and 3.23 show that as the marginal utility of consumption goods increases relative to the marginal utility of health stock, the individual lowers investment in their health stock by purchasing less M_t.

Unlike other analyses of Grossman-type health models (Bolin et al., 2001; Galama & Van Kippersluis, 2018; Jacobson, 2000), I provide an explicit solution for the time paths of the shadow prices: $\lambda_{t,W}$ and $\lambda_{t,H}$:

$$\lambda^{\star}_{t,W} = \lambda_{0,W} e^{(\rho - r)t} \tag{3.24}$$

$$\lambda^{\star}_{t,H} = \lambda_{0,H} e^{(\delta+\rho)t} - \int_t^{\mathcal{T}} e^{(\delta+\rho)t} \left\{ + \frac{\partial U}{\partial H_t} + \lambda_{t,W} \frac{\partial \omega_t}{\partial H_t} T_{t,l} - \theta_t \frac{\partial S_t}{\partial H_t} \right\} dt \tag{3.25}$$

Equations 3.24 and 3.25 together with the three optimality conditions stated above (Equations 3.21-3.23) provide the optimal control variables for a full solution of the time path of the health state variable given by the following:

$$H_t^\star = H_0 e^{-\delta t} + \int_t^{\mathcal{T}} e^{\delta t} I(M_t^\star, T_{t,h}^\star) dt \tag{3.26}$$

The transversality condition stated earlier then provides the optimal health state at the terminal surface:

$$H_{\mathcal{T}} = H_0 e^{-\delta T} + e^{\delta t} I(M_T^\star, T_{T,h}^\star) \geq H_{min} \tag{3.27}$$

3.3.1 Wages and Health

A model was described and solved in the above section. It remains to be discussed what insights the model provides for of our investigation of the impact of the minimum wage on health.

First let's note that increases in the wage rate relax the asset constraint of the individual implying a lower shadow price of assets, $\lambda_{t,W}$. Equation 3.21 shows that the shadow price of assets is proportional to the marginal product of medical care goods and services. Therefore, exogenous increases in the wage rate that is unrelated to health and education, such as a higher minimum wage policy, induce the purchase of medical care goods and services and improves health. This supports the finding that higher minimum wage levels were positively associates with healthcare utilization increases during pregnancy. In addition, the time constraint showed that there is an associated opportunity costs of low health by the relationship of health and sick time, $S_t(H_t)$. This implies that if wages increase, the opportunity cost of sick time increases for all future dates inducing further investment in health.

However, the effect of wages on health, H_t is not unambiguous in our model. To demonstrate this ambiguity, suppose that the wage rate is given by an exogenous component, ω_t^e and an endogenous component which is a function of health and education.

$$\omega_t = \omega_t^e + \omega_t(H_t, E_t) \tag{3.28}$$

The effect of exogenous changes of the wage rates on the objection function, $U_t(H_t, C_t)$ is given by the envelope theorem.

$$\frac{\partial \mathcal{L}}{\partial \omega_t^e} = \lambda_{t,W}^\star [\Omega - T_{t,H}^\star - S_t(H_t^\star)] \tag{3.29}$$

For interior solutions where the constraints are binding, both $\lambda^{\star}_{t,W}$ and $\Omega - T^{\star}_{t,H} - S_t(H^{\star}_t)$ are positive. Therefore exogenous wage hikes increase U_t. However, a higher utility level can be attained by either increased consumption of consumer goods or a higher health stock. Although not modeled explicitly here, some consumption goods may be harmful to health as previously noted by Galama and Van Kippersluis (2018) and in Chapter 2. Therefore exogenous wage increases can be associated with deteriorating health within this framework. The ambiguity of the impact of wage increases is a limitation of the model's prediction and of choice-theoretic approaches to the social determinants of health.

The three channels noted above and the ambiguity of the effect of wage hikes on health have already been recognized by the minimum wage and health literature. My aim is to provide an additional effect of exogenous wage increases on health with a less ambiguous channel that is subject to an empirical investigation in the proceeding sections of this chapter.

3.4 Subjective Life Expectancy

It is well known that variations in incomes, even marginal differences, partially explain variations in life expectancy (Whitehead, Morris, & Black, 1990). An obvious empirical question is whether individuals are aware of this relationship and how this may impact the optimal investment in health within a choice-theoretic framework. Although variation in knowledge about own health may be correlated with income and is not specifically modeled here, the question of whether SLE is related to income level is still relevant in the context of understanding health demand.

I first address what the model implies for the optimal demand for health if individuals knew that their life expectancy is related to own income. Specifically, I am interested in finding the effect of changes in the terminal date, $\mathcal{T}$ has on the time path of $H^{\star}_t$.

Consider the dynamic optimization problem presented earlier where the optimal time path of health is described by

$$H^{\star}_t = H_0 e^{-\delta t} + \int_t^{\mathcal{T}} e^{\delta t} I(M^{\star}_t, T^{\star}_{t,h}) dt \tag{3.30}$$

We know that the optimal health stock at the terminal surface was given earlier by $H_{\mathcal{T}} = H_0 e^{-\delta T} + e^{\delta t} I(M^{\star}_T, T^{\star}_{T,h}) \geq H_{min}$, which is invariant with changes in $\mathcal{T}$. Our interests is to investigate the change in the time path of health stock, H_t in all other periods. For this, the Leibnitz rule[1] is employed to Equation 3.26, which yields:

$$\frac{dH_t^\star}{d\mathcal{T}} = e^{\delta\mathcal{T}} I_{\mathcal{T}}(M_{\mathcal{T}}, T_{\mathcal{T},h}) > 0 \tag{3.31}$$

A step by step of derivation of Equation 3.31 is given in Appendix A.

Equation 3.31 implies that as the terminal time increases (expectation of longer life expectancy), the optimal health stock increases by $\frac{dH_t^\star}{d\mathcal{T}}$. Conversely, if the individual believes that their life expectancy is now lower given some decrease in their income, then they will reduce optimal investment in their health. Interestingly, the effect of changes in the terminal date is not a function of t, but rather some positive constant, $e^{\delta\mathcal{T}} I_{\mathcal{T}}(M_{\mathcal{T}}, T_{\mathcal{T},h})$. A constant $\frac{dH_t^\star}{d\mathcal{T}}$ corresponds to a level shift in the time path of $H_t^\star$. A level shift implies that the individual will increase (decrease) their optimal health stock by the same amount in every $t < \mathcal{T}$. Therefore, if increases in income or the wage rate induces the belief that their will be an increase in their life expectancy, $\mathcal{T} \rightarrow \mathcal{T}'$, then the individual's change in gross investment in health is increased by

$$(\mathcal{T}' - t_c) \times e^{\delta\mathcal{T}} I_{\mathcal{T}}(M_{\mathcal{T}}, T_{\mathcal{T},h}) \tag{3.32}$$

where t_c is the current time that corresponds to the change in income.

3.5 Data Sources

There are two general forms of SLE measures in survey data: direct and indirect (see Rappange, van Exel, and Brouwer (2017) for a discussion). The direct method comprises of soliciting a point estimate of life expectancy from survey participants, while the indirect method solicits a score or ordinal rating of an individual's confidence of living up to a certain age. The second approach incorporates uncertainty of SLE and is studied in this chapter.

I use the 2013 Federal Reserve Board's Survey of Household Economics and Decision-making (SHED) data set to study the relationship between income and SLE. The SHED data set asked the following survey question, which is the outcome variable of interest in

[1]See Appendix A for the Leibnitz rule.

my regression analysis: "On a scale from 0 to 10, where 0 is no chance and 10 is absolutely certain, and you can use any number in between, what are the chances that you will live to at least age 75?" Unfortunately, SHED discontinued asking this question in subsequent surveys and therefore the primary empirical limitation is that my analysis is based on cross-sectional and not panel data. However, the primary advantages of using SHED, (instead of similar data sets, i.e., the Health and Retirement Study [HRS] data) is that the SLE measure in SHED exhibits more variation than HRS and the age group in SHED is younger (Hurd et al., 2004). In addition, SHED has not been previously utilized in the SLE literature to my knowledge.

3.6 Empirical Strategy

I model the SLE measure as a latent variable and apply ordinal logistic regression analysis. Standard ordered logistic estimation strategies suffer from two important limitation. Unlike ordinary least squares, when the assumption of homoskedasticiy fails, not only are the second order estimates biased, but in the case of ordered logit, so are the first order estimates (Williams, 2009). In addition, the standard ordered logistic regression assumes that the effect estimates are proportional across different ordinal categories. The result of an increase in an explanatory variable is assumed to have an equivalent impact across all categories. I remedy both limitations in my empirical strategy by estimating the generalized ordered logistic regression and the heterogeneous choice models.

I first estimate the standard ordered logistic regression, where the probability of $y_i \in Y$ being at or below the j^{th} category from k ordinal cut points, such that $j \leq k$. I then estimate both the generalized ordered logit and the heterogeneous choice model. The generalized form of the the ordered logistic regressions allows for the first order estimates to vary by j. The generalized ordered logit can be expressed as follows:

$$Pr(y_i > j) = \frac{e^{\alpha_j + X_i \beta_j}}{1 + e^{\alpha_j + X_i \beta_j}},\ j = 0, 1, ..., k - 1 \tag{3.33}$$

In the above equation, X_i is a matrix of explanatory variables for individual i, β_j is a vector of estimated coefficients, and e is the exponential function. Notice that β_j is different for each j allowing for varying proportional odds. The probabilities that the latent variable will take on values $0, 1, ..., k$ is then determined by

$$\begin{aligned}
Pr(y_i = 0) =& 1 - \frac{e^{\alpha_0 + X_i\beta_0}}{1 + e^{\alpha_0 + X_i\beta_0}} \\
Pr(y_i = 1) =& \frac{e^{\alpha_0 + X_i\beta_0}}{1 + e^{\alpha_0 + X_i\beta_0}} - \frac{e^{\alpha_1 + X_i\beta_1}}{1 + e^{\alpha_1 + X_i\beta_1}} \\
&\vdots \\
Pr(y_i = k) =& \frac{e^{\alpha_{k-1} + X_i\beta_{k-1}}}{1 + e^{\alpha_{k-2} + X_i\beta_{k-1}}}
\end{aligned} \tag{3.34}$$

As mentioned earlier, when an ordinal response model incorrectly assumes homoskedasticity, the first order parameters are biased. As a solution, I directly specify the sources of heteroskedasticity in an attempt to correct it using the following equations:

$$Pr(y_i > j) = \frac{e^{\alpha_j + X_i\beta_j}}{\sigma} \times (1 + \frac{e^{\alpha_j + X_i\beta_j}}{\sigma})^{-1} \tag{3.35}$$

$$\sigma_i = e^{Z_i\gamma_j} \tag{3.36}$$

where σ is the variance equation for each i given Z_i is matrix of variance explanatory variables with a corresponding vector of coefficients, γ. In my estimates, Z_i is a subset of X_i, which was determined by backward induction.

The variables included in the full equations are the log (base 2) of total household income in year 2012, employment, disability, marital status, college education, and student status. I controlled for gender, race, and ethnicity, as well as an age profile function. Whether the survey participant owned a home, was previously divorced, and experience a negative life event associated with the 2008 recession were also included.

3.7 Results

The results are presented in Tables 3.1-3.3. Figure 3.1 illustrates the distribution of the ordinal responses by percentage for the estimation sample and Table 3.1 presents the summary statistics. Table 3.2 reports the standard ordered logit (proportional odds) model and the heterogeneous choice proportional odds model. household income, disability and college education were found to be statistically significant determinants of σ and validate my use of the latter estimation model. I find that the doubling of income is associates with a 2.5 to 5.6 % likelihood of reporting greater confidence in surviving to age 75. The partial proportional odds model allows me to relax the proportional odds assumption which I found to be violated using the Wolfe-Gould test ($\chi^2_9 = 64.95$, $p < 0.001$) and the Brant test

($\chi^2_9 = 75.86$, $p < 0.001$). The results are summarize in Table 3.3. Other results I find is that periods of unemployment, disability, divorce, negative life event associated with the great recession were negatively associated with SLE. I also find that the relation between age and SLE is U-shaped. Attaining a college education and being Black was found to be positively associated with SLE.

Although the estimated effect of income on SLE was low in Table 3.2, I find that there is significant variation across the ordinal categories. The odds ratios range from 1.08 to as high as 1.24 in the various estimates. Figures 3.2-3.4 illustrate the predicted probabilities graphically. The estimates presented are average effects, but a possible extension to this empirical investigation is to examine the strength of the relationship among different income groups.

3.8 Conclusion

All models estimated in this chapter provide evidence in support of my discussion in Section 3.4 on how exogenous wage hikes can have an impact on optimal demand for health by changing the terminal surface of the optimal control problem. This result is interesting for two reasons. First, it implies that contemporaneous income changes today will have a two-way impact on health: short term income effect on healthcare consumption, and changes in the terminal date of the optimal control problem which I showed leads to a level shift in health investment for every period. Second, given the pathway from income to SLE and changes in demand for health, it can be argued that the income inequality leads to health inequality in a self-fulfilling prophecy. In other words, it is rational for low income individuals to not invest in their health given their belief that they will not survive to bear the costs of depreciated health status in the future. I however interpret my results more modestly: income increases lead to an improvement in SLE and therefore an individual may be more likely to purchase a monthly gym membership to promote their health status in the future. A gym membership, being a constant monthly cost for all future periods, conforms with the level shift result found in Section 3.4.

In this chapter, I found that household income is positively related to SLE. The generalized ordinal logistic models showed that the magnitude of the income and SLE relationship is largest at the bottom of the SLE distribution and not significant for highly confident individuals. I also found that periods of unemployment, disability, divorce, negative life event associated with the great recession were negatively associated with SLE. I find that the relation between age and SLE is U-shaped, which reflects increased uncertainty in the middle of the age distribution and overconfidence of younger respondents. I found a novel result in changes in the optimal demand for health given an exogenous wage hike ,and the implications of my model suggest that SLE is a relevant determinant in health investment within life-cycle variables.

Table 3.1: Summary Statistics of Estimation Sample ($n = 2,471$)

Model Variables	Mean	Std. Dev.
Age (18 - 64)	43	12.7
Male	51.8%	-
Household Income	$79,924	192,834
Metropolitan	84.5%	-
College	36.7%	-
Homeowner	61.2%	-
Negative Life Event (GR)	46.7%	-
Disabled	8.4%	-
Unemployed ($\leq$ 12months)	8.1%	-
SLE (0 - 10)	7.16	2.58

Table 3.2: Subjective Life Expectancy (Confidence of living up to age 75: 0 - 10 scale).

	Proportional Odds			Het. Choice Proportional Odds		
	(1)	(2)	(3)	(4)	(5)	(6)
$\log_2$(Household Income)	1.106†	1.081**	1.040	1.056†	1.045†	1.025*
Unemployed			0.669*			0.813*
Disabled			0.361†			0.639†
Student			1.308			1.120
Married			1.267*			1.086
Divorced			1.272			1.085
Male			0.777**			0.903**
Homeowner			1.068			1.030
Negative Life Event			0.766**			0.904*
College			1.450†			1.176†
Black			1.462*			1.172*
Hispanic			0.915			1.009
Metro			1.254			1.078
Age			0.890†			0.950†
Age^2			1.001†			1.001†
$ln(\sigma)$						
$\log_2$(HH-Income)				-.067†	-.068†	-.051†
Disabled						.239*
College						-0.275†
N	2,471	2,471	2,471	2,471	2,471	2,471
χ^2	48.61†			190.27†		
F-statistic		10.40**	7.386†		36.99†	27.07†
Survey Weights	No	Yes	Yes	Yes	No	Yes
Clustered Std. Err.	No	No	No	No	Yes	No

Note: $^{**}p < 0.1$; $^{**}p < 0.05$; $†p < 0.001$.

Table 3.3: The Effect of Income on Subjective Life Expectancy (scale: $Y = 0$ - 10).

	Partial Proportional Odds Models			
	(1)	(2)	(3)	(4)
Y>0 vs Y≤0	1.196†	1.196†	1.214†	1.186†
	(0.0314)	(0.0210)	(0.0330)	(0.0346)
Y>1 vs Y≤1	1.218†	1.218†	1.236†	1.208†
	(0.0307)	(0.0269)	(0.0347)	(0.0371)
Y>2 vs Y≤2	1.180†	1.180†	1.181†	1.151†
	(0.0276)	(0.0228)	(0.0318)	(0.0333)
Y>3 vs Y≤3	1.171†	1.171†	1.162†	1.132†
	(0.0253)	(0.0227)	(0.0289)	(0.0291)
Y>4 vs Y≤4	1.156†	1.156†	1.140†	1.109†
	(0.0232)	(0.0213)	(0.0277)	(0.0276)
Y>5 vs Y≤5	1.142†	1.142†	1.121†	1.084†
	(0.0182)	(0.0168)	(0.0219)	(0.0230)
Y>6 vs Y≤6	1.126†	1.126†	1.100†	1.062**
	(0.0174)	(0.0149)	(0.0214)	(0.0225)
Y>7 vs Y≤7	1.097†	1.097†	1.071†	1.032
	(0.0168)	(0.0159)	(0.0203)	(0.0209)
Y>8 vs Y≤8	1.055†	1.055†	1.027	0.987
	(0.0167)	(0.0147)	(0.0198)	(0.0204)
Y>9 vs Y≤9	1.022	1.022	1.000	0.961
	(0.0172)	(0.0177)	(0.0206)	(0.0211)
N	2,471	2,471	2,471	2,471
χ^2	103.81†	390.79†		
F-statistic			10.68†	8.519†
Clustered Std. Err.	No	Yes	No	No
Survey Weights	No	No	Yes	Yes
Single Predictor	Yes	Yes	Yes	No
Full Model	No	No	No	Yes

Note: $^{**}p < 0.1$; $^{**}p < 0.05$; $\dagger p < 0.001$.

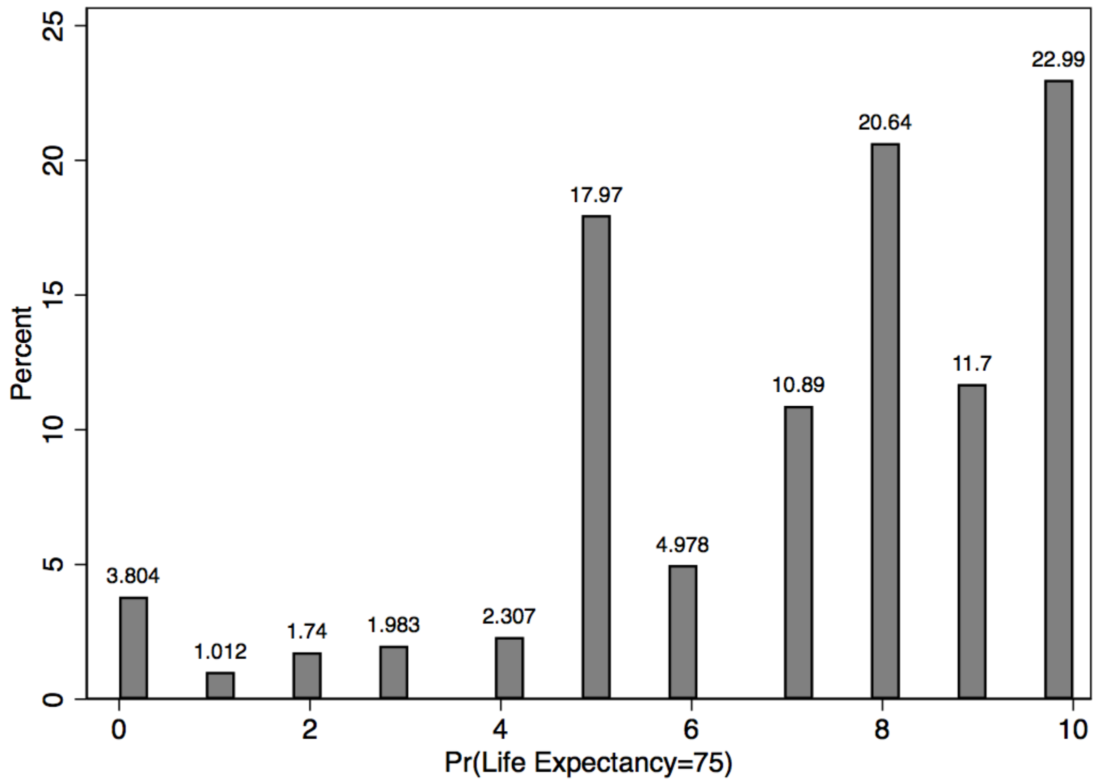

Figure 3.1: Distribution of SLE Scores (0-10.)

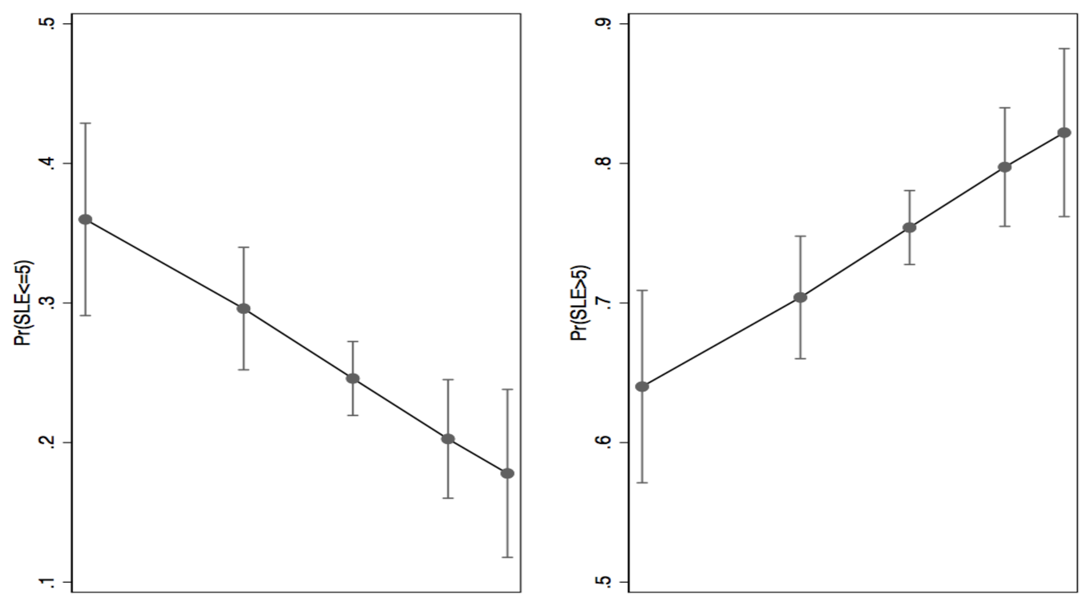

Figure 3.2: Adjusted Predictions of Household Income on Dichotomized SLE. PPO Column (4).

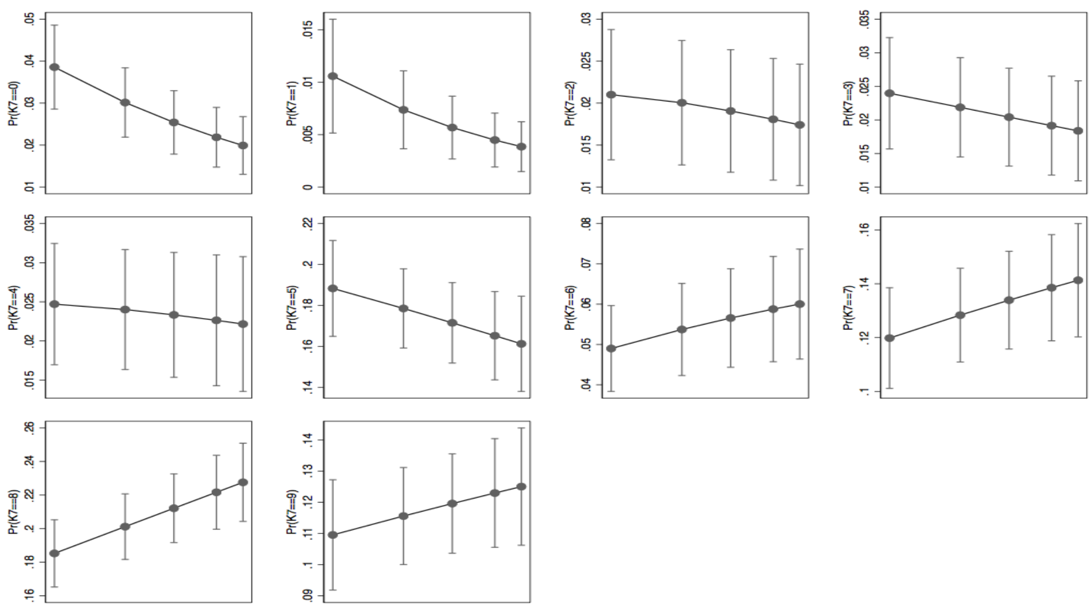

Figure 3.3: Household Income on SLE: PPO Column(4).

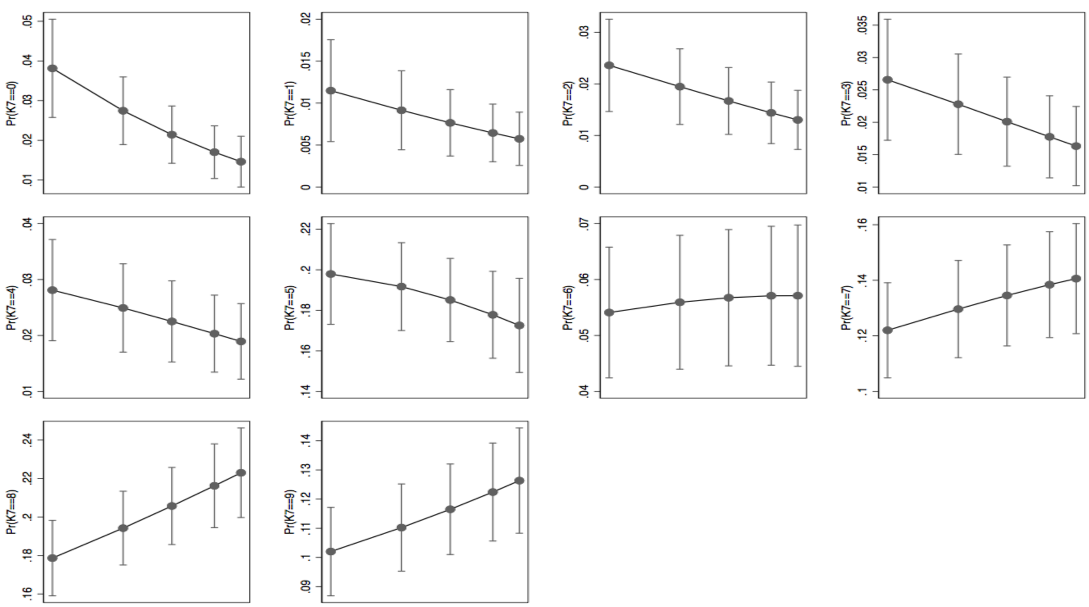

Figure 3.4: Household Income on SLE: HCPO Column (6).

APPENDIX

DERIVATION OF EQUATION 3.31

To derive Equation 3.31, we first note that taking the derivative with respect to the optimal time path of health

$$\frac{d}{d\mathcal{T}}H_t^\star = \frac{\partial}{\partial\mathcal{T}}\left\{H_0 e^{-\delta t} + \int_t^{\mathcal{T}} e^{\delta t} I(M_t^\star, T_{t,h}^\star)dt\right\} \tag{A.1}$$

reduces to

$$\frac{d}{d\mathcal{T}}H_t^\star = \frac{d}{d\mathcal{T}}\left\{\int_t^{\mathcal{T}} e^{\delta t} I(M_t^\star, T_{t,h}^\star)dt\right\} \tag{A.2}$$

Notice that this is of the form of the Leibntiz rule:

$$\frac{d}{dt}\left(\int_{g(t)}^{h(t)} F(x,t)dx\right) = \left\{F[h(t),t]\dot{h}(t) - F[g(t),t]\dot{g}(t)\right\} + \int_{g(t)}^{h(t)} \frac{\partial F(x,t)}{\partial t}dx \tag{A.3}$$

Applying the above equation to Equation 3.26 at the optimal health stock yields

$$\frac{d}{d\mathcal{T}}H_t^\star = e^{\delta\mathcal{T}} I_{\mathcal{T}}(M_{\mathcal{T}})\frac{d\mathcal{T}}{d\mathcal{T}} - e^{\delta t} I(M_t^\star, T_{t,h}^*)\frac{dt}{d\mathcal{T}} + \int_t^{\mathcal{T}} \frac{\partial[e^{\delta t} I(M_t^\star, T_{t,h}^\star)]}{\partial\mathcal{T}}d\mathcal{T} \tag{A.4}$$

where $\frac{d\mathcal{T}}{d\mathcal{T}}$ in the first term is equal to unity, while $\frac{dt}{d\mathcal{T}}$ and $\frac{\partial[e^{\delta t} I(M_t^\star, T_{t,h}^\star)]}{\partial\mathcal{T}} = 0$. Therefore arriving at Equation 3.31.

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