Essays in Health Economics of Inhaled Substances

By

Hojin Park
M.A., The University of Kansas, 2019
B.A., Dong-A University, 2017

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Chair: David Slusky

Donna Ginther

Tami Gurley

Richard Yi

Jarron Saint Onge

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The dissertation committee for Hojin Park certifies that this is the approved version of the following dissertation:

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Abstract

This dissertation consists of three standalone chapters that respectively examine individuals' health behavior associated with inhaled substances: medical marijuana laws on individuals' exit from unemployment, the high particulate matter level forecast and respiratory-related hospital utilization, and the causal relationship between tobacco use and sleep duration.

Chapter 1 is titled "The Impact of Legalizing Medical Marijuana on Exit from Unemployment." Marijuana use could influence individuals' work capacity and willingness to work. Given the rising number of states that implement medical marijuana laws (MMLs), I examine whether unemployed individuals would become more or less likely to exit from the unemployment status through the passage of MMLs. By using the linked monthly Current Population Survey (CPS) data, I trace each individual's labor market transition in response to MMLs. Based on a discrete-time hazard model, I find that MMLs decrease exit from unemployment. Further, I show empirical evidence that a reduction in exit from unemployment is derived from a decreased exit to employment, rather than from changes in labor force participation. This study provides an important perspective that MMLs could have a negative impact on labor market outcomes (JEL Codes: H75, I12, I18, J20, J64).

Chapter 2[1] is titled "Effects of Particulate Matter Forecast on Respiratory-Related Hospital Utilization." Starting in February 2014, the Korean government introduced the particulate matter (PM) forecast to inform individuals of adverse ambient air quality. Although the PM level has been quite high historically, Korean people have not been very sensitive to the PM level until

[1] This chapter is co-authored with Daehwan Kim, Department of Economics, Dong-A University, Busan, South Korea.

recently. By leveraging the regional variations in the monthly reported number of at least "bad" PM forecasts, we estimate the effects of the high PM level forecast on respiratory-related hospital utilization with the panel two-way fixed effects model. Empirical results show that monthly asthma and rhinitis hospital utilization decreases with the higher PM levels conditional on the high PM level forecast. On the other hand, COPD hospital use remains largely unaffected. This study would be the first to examine the effects of the PM forecast on respiratory-related hospital utilization in Korea (JEL Codes: I12, I18).

Chapter 3 is titled "Tobacco Use and Sleep Duration." Given the physiological impacts of nicotine on sleep, previous studies have confirmed the negative relationship between tobacco use and sleep. However, to my best knowledge, no studies have attempted to examine the causal relationship between individuals' tobacco use and sleep duration. In this chapter, I explore the causal direction of tobacco use to sleep by leveraging the state-level tobacco tax policies as instrumental variables (IV). Empirical results show that the causal direction from tobacco use to sleep may not be valid. This study would be the first to examine the causal relationship between tobacco use and sleep using a large-scale public dataset (JEL Codes: I12, I18, I19).

Acknowledgments

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Chapter 1 The Impact of Legalizing Medical Marijuana on Exit From Unemployment[2]

1.1 Introduction

Despite the addictive features of marijuana, medicinal usage of marijuana has been approved by many state legislatures. With the Compassionate Use Act of 1996, California was the first to permit medical marijuana use among qualified patients and many states followed. For adult recreational use, Colorado and Washington first implemented recreational marijuana laws in late 2012, although no retail recreational sales were available until 2014 (Insurance Institute for Highway Safety, 2021). As of August 2021, there were 36 states with medical marijuana laws (MML henceforth) and 19 states with recreational marijuana laws (RML henceforth) in the United States (Insurance Institute for Highway Safety, 2021).

As the increasing number of states legalize, many researchers have evaluated the impact of marijuana legalization through a variety of outcomes. In particular, given the fact that medical marijuana use can help individuals manage chronic conditions and relieve pain, increased access to medical marijuana through the passage of MMLs could influence individuals' work capacity as well as willingness to work. Nevertheless, only a few studies have examined the impact of MMLs on labor market outcomes and no clear-cut consensus has yet been achieved (see subsection 1.2.3 for more details).

[2] I am grateful for thoughtful comments and suggestions from Andrew Keinsley, Catherine Maclean, Daehwan Kim, Donna Ginther, Gregory Leung, Hoa Vu, and Tsvetan Tsvetanov. I also benefited from wonderful audiences of KU Economics internal seminar, MVEA 58th annual conference, MEA 86th annual meetings, and K-State Ag. Economics seminar. All remaining errors are my own.

The current study attempts to evaluate the labor market impact of MMLs. By focusing on unemployed individuals, I examine if MMLs have any impact on the probability that they transition out of unemployment status. The unemployed population may be more likely to have any medical conditions than the general population (Schmitz, 2011) and medical marijuana can be effective. Hypothetically, improved work capacity and perceived health by medical marijuana can have a positive labor market impact among the unemployed with chronic conditions. On the other hand, if medical marijuana users consume marijuana more recreationally and experience work-impeding side-effects from substance use disorder, negative impacts on labor outcomes may be observed.

To test these hypotheses, I use the linked monthly Current Population Survey (CPS) data between 2002 and 2012 within a discrete-time hazard framework. Using the short panel structure of CPS, I trace transitions of each unemployed individual's labor force status and control for weekly unemployment duration. In addition, given the dynamic impact of MMLs and to test for pre-trends in exit hazards between MML and non-MML states, I examine event study models.

The empirical results show that post-MMLs, unemployed individuals are less likely to exit from unemployment. Importantly, based on a competing risks model where two different destinations of the exit are considered, I find that the decreased exit from unemployment is largely due to a reduction in exit to employment, rather than changes in labor force attachment among the unemployed. Hence, unemployed individuals become less likely to find a new job through the passage of MMLs, although they still stay in the labor force. In the case of event study results, no significant differences in exit rates are observed among MML and non-MML states during pre-MML periods. Overall, the results are largely consistent with the static two-way fixed effects results and robust to heterogeneity across states and time, which addresses recent difference-in-differences critiques on heterogeneous treatment effects with a staggered treatment adoption (Callaway and Sant'Anna, 2021; Goodman-Bacon, 2021; Sun and Abraham, 2021)[3]. To the best of my knowledge, no previous studies have examined the unemployed and estimated whether MMLs could have a negative impact on exit from unemployment. This would add to the limited MML literature that investigates labor market outcomes.

Importantly, this study expands on the literature on extended unemployment insurance (UI) and unemployment spells. Particularly, I follow the theoretical and empirical settings of Farber et al. (2015) and Farber and Valletta (2015) that examine the impact of extended UI benefits on exit from unemployment with the discrete-time hazard model. Overall, the literature indicates that extended UI benefits tend to lengthen unemployment durations and/or discourage exit from unemployment (Bratberg and Vaage, 2000; Card and Levine, 2000; Jurajda and Tannery, 2003; Farber et al., 2015; Farber and Valletta, 2015). In addition to the UI dimension, I show that the MML is an important predictor of exit from unemployment. This study lies at the intersection of the MML and extended UI benefit literature that would provide new insight on exit from the unemployment model, which I also find an important contribution.

The remainder of the manuscript proceeds as follows. First, the following section provides a brief background of MML and evaluates a variety of relevant previous studies (section 1.2). Next, the theoretical framework of estimating exit hazards is demonstrated (section 1.3). After explaining the analysis data and setting (section 1.4), the empirical framework (section 1.5) and empirical results (section 1.6, section 1.7, and section 1.8) are provided. Finally, section 1.9 discusses the results and section 1.10 concludes.

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[3] To do this, I use the interaction-weighted (IW) estimator based on Sun and Abraham (2021).

1.2 Background

1.2.1 Marijuana Regulations in the United States

Although an increasing number of states implements or considers marijuana legalization, marijuana use is federally illegal since the Marihuana [sic] Act of 1937, and marijuana has been classified as a Schedule I drug since 1970 by the Controlled Substance Act, meaning no medical use is accepted. In the 1970s, several states started to decriminalize the possession of marijuana (Pacula et al., 2003). Usually, decriminalization of marijuana implies no arrest, prison time, or criminal record for the first-time (and subsequent) possession of a reasonably small amount of marijuana for personal use (NORML, 2021). Many states do not impose penalties on those aged 21 and over. However, some penalties might be given to minors, such as fines, community service, and/or drug education (Marijuana Policy Project, 2021).

Table 1.1 shows the effective dates of MMLs and RMLs for states that have legalized marijuana. As of August 2021, more than half of U.S. states including the District of Columbia have implemented MMLs. In comparison with MMLs, RMLs have been introduced relatively recently. This is one reason why the current study focuses on evaluating MMLs. While RML states allow any adult aged 21 and over to purchase marijuana products in local dispensaries, medical marijuana is restricted to qualified patients and each state has different eligibility conditions. Eligible patients may obtain marijuana from private/collective cultivation and/or state-authorized dispensaries (Sabia and Nguyen, 2018).

Table 1.1 Effective Dates of Marijuana Laws in the United States

State	MMLs	RMLs
Alabama	5/17/2021	
Alaska	6/1/1999	2/24/2015
Arizona	4/14/2011	11/30/2020
Arkansas	11/9/2016	
California	11/6/1996	11/9/2016
Colorado	6/1/2001	12/10/2012
Connecticut	10/1/2012	7/1/2021
Delaware	7/1/2011	
District of Columbia	7/27/2010	2/26/2015
Florida	3/25/2016	
Hawaii	6/14/2000	
Illinois	1/1/2014	1/1/2020
Maine	12/22/1999	1/30/2017
Maryland	6/1/2011	
Massachusetts	1/1/2013	12/15/2016
Michigan	12/4/2008	12/6/2018
Minnesota	5/30/2014	
Missouri	12/6/2018	
Montana	11/2/2004	1/1/2021
Nevada	10/1/2001	1/1/2017
New Hampshire	7/23/2013	
New Jersey	10/1/2010	1/1/2021
New Mexico	7/1/2007	6/29/2021
New York	7/5/2014	3/31/2021
North Dakota	4/17/2017	
Ohio	9/8/2016	
Oklahoma	7/26/2018	
Oregon	12/3/1998	12/4/2014
Pennsylvania	5/17/2016	
Rhode Island	7/1/2006	
South Dakota	7/1/2021	
Utah	5/8/2018	
Vermont	7/1/2004	7/1/2018
Virginia	7/1/2021	7/1/2021
Washington	12/3/1998	12/6/2012
West Virginia	7/1/2019	

Note: Effective dates are as of 8/14/2021. Data are from https://www.iihs.org/ and https://www.procon.org/. MMLs: medical marijuana laws. RMLs: recreational marijuana laws.

1.2.2 Medical Marijuana Use and Labor Market Outcomes

Marijuana refers to products processed from the cannabis plant. The cannabis plant contains compounds known as cannabinoids and there are two major cannabinoids: tetrahydrocannabinol (THC) and cannabidiol (CBD). Smoking, vaping, or even eating cannabis products could affect one's brain and body in many ways. For medicinal use, it is reported that marijuana use can be effective for chronic pain, neuropathic pain, spasticity, nausea, sleep disorders, anxiety, and inflammatory bowel disorders (Hill, 2015; Whiting et al., 2015; Goldenberg et al., 2017). Also, marijuana can be an alternative to other prescribed drugs such as opioids (Ozluk, 2017). Studies have found that marijuana use improves chronic conditions on par with other prescribed drugs, with fewer side effects (Reiman et al., 2017; Vigil et al., 2017).

Nevertheless, some studies demonstrate the negative health impacts of marijuana use. Williams and Skeels (2006) directly examine cannabis consumption in the past week and year and find that cannabis use reduces self-assessed health status. van Ours and Williams (2012) show that cannabis use reduces the physical and mental wellbeing of men and women. Overall, moderate cannabis use might not involve seriously harmful health effects, while heavy cannabis users, who are already susceptible to mental health issues, could experience reduced mental well-being (van Ours and Williams, 2015). Marijuana use alone would be less likely to involve a fatal overdose unlike opioids or alcohol consumption (CDC, 2021).

Many studies have examined the direct relationship between marijuana use and labor market outcomes, without the context of marijuana legalization laws. Studies find that marijuana use may negatively affect labor market outcomes such as wage and employment (Register and Williams, 1992; DeSimone, 2002; van Ours, 2007; Ayllon and Ferreira-Batista, 2018). Although

Williams and van Ours (2020) show that early cannabis users[4] among young males accept job offers more quickly, the wage rate they receive was lower, compared with non-cannabis users. Another array of studies, however, finds null impacts of marijuana on labor outcomes (Kagel et al., 1980; Kaestner, 1994; van Ours, 2006). Overall, results are mixed and may depend on sample and setting.

In the next subsection, I review the literature on marijuana legalization laws. Essentially, the results may differ with the studies mentioned above as MML and RML studies will mostly provide intent-to-treat (ITT) estimates.

1.2.3 Literature on Marijuana Legalization Laws

Given the growing number of states that legalize marijuana use, extant literature has examined a variety of outcomes that MMLs and RMLs have impacts on. This includes, but is not limited to, spillovers to prescribed drugs, cocaine, alcohol, and/or tobacco (Wen et al., 2015; Choi et al., 2016; Ozluk, 2017; Leung, 2019), traffic fatalities (Anderson et al., 2013; Hansen et al., 2018; Cook et al., 2020), birth outcomes (Baggio et al., 2019; Meinhofer et al., 2021), neighborhood crime (Brinkmand and Mok-Lamme, 2019), and academic outcomes and mental health (Leung, 2019). Especially, studies confirm the first stage impact of MMLs on marijuana consumption (Pacula et al., 2015; Wen et al., 2015; Sabia and Nguyen, 2018), with some evidence that there may be a spillover to recreational marijuana use (Wen et al., 2015).

[4] Early cannabis users were defined as individuals who used cannabis before entering the labor market and job search.

Of the many relevant outcomes, labor market outcomes in response to MMLs would be of main interest in this study. Ullman (2017) is the first to estimate the impact of MMLs on a labor market-related outcome. Post-MMLs, the study finds a reduction in sickness absence among full-time employees. On the other hand, Sabia and Nguyen (2018) examine typical labor market outcomes such as employment, hours of work, and wages. Using monthly CPS data, they show that MMLs are not associated with the outcomes among working-age adults. Similarly, Guo et al. (2021) also examine the impact of MMLs on employment and wages but at the county-quarter level. By comparing bordering counties in states with differences in MML status, they find no MML impacts on employment and inconclusive effects on wages. In an alternative specification, they present a suggestive decrease in wages in rural areas, possibly due to reduced mental health. At the state-by-year level, Anderson et al. (2018) demonstrate a decreased expected number of workplace fatalities among workers aged 25 to 44, following MMLs. Importantly, Nicholas and Maclean (2019) focus on older workers (aged 51 and over) with chronic conditions, who would more likely be qualified for medical marijuana. Through the passage of MMLs, results indicate that older workers in the sample experience lower pain, better self-assessed health, and increased hours of work.

Closer to the current study, Jergins (2019) examines the transition of labor force status, using a variety of transition variables. By observing the change in labor force status across American Time Use Survey (ATUS) and CPS, the paper finds that MMLs increase labor force attachment among females (aged 30 to 39) but reduce among males (aged 20 to 29). However, Jergins (2019) does not examine the transition from unemployment and is restricted to observing one-time transitions of each individual. Finally, two MML studies examine the impact on Social Security Disability Insurance (SSDI) and/or workers' compensation (WC) claims. Based on the

Annual Social and Economic Supplement (ASEC) of the CPS data between 1990 and 2013, among workers aged 23 to 62, Maclean et al. (2018) report an increase in SSDI claiming (and WC claiming but imprecise) while Ghimire and Maclean (2020) demonstrate a decline in WC claiming[5]. Although focused on RMLs, two other studies display similar results on SSDI and WC claiming (Abouk et al., 2021; Maclean et al., 2021)[6].

Combined with studies in the previous subsection without marijuana legalization context, it appears that there seems to be no clear-cut consensus about the impact of marijuana use on labor market outcomes. Particularly, whether MMLs would improve or worsen work capacity and willingness to work, and then how that would affect labor market outcomes of individuals are unclear, mainly because only a handful of studies have examined it to date. The current study provides one perspective that MMLs could negatively affect the likelihood of exit from unemployment, which would contribute to the limited literature of MMLs on labor outcomes. In addition, I examine the impact of MMLs on exit from unemployment using the discrete-time hazard framework, controlling for individuals' weekly unemployment duration within a single spell of unemployment. To my best knowledge, this is the first to do so. The present study also attempts to address the recent difference-in-differences critiques that event study results robust to treatment effects heterogeneity across states and time are provided (Sun and Abraham, 2021).

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[5] Regarding work capacity, these may indicate opposing results. While the increased SSDI claiming might imply decreased work capacity, the decline in WC claiming could represent improved work capacity among individuals, post-MMLs. Maclean et al. (2018) hypothesize that work-impeding side effects of marijuana use by medical and/or recreational purposes could have derived the negative impacts of MMLs.

[6] To be precise, Maclean et al. (2021) examine both SSDI and supplemental security income (SSI) for disability assistance claims. Although disability claiming was increased through the passage of RMLs, no change was observed in new beneficiaries.

1.3 Theoretical Framework

To estimate the probability of exit from unemployment among the unemployed, I consider the discrete-time hazard model by controlling for individuals' unemployment duration in discrete time (i.e., weekly or monthly durations). In the discrete-time hazard model, one needs to construct a panel dataset so that one could observe if a spell (: unemployment) ends for each individual at a given spell duration (: unemployment duration). Spells that never end until the last observed period are right-censored.

Following Farber and Valletta (2015)'s framework, let D be a discrete random variable that represents an unemployment duration for each unemployment spell. If a spell ends at a certain duration D^*, one can consider the hazard function $h(D^*)$ of exit from unemployment, considering that the unemployment duration has lasted until D^*. For each individual, $h(\cdot)$ is defined as a probability function that represents the hazard of spell ending, that depends on individual and state-level controls, including unemployment duration.

Oftentimes, individuals need to stay unemployed long enough until they are first observed as "unemployed" in a survey. Let D_0 denote this duration of unemployment. Then, one can construct the conditional probability that an unemployment spell ends at duration D^* as follows:

$$(1.1)\ P(D = D^* | D \geq D_0) = \frac{h(D^*) \prod_{d=1}^{D^*-1} (1 - h(d))}{\prod_{d=1}^{D_0 - 1} (1 - h(d))} = h(D^*) \prod_{d=D_0}^{D^*-1} (1 - h(d)).$$

Note that the probability is conditional on the minimum duration of D_0 to be first observed in the survey and assumes independence across survey months for every unemployed individual.

In the case of spells that never end until the last observed survey (: right-censored), one can consider the conditional probability that an unemployment spell has a duration of at least D^* as:

$$(1.2)\ P(D \geq D^* | D \geq D_0) = \frac{\prod_{d=1}^{D^*}(1-h(d))}{\prod_{d=1}^{D_0-1}(1-h(d))} = \prod_{d=D_0}^{D^*}(1-h(d)).$$

By combining equations (1.1) and (1.2), one can construct the likelihood function for each individual, that addresses both cases that a spell ends within the analysis period and a spell is censored.

Now, consider the latent variable model for individual i at time t:

$$(1.3)\ Y_{it}^* = X_{it}\beta + u_{it}, \quad Y_{it} = 1[Y_{it}^* > 0]$$

where Y_{it}^* is the latent variable, Y_{it} is the observed dependent variable, X_{it} is a vector of controls, and β is a vector of parameters. u_{it} is the disturbance term with a standard normal distribution. Then, the hazard of exit from unemployment of individual i at time t with unemployment duration d is given as:

$$(1.4)\ h(d) = P(Y_{it} = 1 | X_{it}) = P(Y_{it}^* > 0 | X_{it}) = P(-u_{it} < X_{it}\beta | X_{it}) = \Phi(X_{it}\beta)$$

where $\Phi(\cdot)$ is the standard normal cumulative distribution function. Note that equation (1.4) represents the probit model and X_{it} contains an individual unemployment duration to control for a baseline hazard.

Importantly, the hazard function $h(d)$ above estimates the probability of exit from unemployment, which examines a single risk of exiting unemployment status (single risk model). However, one may also be interested in examining whether individuals who exit from unemployment *find a new job* or *leave the labor force*. Hence, a competing risks model which addresses two different destinations of the exit is also considered by estimating exit to employment and exit to not-in-labor-force (NILF), separately.

1.4 Data

1.4.1 Linked CPS and Sample Restriction

To estimate the probability of exit from unemployment, I use basic monthly CPS data from January 2002 through December 2012[7]. The basic monthly CPS dataset is updated every month and administered by the U.S. Census Bureau and Bureau of Labor Statistics (BLS). The CPS was designed to provide recent information on the labor market involvement of the U.S. population. Specifically, it provides a variety of information on labor market outcomes such as labor force status (employed, unemployed, or NILF), weekly wages, hours of work, and unemployment duration including individual demographics. As the earliest possible date of a CPS interview is the 6th of each month, I code for changes in state-level MML status and potential UI weeks as of the 5th of each month, which could possibly have an impact on individuals' decision to exit from unemployment.

[7] The rationale to restrict the data period to 2002 through 2012 is to conform to extended UI benefit data available from the U.S. Department of Labor (DoL), which is an important dimension of the analysis. Also, by restricting to until 2012, one can rule out any confounding impact of RMLs.

The CPS is essentially short panel data. Within a 4-8-4 survey design, each individual (household) would be surveyed and in the sample for the first 4 consecutive months, out of the sample for the following 8 months, and return to the sample for the last 4 months. Given this rotation structure, I construct a linked CPS dataset that traces individuals' labor market transitions. Following Farber et al. (2015), I link each individual in the sample to forward 2 survey months, and restrict the analysis sample among the linked observations (forward 2 months) and those who were unemployed at least 3 months due to job loss[8]. By doing this, one can rule out the possibility of multiple spells of unemployment (i.e., restricted to single spells) and correct for spurious transitions within the "*matched*" data[9]. Figure 1.1 presents the structure of the linking procedure. The final sample would be among the unemployed at least for 3 months (aged 18 to 69) and contains 54,270 observations total between January 2002 and December 2012.

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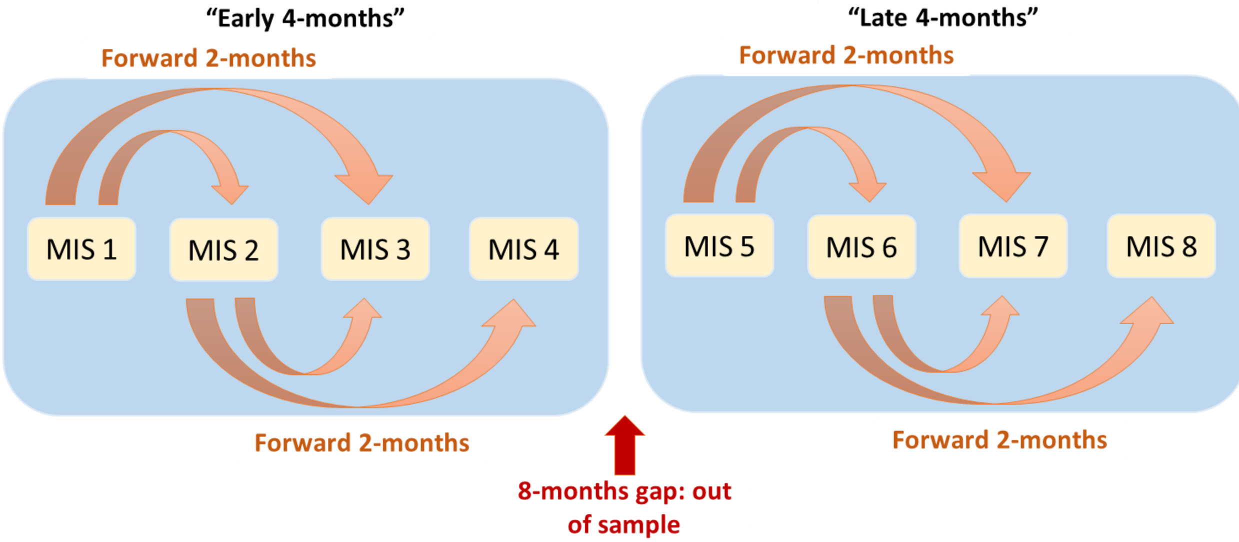
[8] This is again to follow Farber et al. (2015)'s setting. Restricting the sample as among the unemployed at least 3 months due to job loss as the unemployment reason is to allow enough time that extended UI benefits can be an important factor for exit from unemployment, and for eligibility to receive unemployment insurance.

[9] Farber et al. (2015) and Farber and Valletta (2015) refer to linking observations of an individual across survey months as "matching." They note that there could be a concern of spurious transitions in monthly labor force status due to mismeasurement. To address this issue, I re-code for those who were unemployed in month 1, exited from unemployment in month 2, and returned to unemployment in month 3, as being "unemployed" in month 2.

Figure 1.1 A Schematic of the CPS Linking Procedure for a Representative Household



Note: For a representative household surveyed in the sample, the first two months of early and late monthly surveys remain after linking and sample restriction. In each of the first two months, transitions in labor force status are recorded. For example, if an individual was unemployed in month 1 and transitioned out of unemployment status in month 2, then that person is seen as exiting from unemployment following month 1. MIS: month-in-survey.

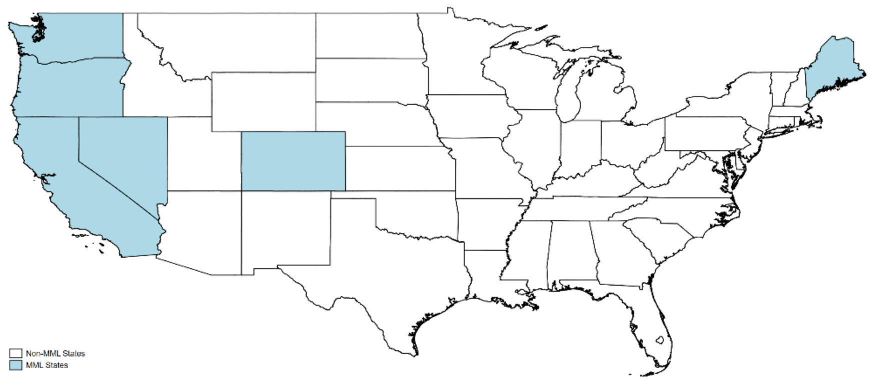
1.4.2 Variables

The variables used in the empirical analysis are defined as follows. The dependent variable, $exit\ from\ U$ is a dummy variable that is equal to 1 if an unemployed individual transitions out of unemployment status in the next monthly survey. In a similar manner, $exit\ to\ E$ and $exit\ to\ NILF$ are formulated to estimate the change in labor force status out of unemployment and transition into employment or economic inactivity. Unemployment duration is defined as the number of weeks being unemployed for each individual. To better control for a baseline hazard in the discrete-time hazard model, various functional forms of unemployment duration are formulated such as monthly unemployment duration, logarithmic unemployment duration, and polynomials of unemployment duration (quadratic and cubic). Gender, marital status, the interaction between gender and marital status, age category (10s, 20s, …, 60s), race/ethnicity groups, education level, and industry category (of individuals' jobs before unemployment) are employed as individual controls.

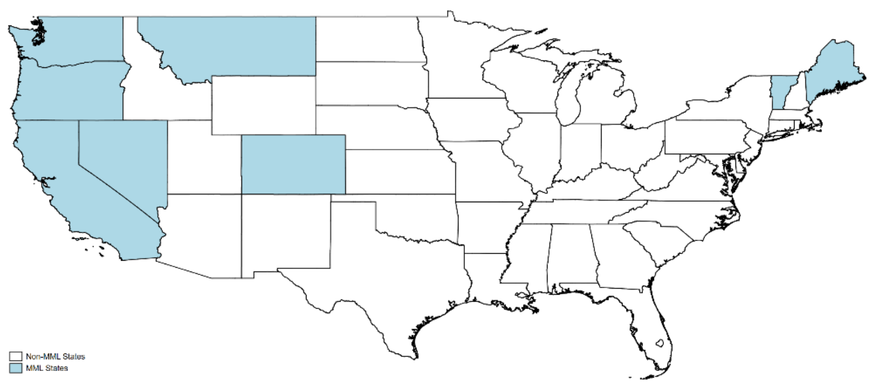
For the independent variables, MML is a dummy variable of primary interest in this study, which is equal to 1 when a state has legalized medical marijuana in a given survey month. MML effective dates are obtained from the Insurance Institute for Highway Safety (2021) and ProCon.org (2021). Figure 1.2 demonstrates trends in medical marijuana legalization across states between 2002 through 2012, which show that more states have implemented medical marijuana laws as time goes by.

Figure 1.2 Trends in Medical Marijuana Legalization During 2002 Through 2012

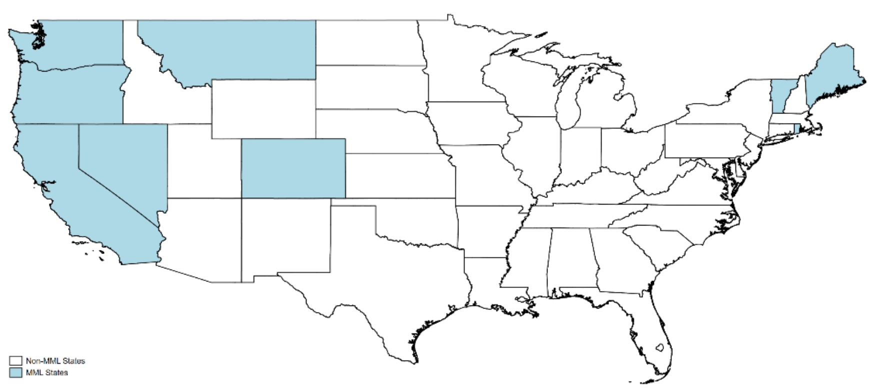
Year 2002



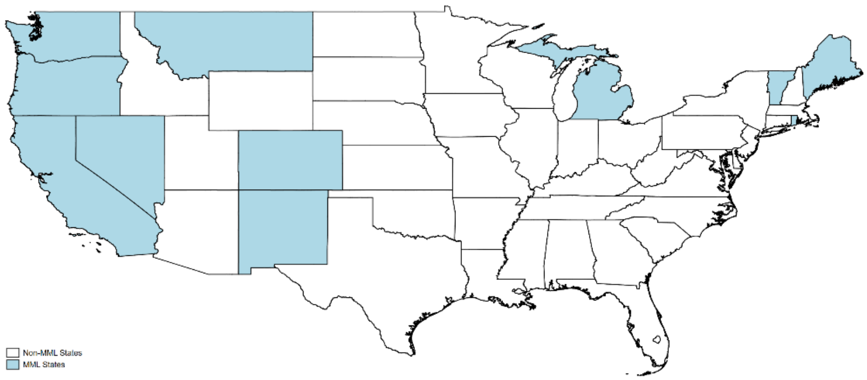
Year 2004



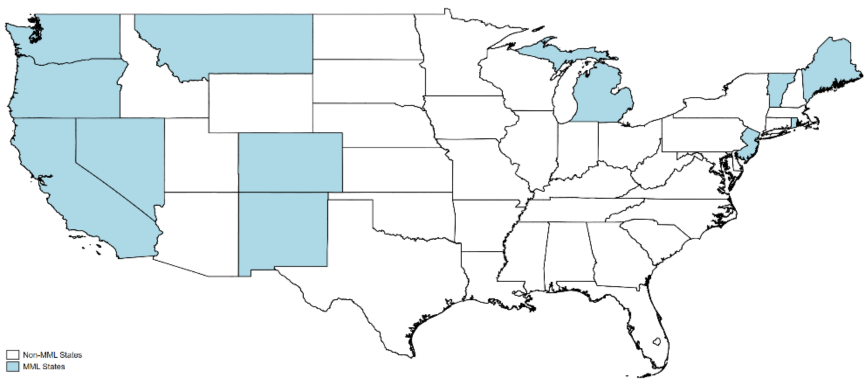
Year 2006



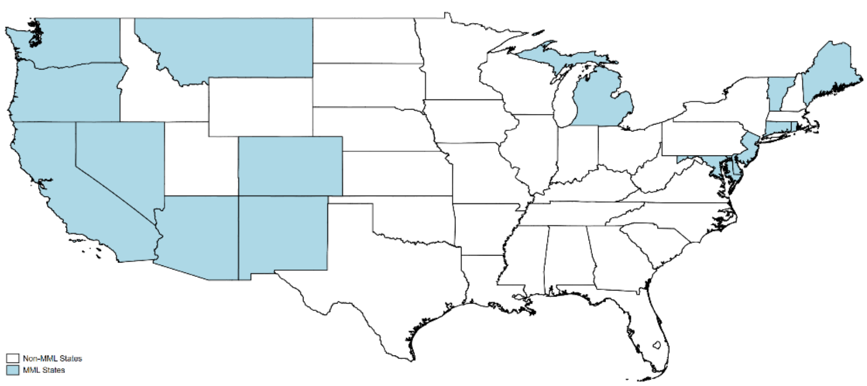
Year 2008



Year 2010



Year 2012



Note: Alaska and Hawaii have been already MML states before 2002 and are not depicted in the maps. Light blue colored states are MML states. MML status is as of December of each year.

$UI\ available$ is the independent variable from Farber et al. (2015) that is equal to 1 if an individual has potential UI benefit weeks that are longer than the current unemployment duration in a given month. To determine the maximum UI benefit duration for each state in a given month, regular UI weeks and weeks available by a variety of extended benefits programs, including extended benefit (EB), temporary extended unemployment compensation (TEUC), and emergency unemployment compensation (EUC08) are obtained from the DoL.

For the state-level controls, seasonally adjusted unemployment rate and growth rate of employment[10] are obtained from the BLS to control for local labor market conditions. As each state could have a different stance on drug use and regulations that can influence labor market outcomes, drug testing laws in three categories (pro-, anti-, and no/neutral-) are controlled following Bernardo and Nieman (2013) and Wozniak (2015). For example, pro-drug testing states may provide incentives on workers' compensation and legal protection with employers who implement drug testing. On the other hand, anti-drug testing states restrict or prohibit any drug testing procedures. Finally, cigarette taxes by state are used in analysis and obtained from the Centers for Disease Control and Prevention (CDC, 2020).

1.4.3 Summary Statistics

Table 1.2 displays the summary statistics for the whole sample (: column (1)), the sample of MML states (pre-MML periods, column (2)), and the sample of non-MML states (during all periods, column (3)). Across samples, one can observe that about 21-23% of the unemployed

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[10] To be precise, Farber et al. (2015) define this growth rate as a 3-month annualized growth rate of log non-farm payroll employment.

exit from unemployment on average. Among those who make it to the exit, about 12-13% of them exit to employment, while the remaining 9-10% exit to NILF. During 2002 through 2012, about 30% of states in the sample have implemented MMLs. About 70% of the unemployed in the whole sample have UI availability. Based on the whole sample, the average potential UI weeks by state are about 63 weeks. It is noticeable that only 8% of the MML states are classified as pro-drug testing compared with about 34% of the non-MML states. On average, each unemployed individual experiences about 44 weeks of unemployment duration, based on the whole sample[11]. The average age of the whole sample is about 42 years. In total, there are 54,270 observations in the analysis period during 2002 through 2012. Column (4) of Table 1.2 provides statistical differences of mean values between columns (2) and (3). Although they are mostly different, that may be natural given the fact that column (2) is based on pre-MML periods.

[11] Obviously, this number is based on the sample restriction of at least 3 months of unemployment.

Table 1.2 Summary Statistics

Sample:	(1) All states	(2) MML states (pre-MML)	(3) Non-MML states	(4) Difference: (3)-(2)
Dependent variables:				
Exit from U	0.216	0.231	0.220	-0.011*
Exit to E	0.120	0.134	0.121	-0.012***
Exit to NILF	0.096	0.097	0.099	0.002
Independent variables:				
MML	0.299	0.000	0.000	-
UI available	0.698	0.648	0.693	0.045***
State-level variables:				
Maximum UI weeks available	63.388	53.192	61.360	8.167***
SA unemployment rate	7.855	7.083	7.369	0.286***
SA growth rate of employment	0.001	-0.003	0.001	0.005***
Pro-drug testing	0.227	0.080	0.347	0.268***
Anti-drug testing	0.108	0.270	0.049	-0.221***
No/neutral-drug testing	0.665	0.650	0.604	-0.047***
Cigarette tax ($)	0.911	0.858	0.752	-0.107***
Individual-level variables:				
Unemployment duration (in weeks)	44.414	41.328	43.754	2.426***
Male	0.612	0.595	0.613	0.018***
Female	0.388	0.405	0.387	-0.018***
Married	0.487	0.473	0.490	0.017**
Unmarried	0.513	0.527	0.510	-0.017**
Age (in years)	42.222	42.358	42.093	-0.265
White	0.643	0.614	0.667	0.053***
Black	0.167	0.228	0.197	-0.031***
Hispanic	0.120	0.109	0.090	-0.018***
Asian	0.037	0.023	0.021	-0.002
Other race	0.032	0.026	0.024	-0.002
Less than high school	0.155	0.160	0.151	-0.008
High school	0.395	0.389	0.411	0.022***
Some college	0.270	0.236	0.267	0.031***
College	0.134	0.151	0.127	-0.023***
College or over	0.047	0.064	0.043	-0.021***
Veteran	0.088	0.081	0.091	0.010***
No veteran	0.912	0.919	0.909	-0.010***
Number of observations	54,270	5,975	32,047	-

Note: Data used are linked CPS between 2002 and 2012. Samples are among those aged 18 to 69 and those who were unemployed for more than 3 months due to job loss. Note that column (2) represents characteristics of MML states during pre-MML years. On the other hand, column (3) shows characteristics of non-MML states during all years. Other race is defined as American Indian and multi-racial people. U: unemployment. E: employment. NILF: not-in-labor-force. MML: medical marijuana law. UI: unemployment insurance. SA: seasonally adjusted. *** p<0.01, ** p<0.05, * p<0.1.

1.5 Empirical Framework

1.5.1 Empirical Model

To examine the impact of MMLs on the probability of exit from unemployment, equation (1.5) is estimated by the probit model within the discrete-time hazard framework, that is developed in section 1.3.

$$(1.5)\ Y_{ist} = \alpha MML_{st} + \beta * UI\ Available_{ist} + X_{ist}\gamma + Z_{st}\lambda + \delta_s + \theta_t + \eta_{st} + u_{ist}$$

where i is the individual unit, s is state, and t represents month-year, which ranges from January 2002 to December 2012. Y_{ist} is a dummy variable that is equal to 1 if an unemployed individual i in state s exits from unemployment, exits to employment, or exits to NILF at month-year t. MML_{st} is a dummy variable equal to 1 if a state s has implemented medical marijuana laws at month-year t. $UI\ Available_{ist}$ is a dummy variable that is equal to 1 if an individual i in state s has longer potential UI weeks available than own unemployment duration at month-year t. X_{ist} is the vector of individual controls and includes a baseline hazard (i.e., unemployment duration)[12]. Z_{st} is the vector of state-level controls. δ_s and θ_t represent state and month-year fixed effects and η_{st} controls for the state-specific linear trends. u_{ist} is the disturbance term with a standard normal distribution and is clustered at the state level[13]. α and β are the coefficients that represent the impacts of marijuana legalization and UI availability, respectively. γ and λ are

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[12] For the preferred specification, I use a set of monthly unemployment duration categories following Farber et al. (2015). That is, a set of dummies for months 4, 5, 6, 7-9, 10-12, and 13 and above is included in the specification (month 3 is the reference category). I also provide results of using different baseline hazard functions in a subsection of robustness checks.

[13] For the preferred specification, results are robust to the state-month level clustering.

vectors of coefficients. Equation (1.5) is in the form of a standard difference-in-differences two-way fixed effects model.

1.5.2 Identification

In equation (1.5) above, α is of my main interest that identifies the impact of MMLs on exit from unemployment. Essentially, it is an intent-to-treat (ITT) estimate in terms of the impact of MMLs on the exit hazard. In principle, my identification strategy is to exploit state-level variations in medical marijuana legalization laws, by controlling for state and time fixed effects as well as state specific linear trends. For the remainder of state-level confounders, seasonally adjusted unemployment rate and growth rate of employment can account for local labor market dynamics that could have influenced individuals' exit from unemployment. Importantly, I also control for state drug-testing laws and UI availability and job industry category for each unemployed individual, following Wozniak (2015) and Farber et al. (2015). One testable identification assumption for the difference-in-differences framework would be parallel trends between the treated (those in MML states) and untreated groups (those in non-MML states) over time in the absence of medical marijuana laws. To test this, the event study model is considered in subsection 1.5.3. In addition, in order to address the recent critiques on the difference-in-differences two-way fixed effects model with staggered treatment adoption (Callaway and Sant'Anna, 2021; Goodman-Bacon, 2021; Sun and Abraham, 2021), I also provide event study results, with an interaction-weighted (IW) estimator (Sun and Abraham, 2021) in a subsection of robustness checks, that are robust to heterogeneity in treatment effects across states and time.

1.5.3 Event Study Model

In practice, equation (1.5) in subsection 1.5.1. examines the static impact of MMLs on exit from unemployment. Now, one examines if there are any dynamic treatment effects of MMLs across time. To do so, consider the event study model as follows:

$$(1.6)\ Y_{ist} = \alpha + \sum_{k=L}^{-2} \beta_k\, Treat_{sk} + \sum_{k=0}^{H} \beta_k\, Treat_{sk} + X_{ist}\gamma + Z_{st}\lambda + \delta_s + \theta_t + \eta_{st} + u_{ist}$$

where k represents the quarter-year dimension and this is to reduce noise from the monthly-level analysis. Note that $k = -1$ is omitted for the reference quarter and equation (1.6) is estimated by the linear probability model (LPM)[14]. $Treat_{sk}$ is an event time dummy variable that is equal to 1 if the current period relative to the first treated period for a state s is quarter-year k. L and H are the lowest and highest quarter-year values around the event time. β_k is the coefficient that represents the impact of MMLs in the relative quarter-year k event time. All other components of equation (1.6) remain the same as earlier. In event study figures, I provide results on a [-8, 7] quarter interval (2 years before and after).

[14] This is to conform to the Sun & Abraham (2021) results, which are robust to heterogeneity in treatment effects across state and time. The results are provided in a subsection of robustness checks.

1.6 Results

1.6.1 The Static Impact of MMLs on Exit From Unemployment

Table 1.3 shows the static impact of MMLs on exit from unemployment using the probit model within the discrete-time hazard model framework. Reported estimates are average marginal effects.

Model 1 in Table 1.3 represents the single risk model and displays that, post-MMLs, the probability of exit from unemployment appears to decrease by 1.43 pp (6.6% decrease relative to the mean exit rate), although at the 10% level of significance. Looking at the UI availability, the likelihood of exit from unemployment is reduced by 3.14 pp (14.5% relative decrease). Model 2 and Model 3 in Table 1.3 demonstrate the results of the competing risks model. Through the passage of MMLs, unemployed individuals are less likely to transition into employment by 2.09 pp (17.4% relative decrease) while the UI availability does not affect the exit to employment much (0.81 pp decrease). Importantly, MMLs do not affect labor force participation among the unemployed, based on Model 3 in Table 1.3. Unemployed individuals are more likely to stay in the labor force, given the UI availability.

Table 1.3 The Static Impact of MMLs on Exit From Unemployment

Variables	Model 1: Exit from U	Model 2: Exit to E	Model 3: Exit to NILF
MML	-0.0143*	-0.0209***	0.00410
	(0.00817)	(0.00514)	(0.00695)
UI available	-0.0314***	-0.00811*	-0.0221***
	(0.00511)	(0.00474)	(0.00359)
Mean of dep var	0.216	0.120	0.096
State	51	51	51
Observations	54,270	54,270	54,270
[Month/year]	[1/2002-12/2012]	[1/2002-12/2012]	[1/2002-12/2012]

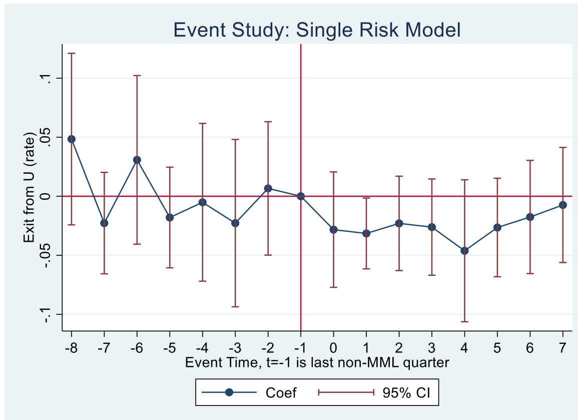
Note: Data used are linked CPS. The sample is among those aged 18 to 69 and those who were unemployed for more than 3 months due to job loss. All models include state, month-year fixed effects, and state-specific linear trends including individual and state-level variables. For a baseline hazard function, monthly unemployment duration categories are included (6 categories total). Robust standard errors clustered at the state level are reported in parentheses. U: unemployment. E: employment. NILF: not-in-labor-force. MML: medical marijuana law. UI: unemployment insurance. *** p<0.01, ** p<0.05, * p<0.1.

1.6.2 The Dynamic Impact of MMLs on Exit From Unemployment, Event Study Model

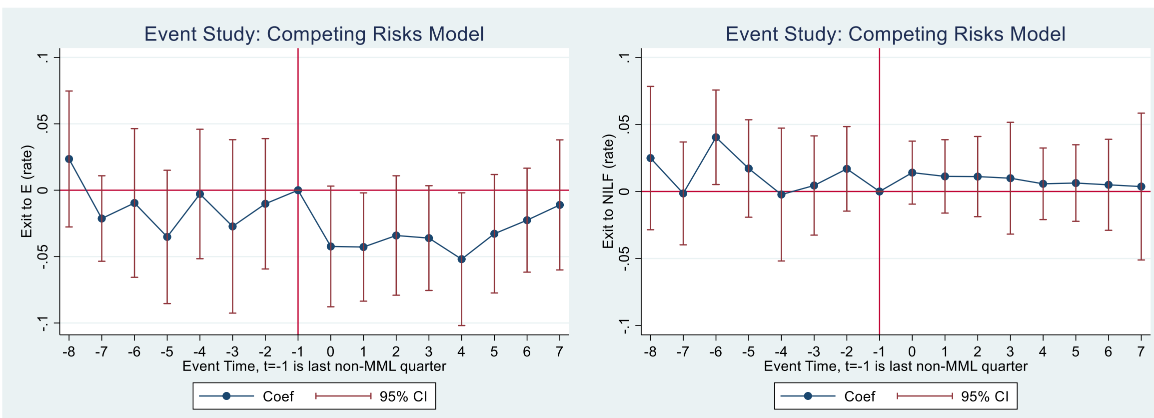
Using the event study design, Figure 1.3 provides the result of the dynamic impact of MMLs on exit from unemployment. Panel A in Figure 1.3 confirms that there is no evidence of pre-trends, compared to the reference quarter (t = -1), during the pre-MML quarters. Looking at the post-treatment periods, a statistically significant reduction in exit from unemployment is observed in the second quarter after treatment, which is in line with the static result of MMLs presented in subsection 1.6.1. In the case of Panel B of Figure 1.3, although one statistically significant increase in exit to NILF is found during pre-periods (t = -6), MML and non-MML states demonstrate common trends in exit hazards overall. The results on post-MMLs are also largely consistent with the static results shown above.

Figure 1.3 The Dynamic Impact of MMLs on Exit From Unemployment

Panel A: Single risk model



Panel B: Competing risks model



Note: Data used are linked CPS between 2002 and 2012. t= -1 is omitted for the reference quarter. The MML variable is now at the quarter level, for the event study specification. The sample is among those aged 18 to 69 and those who were unemployed for more than 3 months due to job loss. All models include state, month-year fixed effects, and state-specific linear trends including individual and state-level variables. For a baseline hazard function, monthly unemployment duration categories are included (6 categories total). Confidence intervals are clustered at the state level. U: unemployment. E: employment. NILF: not-in-labor-force. Coef: coefficient. CI: confidence interval.

1.7 Sub-population Analysis

In this section, I provide an extensive set of sub-population analyses. First, I examine the impact of MMLs on exit from NILF, not from unemployment, to investigate if MMLs have affected individuals' exit from economic inactivity. Next, I attempt to check if restricting the sample to those aged 18 to 60 would result in different outcomes. Compared to the original analysis sample (aged 18 to 69), they may be more active in job seeking and more likely to exit from unemployment. Finally, focused on exit to employment, I examine a variety of sub-samples by age, gender, marital status, veteran status, drug-testing laws, race/ethnicity, and education level.

1.7.1 Sub-population: MMLs on Exit From NILF

Table 1.4 presents the impact of MMLs on exit from NILF, to employment, and to unemployment. Based on Model 1 to 3, one finds no evidence of changes in exit hazards post-MMLs and this is robust to different components of NILF (i.e., retired, disabled, or other). Note that, however, the results may not directly compare to the main results which examine exit hazards from unemployment. This is due to the inability to observe the duration of being NILF in data. On average, about 6.6% of individuals in the NILF sample transition into the labor force.

Table 1.4 The Impact of MMLs on Exit From NILF

Variables	Model 1: Exit from NILF	Model 2: Exit to E	Model 3: Exit to U
MML	0.000759	3.08e-05	0.00103
	(0.00174)	(0.00152)	(0.00111)
Mean of dep var	0.066	0.044	0.021
State	51	51	51
Observations	1,014,459	1,014,459	1,014,459
[Month/year]	[1/2002-12/2012]	[1/2002-12/2012]	[1/2002-12/2012]

Note: Data used are linked CPS. The sample is among those aged 18 to 69 and those who were not in the labor force. All models include state, month-year fixed effects, and state-specific linear trends including individual and state-level variables. Robust standard errors clustered at the state level are reported in parentheses. U: unemployment. E: employment. NILF: not-in-labor-force. MML: medical marijuana law. *** p<0.01, ** p<0.05, * p<0.1.

1.7.2 Sub-population: Aged Among 18 to 60

Table 1.5 shows the result of the MML impacts when restricted to those aged 18 to 60. Overall, the results are consistent with the main results in both effect size and statistical significance, as shown in subsection 1.6.1. One observed change is that exit to employment is no longer affected by the UI availability dimension at any traditional significance level.

Table 1.5 The Impact of MMLs on Exit From Unemployment: Age Restriction From 18 to 60

Variables	Model 1: Exit from U	Model 2: Exit to E	Model 3: Exit to NILF
MML	-0.0165*	-0.0219***	0.00273
	(0.00989)	(0.00588)	(0.00809)
UI available	-0.0283***	-0.00665	-0.0205***
	(0.00543)	(0.00500)	(0.00346)
Mean of dep var	0.216	0.122	0.094
State	51	51	51
Observations	50,588	50,588	50,588
[Month/year]	[1/2002-12/2012]	[1/2002-12/2012]	[1/2002-12/2012]

Note: Data used are linked CPS. The sample is among those aged 18 to 60 and those who were unemployed for more than 3 months due to job loss. All models include state, month-year fixed effects, and state-specific linear trends including individual and state-level variables. For a baseline hazard function, monthly unemployment duration categories are included (6 categories total). Robust standard errors clustered at the state level are reported in parentheses. U: unemployment. E: employment. NILF: not-in-labor-force. MML: medical marijuana law. UI: unemployment insurance. *** p<0.01, ** p<0.05, * p<0.1.

1.7.3 Sub-population: Age, Gender, Marital Status, Veteran Status

Table 1.6 shows the impact of MMLs on exit to employment by a variety of demographic variables. First, in Model 1 of Table 1.6, I separate the sample between young and older adults (10-30s vs 40-60s). Given the statistical significance, it appears that the main results of the whole population may be derived from older adults. In model 2, female and male samples demonstrate similar results, in response to MMLs. In model 3, unmarried people are more responsive to MMLs. Importantly, veteran people experience a large decrease in exit to employment, post-MMLs, compared to non-veteran individuals, although at the 5% level of significance. Across specifications, the UI availability seems to be largely insignificant in exit to employment, which is similar to the main result shown in subsection 1.6.1.

Table 1.6 The Impact of MMLs on Exit to Employment: Age, Gender, Marital Status, Veteran Status

Variables	Model 1: age		Model 2: gender		Model 3: marital status		Model 4: veteran status	
	10-30s	40-60s	Female	Male	Married	Unmarried	Veteran	No veteran
MML	-0.0205*	-0.0203**	-0.0202***	-0.0214***	-0.0156*	-0.0253***	-0.0477**	-0.0184***
	(0.0119)	(0.00832)	(0.00688)	(0.00648)	(0.00868)	(0.00894)	(0.0191)	(0.00501)
UI Available	-0.0132*	-0.00500	-0.0140*	-0.00445	-0.00781	-0.00722	-0.0113	-0.00819*
	(0.00714)	(0.00550)	(0.00751)	(0.00490)	(0.00710)	(0.00591)	(0.0144)	(0.00485)
Mean of dep var	0.134	0.110	0.110	0.126	0.126	0.113	0.122	0.120
State	51	51	51	51	51	51	51	51
Observations	22,632	31,638	21,065	33,205	26,446	27,824	4,616	49,508
[Month/year]	[1/2002-12/2012]	[1/2002-12/2012]	[1/2002-12/2012]	[1/2002-12/2012]	[1/2002-12/2012]	[1/2002-12/2012]	[1/2002-12/2012]	[1/2002-12/2012]

Note: Data used are linked CPS. The sample is among those aged 18 to 69 and those who were unemployed for more than 3 months due to job loss. All models include state, month-year fixed effects, and state-specific linear trends including individual and state-level variables. For a baseline hazard function, monthly unemployment duration categories are included (6 categories total). Robust standard errors clustered at the state level are reported in parentheses. In some specifications, several observations that predict failure perfectly are dropped. MML: medical marijuana law. UI: unemployment insurance. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

1.7.4 Sub-population: Drug-Testing Laws

Table 1.7 provides results of the MML impact on exit to employment by state-level legal stance on drug-testing. Noticeably, there is no statistically significant impact of MMLs on the exit hazard among pro-drug testing states. On the other hand, anti-drug testing and no/neutral-drug testing states display similar results and that coincides with the main result on exit to employment. The UI availability variable again shows similar results as before.

Table 1.7 The Impact of MMLs on Exit to Employment: Drug-Testing Laws

Variables	Model 1: Pro-drug testing	Model 2: Anti-drug testing	Model 3: No/neutral-drug testing
MML	-0.0111	-0.0237***	-0.0222***
	(0.0113)	(0.00895)	(0.00661)
UI available	0.00412	-0.0320*	-0.00845*
	(0.0118)	(0.0168)	(0.00501)
Mean of dep var	0.120	0.133	0.118
State	51	51	51
Observations	12,312	5,783	36,114
[Month/year]	[1/2002-12/2012]	[1/2002-12/2012]	[1/2002-12/2012]

Note: Data used are linked CPS. The sample is among those aged 18 to 69 and those who were unemployed for more than 3 months due to job loss. All models include state, month-year fixed effects, and state-specific linear trends including individual and state-level variables. For a baseline hazard function, monthly unemployment duration categories are included (6 categories total). Robust standard errors clustered at the state level are reported in parentheses. In some specifications, several observations that predict failure perfectly are dropped. MML: medical marijuana law. UI: unemployment insurance. *** p<0.01, ** p<0.05, * p<0.1.

1.7.5 Sub-population: Race/Ethnicity

Table 1.8 presents the results of the MML impact by race/ethnicity heterogeneity. Overall, the UI availability does not change the exit rate to employment. Although MMLs influence White, Black, and Hispanic people as similarly as before (with somewhat different effect sizes), Asian people are largely unresponsive to MMLs. Although at the 10% level of significance, the Other race sample of Model 5 indicates an increase in exit to employment by about 9 pp.

Table 1.8 The Impact of MMLs on Exit to Employment: Race/Ethnicity

Variables	Model 1:	Model 2:	Model 3:	Model 4:	Model 5:
	White	Black	Hispanic	Asian	Other race
MML	-0.0165**	-0.0356**	-0.0437**	-0.0101	0.0897*
	(0.00796)	(0.0180)	(0.0179)	(0.0658)	(0.0516)
UI available	-0.00932	-0.0110	-0.0186	0.0551**	0.0320
	(0.00643)	(0.00896)	(0.0120)	(0.0249)	(0.0335)
Mean of dep var	0.123	0.094	0.140	0.129	0.167
State	51	51	51	51	51
Observations	34,918	9,016	6,449	1,611	1,397
[Month/year]	[1/2002-12/2012]	[1/2002-12/2012]	[1/2002-12/2012]	[1/2002-12/2012]	[1/2002-12/2012]

Note: Data used are linked CPS. The sample is among those aged 18 to 69 and those who were unemployed for more than 3 months due to job loss. All models include state, month-year fixed effects, and state-specific linear trends including individual and state-level variables. For a baseline hazard function, monthly unemployment duration categories are included (6 categories total). Robust standard errors clustered at the state level are reported in parentheses. In some specifications, several observations that predict failure perfectly are dropped. Other race is defined as American Indian and multi-racial people. MML: medical marijuana law. UI: unemployment insurance. *** p<0.01, ** p<0.05, * p<0.1.

1.7.6 Sub-population: Education Level

Finally, Table 1.9 provides the results by different educational levels. Looking at Model 4 of Table 1.9, unemployed individuals with a college degree are less likely to exit to employment with a large effect size (5.05 pp change). Overall, other samples appear to be unresponsive to MMLs. Among those with a college degree or beyond, the UI availability increases the likelihood of exit to employment by 4.02 pp.

Table 1.9 The Impact of MMLs on Exit to Employment: Education Level

Variables	Model 1: Less than high school	Model 2: High school	Model 3: Some college	Model 4: College	Model 5: College or over
MML	-0.0413*	-0.0214	0.00313	-0.0505***	-0.0211
	(0.0218)	(0.0164)	(0.0151)	(0.0145)	(0.0383)
UI available	-0.00176	-0.0108	-0.0127	-0.00690	0.0402**
	(0.00976)	(0.00867)	(0.00873)	(0.0128)	(0.0205)
Mean of dep var	0.122	0.119	0.116	0.126	0.137
State	51	51	51	51	51
Observations	8,396	21,410	14,634	7,299	2,287
[Month/year]	[1/2002-12/2012]	[1/2002-12/2012]	[1/2002-12/2012]	[1/2002-12/2012]	[1/2002-12/2012]

Note: Data used are linked CPS. The sample is among those aged 18 to 69 and those who were unemployed for more than 3 months due to job loss. All models include state, month-year fixed effects, and state-specific linear trends including individual and state-level variables. For a baseline hazard function, monthly unemployment duration categories are included (6 categories total). Robust standard errors clustered at the state level are reported in parentheses. In some specifications, several observations that predict failure perfectly are dropped. MML: medical marijuana law. UI: unemployment insurance. *** p<0.01, ** p<0.05, * p<0.1.

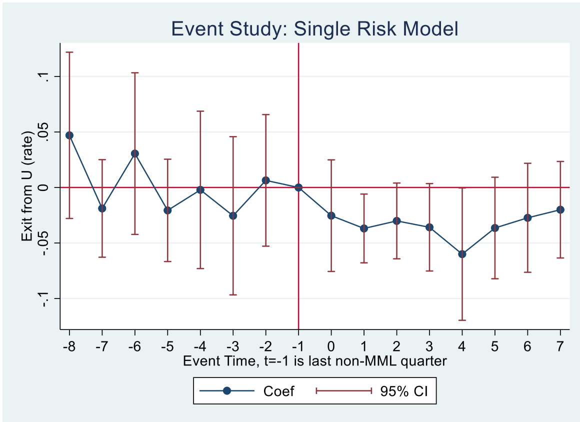
1.8 Robustness Checks

1.8.1 Event Study Model: Fixed Effects Only

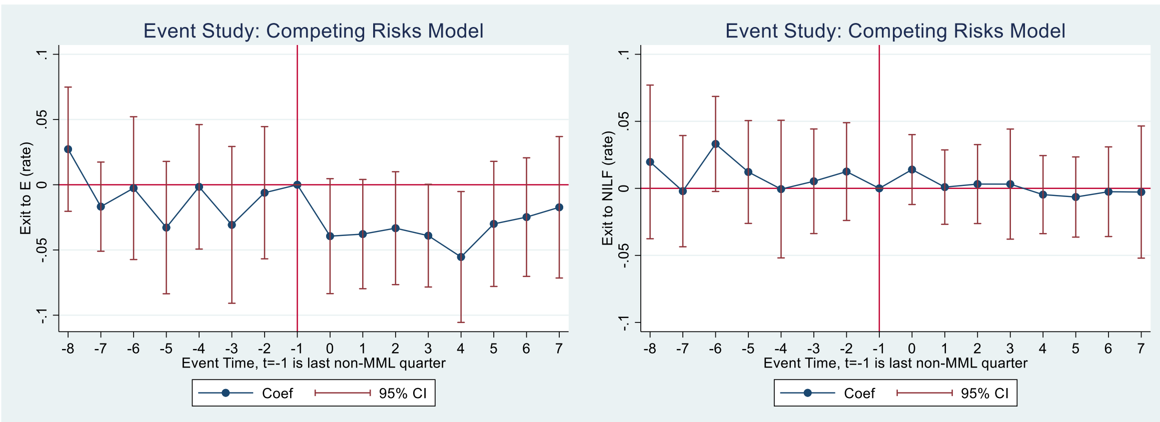
One might be concerned about the appropriate specification for running event study regression. In this subsection, I provide event study results with only state and month-year fixed effects in Figure 1.4. Note that state-level clustered errors are still utilized for statistical significance. Similar to Figure 1.3, the results are largely consistent with each other. In addition, no pre-trends are observed in any exit outcomes.

Figure 1.4 The Dynamic Impact of MMLs on Exit From Unemployment: Fixed Effects Only

Panel A: Single risk model



Panel B: Competing risks model



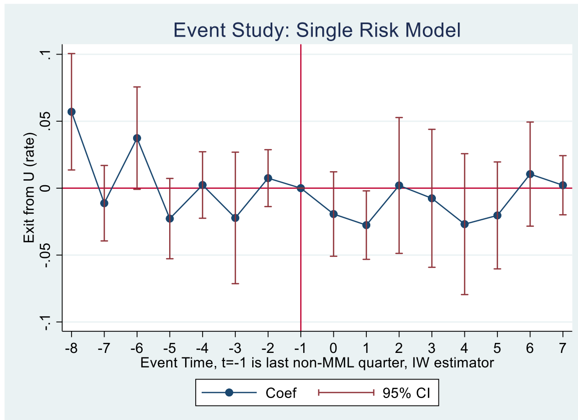
Note: Data used are linked CPS between 2002 and 2012. t= -1 is omitted for the reference quarter. The MML variable is now at the quarter level, for the event study specification. The sample is among those aged 18 to 69 and those who were unemployed for more than 3 months due to job loss. All models include state and month-year fixed effects but without any controls. Confidence intervals are clustered at the state level. U: unemployment. E: employment. NILF: not-in-labor-force. Coef: coefficient. CI: confidence interval.

1.8.2 Event Study Model: Interaction-Weighted (IW) Estimator

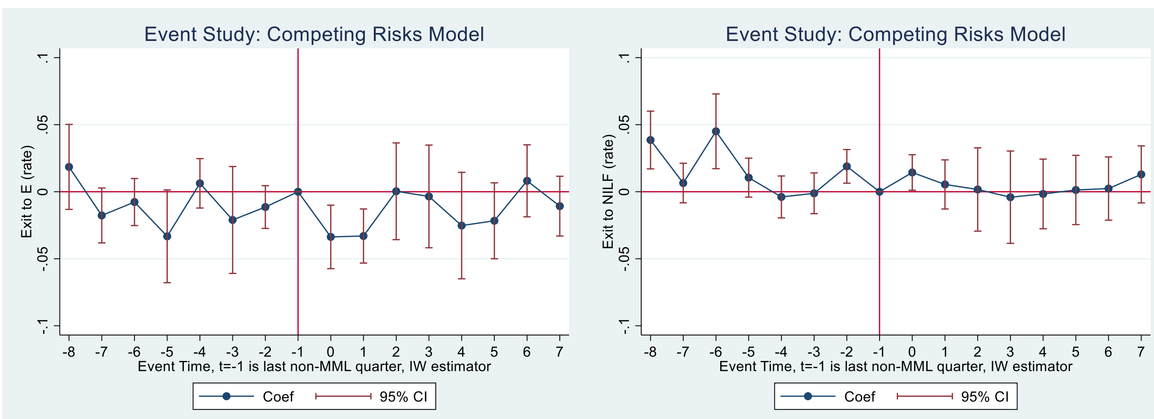
Considering a rising concern on the two-way fixed effects model with staggered treatment adoption, I attempt to provide event study results that are robust to heterogeneous treatment effects across states and time. By dropping "already-treated (or always-treated)" observations from the analysis sample, the event study model with an interaction-weighted (IW) estimator is employed (Sun and Abraham, 2021). Figure 1.5 provides the results of three different outcomes. Although with several statistically significant increases on pre-treatment periods, the results are broadly in line with the ones in Figure 1.3.

Figure 1.5 The Dynamic Impact of MMLs on Exit From Unemployment: Interaction-Weighted (IW) Estimator

Panel A: Single risk model



Panel B: Competing risks model



Note: Data used are linked CPS between 2002 and 2012. t= -1 is omitted for the reference quarter. The MML variable is now at the quarter level, for the event study specification. The sample is among those aged 18 to 69 and those who were unemployed for more than 3 months due to job loss. All models include state, month-year fixed effects, and state-specific linear trends including individual and state-level variables. For a baseline hazard function, monthly unemployment duration categories are included (6 categories total). Confidence intervals are clustered at the state level. To account for possible heterogeneous treatment effects across states and time, Sun and Abraham (2021)'s interaction-weighted (IW) estimator is employed to generate the figures (Stata command: *eventstudyinteract*). To conform to Sun and Abraham (2021)'s setting, "always-treated" MML states (treated pre-2002) are excluded from the analysis. U: unemployment. E: employment. NILF: not-in-labor-force. Coef: coefficient. CI: confidence interval.

1.8.3 Alternative Model Specifications

As alternative model specifications, the linear probability model and logit model are examined in comparison to the probit model that is utilized in the main specification. The LPM specification particularly considers concerns about the incidental parameters problem of non-linear models with fixed effects. Across Model 1 and Model 2 of Table 1.10, one can observe that the results are mostly robust to alternative specifications, but with some differences in effect size and significance level across outcomes.

Table 1.10 The Impact of MMLs on Exit From Unemployment: Alternative Specifications

Variables	Model 1: linear probability model			Model 2: logit model		
	Exit from U	Exit to E	Exit to NILF	Exit from U	Exit to E	Exit to NILF
MML	-0.0130	-0.0177***	0.00471	-0.0149*	-0.0208***	0.00435
	(0.00787)	(0.00417)	(0.00677)	(0.00829)	(0.00529)	(0.00697)
UI available	-0.0299***	-0.00495	-0.0250***	-0.0315***	-0.00961**	-0.0215***
	(0.00504)	(0.00455)	(0.00380)	(0.00512)	(0.00479)	(0.00355)
Mean of dep var	0.216	0.120	0.096	0.216	0.120	0.096
State	51	51	51	51	51	51
Observations	54,270	54,270	54,270	54,270	54,270	54,270
[Month/year]	[1/2002-12/2012]	[1/2002-12/2012]	[1/2002-12/2012]	[1/2002-12/2012]	[1/2002-12/2012]	[1/2002-12/2012]

Note: Data used are linked CPS. The sample is among those aged 18 to 69 and those who were unemployed for more than 3 months due to job loss. All models include state, month-year fixed effects, and state-specific linear trends including individual and state-level variables. For a baseline hazard function, monthly unemployment duration categories are included (6 categories total). Robust standard errors clustered at the state level are reported in parentheses. U: unemployment. E: employment. NILF: not-in-labor-force. MML: medical marijuana law. UI: unemployment insurance. *** p<0.01, ** p<0.05, * p<0.1.

1.8.4 Alternative Baseline Hazard Functions

Table 1.11 provides the results of using various baseline hazard functional forms, instead of the monthly unemployment duration categories that are used in the main specification. Looking at the impacts of MMLs on exit to employment, the results are robust to different baseline hazard functions across Model 1 to 7 of Table 1.11. The UI availability also presents similar results as previously, except for Model 1. The statistically significant increase due to available UI benefits in Model 1 may indicate a possible correlation between the UI availability and the uncontrolled individual unemployment duration[15], thus confirming the importance of including an appropriate baseline hazard function in the discrete-time hazard framework.

[15] Intuitively, there would likely be a negative correlation between the UI availability and individuals' unemployment duration, considering how the UI availability is defined. Individuals with a shorter unemployment duration would more likely be having a potential UI duration that is longer than their own unemployment duration.

Table 1.11 The Impact of MMLs on Exit to Employment: Alternative Baseline Hazard Functions

Variables	Model 1: No baseline hazard	Model 2: Linear	Model 3: Weekly dummies	Model 4: Monthly dummies	Model 5: Logarithmic	Model 6: Polynomial: quadratic	Model 7: Polynomial: cubic
MML	-0.0218***	-0.0212***	-0.0211***	-0.0208***	-0.0208***	-0.0209***	-0.0209***
	(0.00478)	(0.00510)	(0.00509)	(0.00535)	(0.00516)	(0.00516)	(0.00520)
UI available	0.0340***	-0.0163***	-0.0171***	-0.0166***	-0.0150***	-0.0176***	-0.0187***
	(0.00334)	(0.00485)	(0.00516)	(0.00509)	(0.00493)	(0.00495)	(0.00502)
Mean of dep var	0.120	0.120	0.120	0.120	0.120	0.120	0.120
State	51	51	51	51	51	51	51
Observations	54,270	54,270	54,136	54,219	54,270	54,270	54,270
[Month/year]	[1/2002-12/2012]	[1/2002-12/2012]	[1/2002-12/2012]	[1/2002-12/2012]	[1/2002-12/2012]	[1/2002-12/2012]	[1/2002-12/2012]

Note: Data used are linked CPS. The sample is among those aged 18 to 69 and those who were unemployed for more than 3 months due to job loss. All models include state, month-year fixed effects, and state-specific linear trends including individual and state-level variables. Robust standard errors clustered at the state level are reported in parentheses. In some specifications, several observations that predict failure perfectly are dropped. MML: medical marijuana law. UI: unemployment insurance. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

1.9 Discussion

Given the rising number of states that legalize medical marijuana, the current study examines if medical marijuana laws have an impact on exit from unemployment using the discrete-time hazard framework. Using the linked CPS data between 2002 and 2012, the empirical results provide some evidence that unemployed individuals are less likely to exit from unemployment through the passage of MMLs. Based on the competing risks model, it is shown that the reduction in exit from unemployment is derived from a decreased exit to employment (by 2.09 pp, 17.4% relative decrease to the mean), rather than through changes in labor force participation among the unemployed. Thus, unemployed individuals become less likely to find a new job while they still stay in the labor force.

Across various event study results, one could confirm that there are overall no significant differences between MML and non-MML states in exit rates during pre-MML periods. The results on post-MML periods are largely in line with the static results.

In sub-population analyses, I find no impact of MMLs on individuals not-in-labor-force, unlike among the unemployed, and that the sample restriction to age 18 to 60 does not change the main results. Focused on exit to employment, sub-population results indicate that the main results are mainly derived by older adults, the unmarried, veterans, White, Black, Hispanic, and individuals with a college degree. It is noteworthy that individuals in pro-drug testing states do not show any statistically significant changes in response to MMLs, while ones in other states demonstrate the same results as previously. This may show a possibly limited impact of MMLs among pro-drug testing states. In robustness checks, I show that event study results are robust to the change in specification and heterogeneity in treatment effects across states and time. The results are also robust with the LPM and logit models. Finally, I also test a variety of baseline hazard functions and find that the results are all similar, except for the case when no baseline hazard is included in the regression.

In terms of the impact of MMLs on labor market outcomes, Jergins (2019) may be the only study that can be somewhat compared to this study. Although the paper does not examine transitions from unemployment, the paper shows that, post-MMLs, women aged 30 to 39 are more likely to exit from NILF while men aged 20 to 29 and 30 to 39 are more likely to exit to NILF, between 2003 and 2015. In the current study, however, results from the NILF sample implies no changes due to MMLs and these may be natural given different analysis periods, sample restrictions, and settings. Compared with the other labor outcome studies in terms of MMLs, this study presents negative MML impacts, while most claim positive impacts of MMLs (Ullman, 2017; Anderson et al., 2018; Nicholas and Maclean, 2019; Ghimire and Maclean, 2020). Again, this could largely depend on the sample and setting. As Sabia and Nguyen (2018), Maclean et al. (2018), and Guo et al. (2021) find null and/or negative MML impacts on labor market outcomes, the impact of MMLs on labor outcomes is yet to be conclusive.

In the case of the UI availability dimension, I find a reduction in exit from unemployment by 3.14 pp, and this is derived by a decreased exit to NILF (by 2.21 pp), which are consistent with the findings in Farber et al. (2015) and Farber and Valletta (2015) in both effect size and statistical significance. Although spanned on different analysis periods, their estimates of *UI available* are around 2-3 pp (Farber et al., 2015) and 2-5 pp changes (Farber and Valletta, 2015). Given the fact that Farber and Valletta (2015) define the UI availability in a slightly different way, the differences in effect size are quite reasonable.

1.10 Conclusion

The present study contributes to the existing literature in several aspects. First, the paper examines the impact of MMLs on the probability of exit from unemployment using the discrete-time hazard model by controlling for unemployment duration given a single unemployment spell. To the author's best knowledge, this paper would be the first to do so. Considering the limited literature of MMLs on labor market outcomes, the current study would provide one important perspective that MMLs could have a negative impact on individuals' labor outcomes, particularly among the unemployed. Importantly, this paper also attempts to address the recent critiques on the two-way fixed effects model, given staggered treatment adoption. By using the interaction-weighted (IW) estimates, the present study provides event study results that are robust to heterogeneity across states and time. Finally, this study presents additional insight into the literature of extended UI benefit. As noted previously, the current study builds on Farber et al. (2015) and Farber and Valletta (2015) and shows that medical marijuana legalization could be a major factor to predict the probability of exit from unemployment, in addition to the availability of UI, which has previously been unexplored in the extant literature. The current study will contribute to the existing literature in that it lies at the intersection of MML and extended UI benefit literature.

There could be many channels behind the findings of this study. First, unlike the beliefs in medical marijuana use that could enhance work capacity and help manage chronic conditions, using medical marijuana might not help someone find a job. As previous studies note (Williams and Skeels, 2006; van Ours and Williams, 2012), marijuana use may be associated with adverse health outcomes. If marijuana use involves work-impeding side effects, that could worsen individuals' labor market outcomes. On the other hand, although medical marijuana use might not generate adverse health impacts, patients of medical marijuana users might require more time until they find a new job due to medical treatment associated with marijuana use. Importantly, there may be cases that patients use medical marijuana for recreational purposes. As Wen et al. (2015) indicate, there is likely a spillover to recreational marijuana use from medical marijuana access. If that is the case, there could be negative labor market impacts, post-MMLs, due to substance use disorder. Relatedly, first-time marijuana users given medical marijuana access are subject to the gateway effect that they might transition to harder drugs such as heroin and cocaine, thus worsening labor outcomes. Examining economic substitutability and/or complementarity, studies find that marijuana use may be related to the usage of other prescribed drugs, cocaine, alcohol, and/or tobacco (Wen et al., 2015; Choi et al., 2016; Ozluk, 2017; Leung, 2019).

A caveat of this paper is that other than delineating the sample by a set of sub-populations, I do not disentangle the channel through which MMLs could have discouraged the unemployed individuals from the exit from unemployment. Another caveat is that the study provides the intent-to-treat (ITT) estimates of MMLs on exit hazards and is not able to observe if the unemployed individuals consume medical marijuana, which could have affected labor outcomes. Finally, more state-level controls that are typically included in the MML literature may need to be considered, such as beer tax, minimum wage, prescription drug monitoring program, naloxone and good Samaritan laws, and pain clinic management law (Sabia and Nguyen, 2018; Ghimire and Maclean, 2020; Abouk et al., 2021). Considering the various potential channels discussed earlier, future research is warranted to possibly unravel the unknown mechanisms.

As more and more states participate in the wave of legalizing medical marijuana, policymakers may need to evaluate all the possible intended and unintended consequences of allowing medical marijuana use. In light of my findings, unemployed individuals could experience difficulties in finding a new job while still being attached to the labor force, and this needs to be taken into account among states that attempt to introduce the medical marijuana law.

Chapter 2 Effects of Particulate Matter Forecast on Respiratory-Related Hospital Utilization[16]

2.1 Introduction

2.1.1 Background

As ambient air pollutants could affect health outcomes negatively (Currie and Neidell, 2005), it would be important to analyze the health impacts of such harmful matters empirically. Air pollutants are usually defined as gaseous or particulate matters (PM, hereafter) that lead to air pollution. Sulfur dioxide (SO_2), carbon monoxide (CO), nitrogen dioxide (NO_2), ozone (O_3), and particulate matter ($PM_{10}\ and\ PM_{2.5}$) are primary and typical air pollutants that worsen air quality with adverse health impacts in cities. Among them, particulate matter ($PM_{10}\ and\ PM_{2.5}$) has been one of the main causes of both acute and chronic respiratory-related diseases (WHO, 2013; Kim et al., 2015).

$PM_{10}\ and\ PM_{2.5}$ are defined by an aerodynamic diameter of 10 $\mu g/m^3$ or less and 2.5 $\mu g/m^3$ or less, respectively. They could have originated from natural sources (e.g., volcanic eruptions) and a mixture of other air pollutants such as SO_2, the combustion of automobile fuels, coal power plants, and seaports. In 2013, the top 5 contributors of $PM_{2.5}$ in Korea were industrial establishments (41%), construction machinery (17%), power plants (14%), diesel cars (11%), and dust scattering[17] (6%) (National Institute of Environmental Research, 2013)[18]. PMs may

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[16] This chapter is co-authored with Daehwan Kim from Dong-A University, Busan, South Korea. We appreciate the valuable comments by Matthew Neidell as a discussant during the 10th ASHEcon annual conference. We would also like to thank the National Institute of Environmental Research of Korea for providing us with daily particulate matter forecast data. All remaining errors are our own.
[17] Dust scattering refers to unfiltered dust emitted in the air from factories or construction sites.
[18] Especially, the majority of $PM_{2.5}$ comes from the precursor matters in the air such as sulfur oxides (SO_x), nitrogen oxides (NO_x), ammonia (NH_3), and volatile organic compounds (VOC_s) through the secondary reaction.

aggravate respiratory-related diseases such as asthma and chronic obstructive pulmonary disease (COPD) and lower lung functioning. As $PM_{2.5}$ is fine enough to enter the human body without getting filtered by the mucous membrane in the nose, it can directly affect the lung sac and thus increase morbidity and cause early death from respiratory illnesses (National Institute of Environmental Research, 2018).

The PM concentration level in Korea has demonstrated decreasing trends due to the government policies to improve air quality (Ministry of Environment, 2017; Ministry of Environment, 2018). The Korean government appropriated 0.9 trillion won ($0.82 billion) in 2016, 2.0 trillion won ($1.82 billion) in 2019, and 3.4 trillion won ($3.09 billion) in 2019 as a form of a supplementary budget to control PM problems specifically. For major PM control policies, the Korean government has committed to increasing the share of renewable energy plants by 20% by 2030, enlarging the supply of environment-friendly vehicles including electric ones, replacing metropolitan buses with compressed natural gas (CNG)-fueled vehicles, and reducing the re-entrainment dust by vehicles on the roads[19] (National Assembly Budget Office, 2019).

Nevertheless, the PM concentration in Korea is still at a relatively high level compared to other Organisation for Economic Co-operation and Development (OECD) countries. Table 2.1 compares PM concentration levels across major metropolitan cities worldwide. As we can see, Seoul in Korea has suffered from particularly higher PM concentration levels compared to other major cities in the world.

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[19] Re-entrainment dust on the roads refers to dust scattered in the air by emission, tire wear, or brake pad wear of vehicles (National Assembly Budget Office, 2019).

Table 2.1 Particulate Matter Levels by Major Metropolitan Cities Worldwide Between 2011 and 2019

Year	Seoul, Korea		Los Angeles, US		Tokyo, Japan		Paris, France		London, UK	
	PM_{10}	$PM_{2.5}$	PM_{10}	$PM_{2.5}$	PM_{10}	$PM_{2.5}$	PM_{10}	$PM_{2.5}$	PM_{10}	$PM_{2.5}$
2011	47	-	29	13.3	21	15.7	27	-	23	17
2012	41	-	30	12.7	20	14.2	26	16	19	16
2013	45	-	29	-	21	15.8	26	19	18	12
2014	46	-	30	15.2	20	16	22	15	20	15
2015	45	23	37	12.6	19	13.8	23	14	19	11
2016	48	26	34	14.7	17	12.6	22	14	20	12
2017	44	25	33	14.8	17	12.8	21	14	17	11
2018	40	23	33	13.3	-	-	21	14	17	10
2019	42	25	29	13.4	16	10.5	20	13	18	11

Note: This table was reconstructed using Air Korea's web data (https://www.airkorea.or.kr/web/contents/contentView/?pMENU_NO=127&cntnts_no=4) (Accessed on June 9, 2021), In Korean 2) The unit of particulate matter is $\mu g/m^3$

The Korean government has also introduced PM forecast and alert policies. To briefly explain, the PM forecast is like a regular weather forecast. It provides residents in each region (province) of Korea with elevated PM_{10} and $PM_{2.5}$ level information. For example, a daily forecast regarding PM levels in Seoul is broadcasted through television after regular news sessions. Or, people can easily check the level of PM of the place where they currently reside by smartphone applications or web search. In the case of metropolitan cities, people may easily observe digital display boards around the bus top or downtown areas, informing current air quality including PM levels. This forecast would be very important as, with this forecast, individuals could better anticipate daily air quality so that they could decide whether to restrain from outdoor activities. This PM forecast was introduced throughout the country in February 2014 and January 2015, respectively, for PM_{10} and $PM_{2.5}$ (National Institute of Environmental Research, 2018).

The forecast system has four different air quality levels according to the PM concentration level. For instance, 0-30 $\mu g/m^3$ of PM_{10} is seen as "good," 31-80 as "moderate," 81-150 as "bad," and 151 or above as "very bad" air quality. In the case of $PM_{2.5}$, 0-15 $\mu g/m^3$ is considered "good," 16-35 as "moderate," 36-75 as "bad," and 76 or above as "very bad" air quality [20].

There is the PM alert (: advisory or warning) system in addition to the forecast. The purpose of the PM alert system is to inform individuals about more severe PM concentration levels by region. This alert is issued and released by the city mayor or province governor. Since 2015, the system has been extended throughout the country and the alert is based on the average hourly level of PM concentration[21]. If the alert is issued in a specific region, the residents will be notified by phone call, warning message, or television so that they could immediately cope with the hazardous atmosphere quality.

2.1.2 Previous Studies

There has been a plethora of research on air pollution, which have confirmed the arguably negative impact on health outcomes (Chay and Greenstone, 2003; Currie and Neidell, 2005; Chen et al., 2018; Zhang et al., 2018; Alexander and Schwandt, 2019; Clay and Muller, 2019; Anderson, 2020). Other than health outcomes, air pollution has been shown to negatively affect labor market outcomes (Fan and Grainger, 2019), outdoor activities (Parsons, 2001;

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[20] The four air quality levels for PM were determined by government officials and public discussions, considering previous studies. For example, when exposed to PM_{10} levels of "bad" or "very bad" intervals, increased cardiovascular diseases, chronic obstructive pulmonary disease (COPD), asthma, and all-cause mortality rates were observed in other countries (Ministry of Environment, 2019). $PM_{2.5}$ intervals were determined as about the half level of each PM_{10} interval. In addition, $PM_{2.5}$ cutoffs have been tightened to the current level since March 2018. Before then, 16-50 $\mu g/m^3$ was considered "moderate," 51-100 as "bad," and 101 or above as "very bad" ("good" interval was the same as current) air quality.

[21] To be specific, an advisory (or warning) may be issued if a region suffers from (at least) a 2-hour average PM_{10} concentration level of 150 $\mu g/m^3$ or above (300 $\mu g/m^3$ or above for warning). For $PM_{2.5}$, it is 90 $\mu g/m^3$ or above (180 $\mu g/m^3$ or above for warning) (National Institute of Environmental Research, 2018). Before 2015, each region was based on different cutoff points to issue the PM alert.

Neidell, 2009; Janke 2014), and academic outcomes (Currie et al., 2009; Lavy et al., 2014; Ebenstein et al., 2016).

In particular, the literature has explored the adverse impact of PM on respiratory-related hospital utilization (Xu et al., 2016; Guo et al., 2018; Katherine et al., 2018; Giaccherini et al., 2021), which we would like to examine in this research by introducing the forecast dimension. Of the research on the PM in Korea, Kim et al. (2015) claim that $PM_{10}\ and\ PM_{2.5}$ are associated with all-cause, cardiovascular, and respiratory mortality. Similarly, Kim et al. (2018) examine the effects of $PM_{2.5}\ and\ PM_{10}$ on mortality in Korea and conclude that there is a positive association between PM and mortality. Yet, their data are restricted to pre-forecast periods so their results might merely explain the association between the PM level and mortality outcomes, before the extensive reports on the PM from the mass media surge. In addition, they focus on Seoul or three metropolitan cities in Korea (i.e., Seoul, Busan, and Incheon), which compromises the representativeness of the data. In order to control for the long-term trends of PM and the recent air quality policies, utilization of the recent dataset that incorporates all provinces of Korea with a long data period would be necessary.

Importantly, while the air pollution literature has explored the direct relationship between the air pollutant concentration level and health outcomes, they mostly ignore individuals' avoidance behavior, prompted by air quality forecasts or alerts, which could also influence the relevant health outcomes. Such a forecast or alert would function as additional information on the risk of adverse air quality, independent of biological responses to the concentration level itself.

A few important studies have investigated the impact of air quality forecasts or alerts in an effort to control for individuals' avoidance behavior. Neidell (2009) assesses if smog alerts for ozone concentrations have any impact on asthma in Southern California. He finds that the alerts significantly reduce daily outdoor activities as well as asthma hospitalizations, which confirms the avoidance behavior among individuals. Similarly, Janke (2014) explores the impacts of air quality on children's respiratory health, using the air quality forecast in the UK. According to the paper, the forecast decreases children's respiratory-related emergency admissions.

Closer to the current research, Dardati et al. (2021) estimate the impact of $PM_{2.5}$ on respiratory emergency room visits in Chile, by introducing the $PM_{2.5}$ alert dimension. In a similar manner, several Korean studies investigate the impact of PM in addition to the Korean PM alert system and show that the PM alert plays an important role in mitigating the higher PM impact on health outcomes (Altindag et al., 2017; Kim, 2021; Anderson et al., 2022). Hence, given additional information on the risk, people may change and avoid risky behaviors and that could influence their health outcomes.

Our research question is to answer if the recently introduced PM forecast influences individuals' respiratory-related hospital utilization. While Korean people have already experienced quite higher levels of PM, biologically, the national introduction of the PM forecast since February 2014 could have been exogenous to individuals' cognition of adverse air quality, thus affecting their hospital utilization.

By constructing the region-month level panel data, the current study examines the impact of the high PM level forecast between February 2014 and December 2019. Empirical results indicate that the high PM level forecast appears to be effective in mitigating the adverse health impact of the higher PM levels through individuals' avoidance behavior. The impacts are particularly significant for asthma and rhinitis hospital utilization while COPD hospital utilization remains largely unaffected by the forecast.

To our best knowledge, no previous studies have scrutinized the impact of the PM forecast on respiratory-related hospital utilization in Korea. Although there may have already been biological impacts of ambient PM concentrations, the recently introduced forecast could be seen as additional health information as people become more informed about the health risk of PM. While most air pollution studies focus on the impact of the concentration level itself, this study would shed light on understanding the impact of providing additional information about the risk on individuals' health behavior, which has less been investigated in the existing literature.

The remainder of this chapter proceeds as follows. Section 2.2 demonstrates data and econometric methods. In section 2.3, we provide empirical results, and we briefly discuss in section 2.4.

2.2 Data and Methods

2.2.1 Data

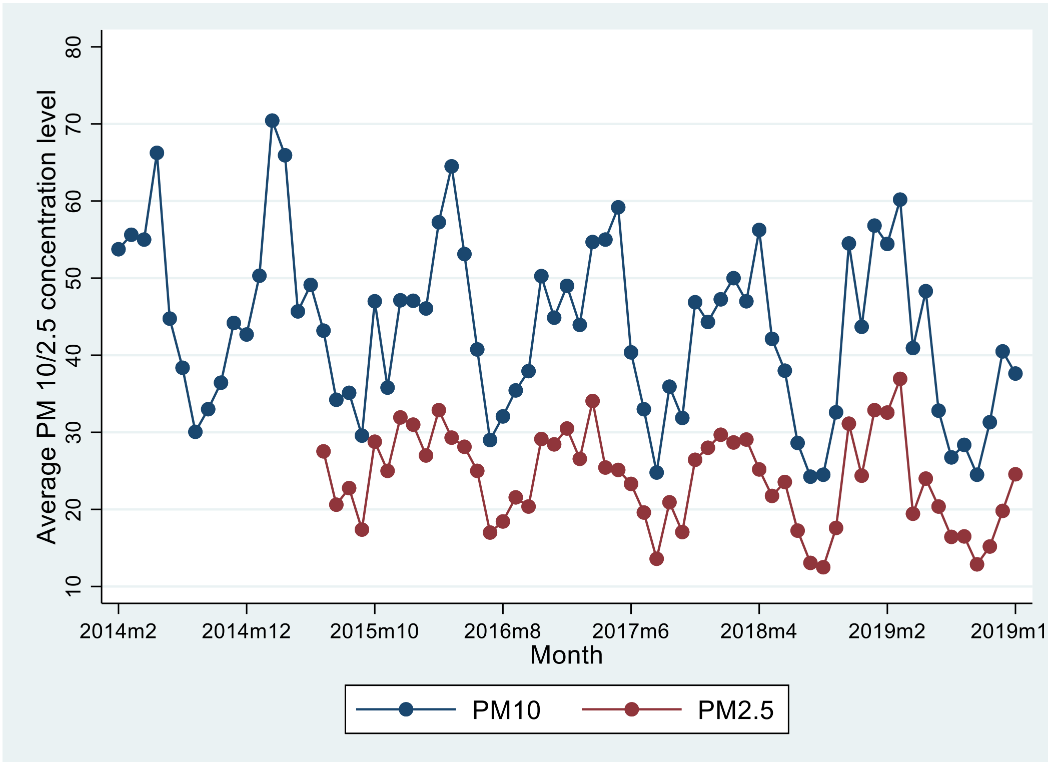
To analyze the effect of PM forecast on respiratory-related hospital utilization, we construct three different datasets and then have them merged for empirical analysis.

First, the air pollutant concentration level dataset is constructed based on the Monthly Report of Air Quality (MRAQ, hereafter) between January 2012 through December 2019. The MRAQ is composed every month by the National Institute of Environmental Research (NIER, hereafter) of Korea after they process raw data of major gaseous air pollutants including PM_{10} and $PM_{2.5}$. The raw data are processed every hour and collected from atmospheric stations throughout the country, proportional to the size of a city or province.

That is, in every hour, each atmospheric station observes and reports a corresponding air pollutant concentration level. Then, the mean value of the one-hour concentration level for a city or province is determined by averaging reported one-hour level values from all stations within that region. In a similar fashion, the monthly PM level of a region (province) is computed by the average of all reported mean values of one-hour level in a month. In December 2019, there were 405 (for PM_{10}) and 400 (for $PM_{2.5}$) atmospheric stations throughout the country. The NIER provides the monthly-converted data at the regional (provincial) level in the MRAQ. From the MRAQ, we extract the reported monthly mean values of both $PM_{10}\ and\ PM_{2.5}$ at the regional level (in addition to other air pollutants). We restrict our data period to between February 2014 and December 2019 because the PM forecast was first started in February 2014.

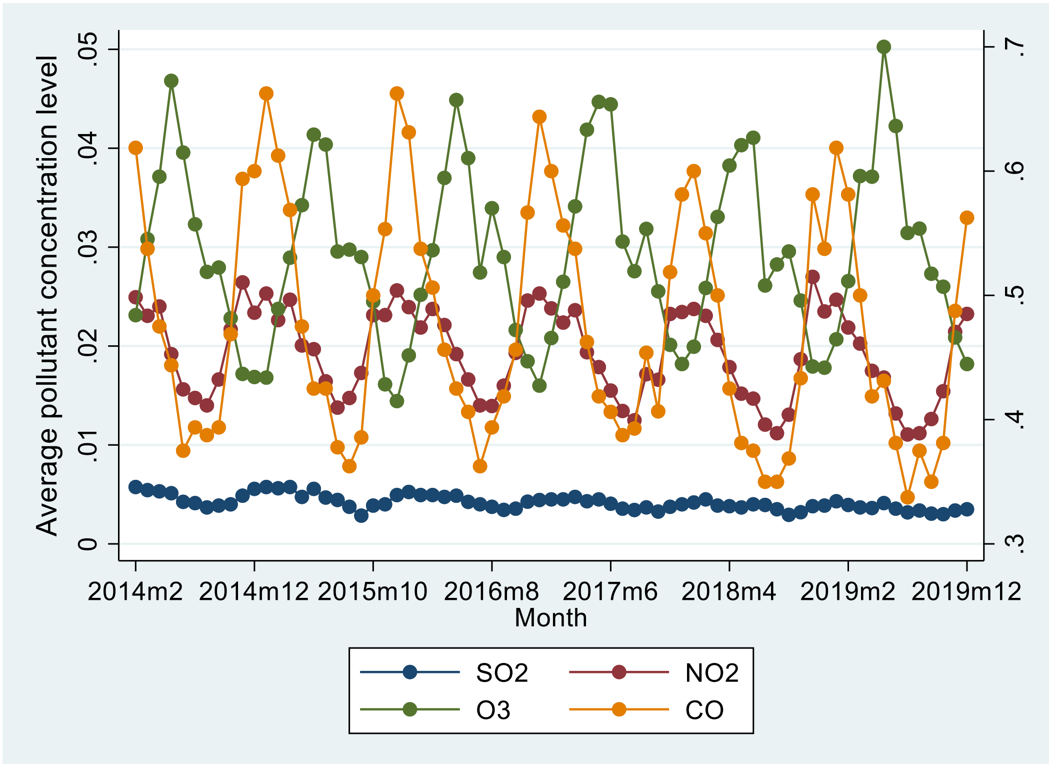
To illustrate air quality in Korea during the analysis period, Figure 2.1 is constructed and it confirms decreasing trends of both PM_{10} and $PM_{2.5}$ concentration levels at the national level, between February 2014 and December 2019. We can easily observe that PM levels display seasonal variations. In addition, Figure 2.2 shows trends of other gaseous air pollutants' concentration levels. Except for ozone (O_3), the other three air pollutants demonstrate reasonably decreasing trends during the data period. Similarly, they display seasonal changes. In Table 2.2, we also present regional PM levels during the analysis period. As we can see, there exist sufficient regional variations in the PM levels, while they are not much dispersed from the national ones.

Figure 2.1 Trends in Particulate Matter Concentration Levels in Korea Between February 2014 and December 2019



Note: The unit of particulate matter is $\mu g/m^3$. $PM_{2.5}$ is recorded starting from June 2015. Although not shown here, a decreasing trend is also observed in pre-analysis periods (i.e., before 2014)

Figure 2.2 Trends in Air Pollutant Concentration Levels in Korea Between February 2014 and December 2019



Note: The unit of SO_2, NO_2, O_3, and CO is parts per million (ppm). SO_2, NO_2 and O_3 follow the left vertical axis scale while CO is scaled on the right vertical axis

Table 2.2 Regional Particulate Matter Levels Between February 2014 and December 2019

Region	PM_{10} level			$PM_{2.5}$ level		
	Mean	SD	N	Mean	SD	N
1=Seoul	43.9	13.9	71	24.2	7.2	55
2=Busan	43.4	9.9	67	24.2	5.6	54
3=Daegu	42.3	10.7	68	23.1	5.9	51
4=Incheon	46.8	12.4	67	24.8	6.5	54
5=Gwangju	41.2	10.9	67	24.0	6.1	54
6=Daejeon	43.5	13.1	69	22.4	7.0	55
7=Ulsan	42.4	10.2	68	22.7	5.2	55
8=Gyeonggi	50.0	14.8	69	26.1	8.3	55
9=Gangwon	44.8	14.1	67	24.4	7.9	53
10=Chungbuk	46.7	14.4	69	27.2	9.6	55
11=Chungnam	44.4	11.9	69	24.5	6.8	51
12=Jeonbuk	47.6	13.7	69	28.5	8.9	50
13=Jeonnam	36.1	8.3	69	21.3	4.8	55
14=Gyeongbuk	43.0	11.4	68	24.5	7.8	55
15=Gyeongnam	43.1	9.0	71	21.9	4.7	55
16=Jeju	39.7	10.2	67	20.4	4.7	49
National	43.7	12.3	1,095	24.0	7.1	856

Note: The unit of particulate matter is $\mu g/m^3$. Sejong special self-governing city was excluded from the sample as it starts to fully appear on air pollutant data since January 2016. The analysis dataset is essentially constructed as a balanced panel but several regions have missing PM values due to incomplete air quality observations

For the forecast information, we contacted the government officials by the Freedom of Information request to obtain the daily PM_{10} and $PM_{2.5}$ forecast data for all regions until December 2019. For each daily forecast information, there are four daily forecasts to indicate if the PM concentration level exceeds certain cutoff points for PM_{10} and $PM_{2.5}$ (: 5:00 AM, 11:00 AM, 5:00 PM, and 11:00 PM), separately. As most people would likely refer to the 5:00 AM forecast every day, before they commute to school or work, we mainly utilize the 5:00 AM forecast information to define a region-month level forecast variable for estimation.

$High\ Forecast_{10}$ is defined as the number of days that a region in a month had at least a "bad" 5:00 AM PM_{10} forecast. Similarly, $High\ Forecast_{2.5}$ is constructed to count the number of at least "bad" 5:00 AM $PM_{2.5}$ forecast days for each region in a month. Importantly, people may not distinguish between "bad" PM_{10} and $PM_{2.5}$ forecasts. Thus, we also define the combined PM forecast variable (: $High\ Forecast$) as the number of days of a region whose reported 5:00 AM forecasts of either PM_{10} or $PM2.5$ were “bad” or “very bad” in a month.

Finally, we utilize the Healthcare Bigdata Hub (HBH, hereafter) portal that provides the monthly and regional level hospital utilization information, from its web database, based on the Korean Standard Classification of Diseases (KCD) codes, which resemble the International Classification of Diseases (ICD). The HBH is operated by the Health Insurance Review & Assessment Service of Korea and available variables for each disease are the number of patients[22], number of hospital visits (inpatient and outpatient), number of insurance claims filed, total medical care expenses incurred, and medical care expenses covered by the insurer. From the HBH, we define $Patients$ (=number of patients), $Visits$ (=number of hospital visits in days), and $Expenses$ (=total medical care expenses incurred upon visits, in USD) as the outcome variables for asthma (J45 and J46), chronic obstructive pulmonary disease (COPD) (J44), and rhinitis (J30 and J31)[23].

The final merged dataset thus provides information on air pollutant concentration levels, the number of days that had at least a “bad” 5:00 AM forecast, and hospital utilization for each respiratory-related disease at the region-month level between February 2014 and December 2019 (1,095 non-missing observations total). In addition, we include a set of regional (provincial) control variables such as population, unemployment rates, mean temperature (℃), mean relative humidity (%), total precipitation (00-24hr, 10,000 mm), and mean wind speed (m/s) at the

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[22] Number of patients is obtained by recording the patients who have received medical services and thus incurred medical expenses given a month in a year.

[23] J45 = asthma, J46 = status asthmaticus, J44 = Other chronic obstructive pulmonary diseases, J30 = vasomotor and allergic rhinitis, and J31 = chronic rhinitis, nasopharyngitis, and pharyngitis (Health Insurance Review & Assessment Service, 2020).

monthly level, which are commonly used in the previous studies[24]. Finally, as monthly respiratory-related hospital utilization for a region can be seasonal, we follow Kim (2021) to include the average number of historical hospital utilization for each outcome of interest (i.e., averaging numbers of each outcome variable across the same months in the other years, excluding the current month's number), as a control variable.

Table 2.3 provides summary statistics for the variables used in empirical analysis. Given the wide ranges of each outcome variable, we can understand that respiratory-related hospital utilization may be highly seasonal and vary by region. Also, among the three respiratory diseases, rhinitis is the most prevalent and has incurred the largest medical expenses.

Looking at the PM forecast variables, on average, each region has 2.0 and 2.9 monthly days of at least a "bad" PM_{10} or $PM_{2.5}$ level, respectively. To its maximum, a region suffered from 21 days (29 days) of at least "bad" PM_{10} ($PM_{2.5}$) in a month. Note that there are 856 non-missing observations for $PM_{2.5}$ specific variables, during the data period[25]. The average PM_{10} and $PM_{2.5}$ levels are 43.7 and 24.0, respectively. As well, we observe that in certain months, regions may suffer from higher PM levels given the maximum values of PM_{10} and $PM_{2.5}$.

[24] Population and unemployment rates are from the Korean Statistical Information Service (KOSIS) and the remaining weather variables are obtained from the Open MET Data Portal by the Korea Meteorological Administration (KMA).
[25] This is because $PM_{2.5}$ specific variables are spanned over June 2015 through December 2019, given the data availability.

Table 2.3 Summary Statistics Between February 2014 and December 2019

Variables	N	Mean	SD	Min	Max
Dependent variables					
(Asthma)					
Patients	1,095	16,313	15,005	2,253	81,852
Visits	1,095	27,110	24,112	3,153	140,063
Expenses	1,095	738,538	595,226	78,335	3,165,116
(COPD)					
Patients	1,095	3,248	2,461	590	11,486
Visits	1,095	7,219	4,498	1,074	22,050
Expenses	1,095	540,526	368,902	63,513	2,320,748
(Rhinitis)					
Patients	1,095	69,035	77,329	8,226	433,004
Visits	1,095	96,011	109,523	10,642	625,572
Expenses	1,095	1,412,370	1,622,898	170,178	9,132,398
PM forecast variables					
$High\ Forecast_{10}$	1,095	2.0	2.9	0.0	21.0
$High\ Forecast_{2.5}$	856	2.9	4.1	0.0	29.0
$High\ Forecast$	1,095	3.3	4.2	0.0	29.0
Air pollutant variables					
PM_{10} $(\mu g/m^3)$	1,095	43.7	12.3	20.0	88.0
$PM_{2.5}$ $(\mu g/m^3)$	856	24.0	7.1	9.0	47.0
SO_2 (ppm)	1,095	0.004	0.002	0.001	0.012
NO_2 (ppm)	1,095	0.019	0.007	0.003	0.040
O_3 (ppm)	1,095	0.029	0.010	0.009	0.062
CO (ppm)	1,095	0.477	0.128	0.200	1.000
Regional control variables					
Population (#)	1,095	3,237,978	3,224,502	595,913	13,239,666
Unemployment rate (%)	1,095	3.4	1.0	1.2	6.7
Temperature (℃)	1,095	13.5	9.0	-5.0	29.0
Relative humidity (%)	1,095	67.6	10.3	39.0	91.0
Total precipitation (00-24hr, 10,000 mm)	1,095	100.2	93.4	0.0	642.2
Wind speed (m/s)	1,095	2.1	0.7	0.9	5.3

Note: The units of patients, visits, and expenses are persons, days, and USD (converted from Korean won; 1 USD is about 1,100 Korean won), respectively. $High\ Forecast_{2.5}$ and $PM_{2.5}$ figures are based on data between June 2015 and December 2019. All variables are recorded at the month-year level

2.2.2 Empirical Model

In order to examine the effect of the PM forecast on respiratory-related hospital utilization, equation (2.1) is constructed using a regional-monthly level panel dataset.

$$(2.1)\quad Outcome_{rt} = \alpha PM_{10,rt} + \beta High\ Forecast_{10,rt} + \gamma PM_{10,rt} \times High\ Forecast_{10,rt} + X_{rt}\delta + \eta_r + \theta_t + u_{rt}$$

$$r = 1, 2, \ldots, 16\ and\ t = Feb.2014, Mar.2014, \ldots, Dec.2019.$$

where *r* represents region and *t* indicates the month-by-year index that ranges from February 2014 to December 2019. $Outcome_{rt}$ can be the number of patients, the number of hospital visits in days (inpatient and outpatient), or total medical care expenses incurred for Asthma, chronic obstructive pulmonary disease (COPD), and rhinitis, respectively, for region *r* in month-year t. $PM_{10,rt}$ is the observed average PM concentration level ($\leq 10\mu g/m^3$) for region *r* in month-year *t*. $High\ Forecast_{10,rt}$ is the number of days that region *r* in month-year *t* had at least a "bad" 5:00 AM $PM_{10,rt}$ forecast[26]. Following Altindag et al. (2017), Dardati et al. (2021), Kim (2021), and Anderson et al. (2022), we also introduce the interaction term between $PM_{10,rt}$ and $High\ Forecast_{10,rt}$ (: $PM_{10,rt} \times High\ Forecast_{10,rt}$) to estimate the impact of the higher PM levels conditional on announced at least "bad" $PM_{10,rt}$ forecasts for each month.

X_{rt} is the vector of regional controls that could affect the dependent variable other than primary regressors, including other gaseous air pollutants and the historical average of

[26] Before November 16, 2014, only the 11:00 AM forecast was available so we employ the 11:00 AM forecast to define $High\ Forecast_{10,rt}$ until November 16, 2014.

respiratory-related hospital utilization. η_r and θ_t represent the region and month-by-year fixed effects, respectively. u_{rt} is the disturbance term and clustered at the regional level given the seasonal variation in PM levels.

Importantly. due to the potentially high correlation among the primary regressors (i.e., $PM_{10,rt}$, $High\ Forecast_{10,rt}$, and $PM_{10,rt} \times High\ Forecast_{10,rt}$) in our setting, we focus on interpreting the interaction term to examine the mitigating impact of the PM forecast[27]. Therefore, γ is the coefficient of our main interest, which identifies the impact of the higher PM_{10} levels given the PM_{10} forecast on individuals' aggregate behaviors of hospital utilization. We hypothesize that γ could be either positive or negative-valued given the additional information on the risk of adverse air quality. For instance, if people restrain from outdoor activities as they become more informed about the high PM levels, individuals will show less respiratory-related hospital utilization. On the other hand, if people become too worried about the risk given the forecast, they may feel unhealthier than usual, and thus use medical services more often.

Starting from June 2015, $PM_{2.5}$ concentration level was publicly available. Thus, instead of the PM_{10} dimension, we re-examine equation (2.1) with $PM_{2.5,rt}$ and $High\ Forecast_{2.5,rt}$ between June 2015 to December 2019. Similar to the PM_{10} counterparts, $PM_{2.5,rt}$ represents the observed average PM level ($\leq 2.5\mu g/m^3$) for region *r* in month-year *t*. $High\ Forecast_{2.5,rt}$ now indicates the number of days that region *r* in month-year *t* had at least a "bad" 5:00 AM forecast of $PM_{2.5}$. Note that in either PM_{10} or $PM_{2.5}$ analysis, we alternatively use the combined

[27] For this respect, we report estimates on the interaction terms across specifications in the Results section. Alternatively, we show relevant p-values for testing the joint significance of the correlated variables to see if they contribute to the corresponding specification significantly.

PM forecast variable (: $High\ Forecast_{rt}$) as explained in the previous subsection, by assuming that individuals may not distinguish between the PM_{10} and $PM_{2.5}$ forecasts.

Finally, we also use the dummy variable approach to see if the introduction of the PM forecast system itself has any impact on individuals' hospital utilization. Spanned over January 2012 through December 2019, we define $PM_{10}\ Forecast_t$ as a dummy variable to represent the month-year period since February 2014 and have it interacted with $PM_{10,rt}$ in empirical analysis.

2.2.3 Identification

As mentioned earlier, there have already been negative impacts of the high PM levels in Korea. The mass media has recently pointed out the risk of inhaling the PM, so Korean people have seriously been aware of the danger since then. Furthermore, we hypothesize that the recently introduced PM forecast has influenced individuals' cognition of adverse air quality, thus affecting respiratory-related hospital utilization.

Given the simultaneous introduction of the PM forecast (PM_{10}) in February 2014 ($PM_{2.5}$ forecast in January 2015) throughout the country, we could consider using the dummy variable approach to evaluate the impact of the forecast implementation on health outcomes, interacting with PM levels. We do this as an additional analysis. However, this is only plausible using the PM_{10} dimension since the $PM_{2.5}$ information was publicly available no earlier than June 2015. More importantly, the forecast system was implemented in February 2014 and effective for all regions of Korea at the same time, so we could not construct the quasi-experimental setting.

Alternatively, the regression discontinuity design can also be considered and probably be ideal, by leveraging the known "bad" threshold points of the forecast. In this case as well, unfortunately, we do not have access to daily hospital utilization data, which are restricted and only accessible within Korea[28].

Instead, we rely on the panel two-way fixed effects model and use the actual daily PM forecasts that are announced publicly. Essentially, there exist natural differences in ambient PM levels, and thus in the frequency of the at least "bad" forecast by region. By controlling for the region and month-by-year fixed effects, we could effectively estimate the impact of the high PM forecast on respiratory-related hospital utilization, by leveraging the within-region variation in PM levels across months. Also, controlling for the historical average of hospital utilization would be effective in further alleviating the endogeneity by seasonality.

2.3 Results

We are primarily interested in the interaction terms to see if the PM forecast could mitigate the higher PM levels by individuals' avoidance behavior (Altindag et al., 2017; Dardati et al., 2021; Kim, 2021; Anderson et al., 2022). Hence, we focus on interpreting estimates on the interactions between PM level and high PM forecast, and p-values for joint significance of the correlated variables (e.g., PM_{10}, $High\ Forecast_{10}$, and $PM_{10} \times High\ Forecast_{10}$) are reported.

Table 2.4 displays the effects of the high PM level forecast on asthma hospital utilization, based on equation (2.1). Panel A in Table 2.4 shows that higher PM_{10} levels per one more at least "bad" PM forecast would reduce regional asthma patients, although at the 10% level of significance. In Column (6), we observe that medical expenses incurred due to asthma patients

[28] Furthermore, the exact protocol of daily PM forecasts that weather forecast officials in practice decide to announce every day is not known. Although using the PM "alert" rather than "forecast," Anderson et al. (2022) employ the fuzzy regression discontinuity design to address the issue that the running variable, daily PM levels, could not fully predict the PM alert.

decrease with the higher PM_{10} levels conditional on the PM forecast by \$156.9 (mean = \$738,538, $p < 0.05$). Results on joint significance demonstrate that our primary regressors have sufficient explanatory power across specifications. We find no other statistically significant estimates in Panel A. In Panel B in Table 2.4, we provide the results of $PM_{2.5}$ and observe more consistent results compared to PM_{10} results. Overall, we find that the high $PM_{2.5}$ level forecast mitigates the impact of higher $PM_{2.5}$ levels observed, possibly through avoidance behavior. In Columns (1) and (2), we find that regional asthma patients decrease by about 8.7 with the higher $PM_{2.5}$ levels conditional on the PM forecast (mean = 15,607, $p < 0.05$). Although statistically significant at the 10% level, asthma visits and incurred medical expenses appear to decrease given the high PM forecast. Tests of joint significance occasionally result in weak explanatory power.

Table 2.4 Effects of Particulate Matter Forecast on Asthma Hospital Utilization

Variables	Model 1: Patients		Model 2: Visits		Model 3: Expenses	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Analysis with the PM_{10} dimension						
$PM_{10} \times High\ Forecast_{10}$	-0.893		-4.571		-109.5	
	(1.733)		(4.530)		(97.01)	
$PM_{10} \times High\ Forecast$		-3.181*		-6.553		-156.9**
		(1.612)		(3.773)		(61.84)
Mean DV	16,313	16,313	27,110	27,110	738,538	738,538
R^2	0.815	0.816	0.798	0.800	0.741	0.743
Joint significance	0.0542	0.0023	0.0824	0.0125	0.0078	0.0475
Observations	1,095	1,095	1,095	1,095	1,095	1,095
[Month/year]	[2/2014-12/2019]	[2/2014-12/2019]	[2/2014-12/2019]	[2/2014-12/2019]	[2/2014-12/2019]	[2/2014-12/2019]
Panel B. Analysis with the $PM_{2.5}$ dimension						
$PM_{2.5} \times High\ Forecast_{2.5}$	-8.742**		-15.26*		-205.9*	
	(4.045)		(8.065)		(116.8)	
$PM_{2.5} \times High\ Forecast$		-8.701**		-15.50*		-215.1*
		(3.659)		(7.363)		(106.2)
Mean DV	15,607	15,607	25,562	25,562	734,612	734,612
R^2	0.841	0.841	0.821	0.821	0.766	0.767
Joint significance	0.0938	0.0755	0.1087	0.0890	0.1587	0.1462
Observations	856	856	856	856	856	856
[Month/year]	[6/2015-12/2019]	[6/2015-12/2019]	[6/2015-12/2019]	[6/2015-12/2019]	[6/2015-12/2019]	[6/2015-12/2019]

Note: Standard errors clustered at the regional level are in parentheses. The units of patients, visits, and expenses are persons, days, and USD (converted from Korean won; 1 USD is about 1,100 Korean won), respectively. Regional control variables, region fixed effects, and month-by-year fixed effects are included in every specification but are not shown for the sake of brevity. DV: dependent variable; Joint significance: p-value for testing the joint significance of corresponding PM level, PM forecast, and their interaction variables. *, **, *** represents statistical significance at 10%, 5%, and 1%, respectively

Table 2.5 now presents the effects of the high PM level forecast on COPD hospital utilization. Unlike the results from asthma hospital use, we rarely observe statistically significant coefficients. As shown in Panel A, COPD hospital utilization may be unresponsive to both higher PM_{10} levels and PM forecast. While we observe some effects of the higher PM forecast interacted with $PM_{2.5}$ levels, in Panel B, they appear to be marginal in magnitude and significant at the 10% level.

Table 2.5 Effects of Particulate Matter Forecast on COPD Hospital Utilization

Variables	Model 1: Patients		Model 2: Visits		Model 3: Expenses	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Analysis with the PM_{10} dimension						
$PM_{10} \times High\ Forecast_{10}$	0.168		0.374		25.64	
	(0.207)		(0.690)		(80.69)	
$PM_{10} \times High\ Forecast$		-0.0405		0.354		15.86
		(0.186)		(0.558)		(75.91)
Mean DV	3,248	3,248	7,219	7,219	540,526	540,526
R^2	0.527	0.533	0.611	0.612	0.521	0.526
Joint significance	0.1383	0.0088	0.3242	0.1017	0.1277	0.0845
Observations	1,095	1,095	1,095	1,095	1,095	1,095
[Month/year]	[2/2014-12/2019]	[2/2014-12/2019]	[2/2014-12/2019]	[2/2014-12/2019]	[2/2014-12/2019]	[2/2014-12/2019]
Panel B. Analysis with the $PM_{2.5}$ dimension						
$PM_{2.5} \times High\ Forecast_{2.5}$	-0.470*		0.00741		35.73	
	(0.245)		(0.773)		(116.9)	
$PM_{2.5} \times High\ Forecast$		-0.488*		0.0510		43.74
		(0.255)		(0.750)		(107.5)
Mean DV	3,195	3,195	7,026	7,026	548,509	548,509
R^2	0.478	0.479	0.572	0.572	0.555	0.555
Joint significance	0.0890	0.1244	0.4079	0.3526	0.0399	0.0051
Observations	856	856	856	856	856	856
[Month/year]	[6/2015-12/2019]	[6/2015-12/2019]	[6/2015-12/2019]	[6/2015-12/2019]	[6/2015-12/2019]	[6/2015-12/2019]

Note: Standard errors clustered at the regional level are in parentheses. The units of patients, visits, and expenses are persons, days, and USD (converted from Korean won; 1 USD is about 1,100 Korean won), respectively. Regional control variables, region fixed effects, and month-by-year fixed effects are included in every specification but are not shown for the sake of brevity. DV: dependent variable; Joint significance: p-value for testing the joint significance of corresponding PM level, PM forecast, and their interaction variables. *, **, *** represents statistical significance at 10%, 5%, and 1%, respectively

Table 2.6 provides the effects of the high PM forecast on rhinitis hospital utilization. In Columns (2) and (4) of Panel A, we find that the high PM forecast alleviates the impact of higher PM_{10} concentration by reduction of 9.895 and 14.85 rhinitis patients and visits, respectively (mean = 69,035 and 96,011, respectively, $p < 0.05$), per one more at least “bad” PM forecast. In the case of $PM_{2.5}$ analysis in Panel B, the results are similar but significant at the 10% level.

Based on the results of joint significance, it appears that the interaction terms are exclusively significant in explaining rhinitis hospital utilization.

Table 2.6 Effects of Particulate Matter Forecast on Rhinitis Hospital Utilization

Variables	Model 1: Patients		Model 2: Visits		Model 3: Expenses	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Analysis with the PM_{10} dimension						
$PM_{10} \times High\ Forecast_{10}$	-2.063		-3.896		-72.85	
	(3.084)		(4.216)		(165.1)	
$PM_{10} \times High\ Forecast$		-9.895**		-14.85**		-261.0
		(4.394)		(6.558)		(151.8)
Mean DV	69,035	69,035	96,011	96,011	1,412,370	1,412,370
R^2	0.922	0.922	0.919	0.920	0.870	0.872
Joint significance	0.2197	0.1718	0.2169	0.1864	0.3612	0.1319
Observations	1,095	1,095	1,095	1,095	1,095	1,095
[Month/year]	[2/2014-12/2019]	[2/2014-12/2019]	[2/2014-12/2019]	[2/2014-12/2019]	[2/2014-12/2019]	[2/2014-12/2019]
Panel B. Analysis with the $PM_{2.5}$ dimension						
$PM_{2.5} \times High\ Forecast_{2.5}$	-20.66*		-30.38*		-344.7	
	(9.959)		(14.44)		(204.9)	
$PM_{2.5} \times High\ Forecast$		-21.67*		-32.71*		-364.7
		(10.76)		(15.80)		(216.3)
Mean DV	70,260	70,260	97,396	97,396	1,461,701	1,461,701
R^2	0.926	0.926	0.921	0.921	0.885	0.885
Joint significance	0.2604	0.2898	0.2502	0.2733	0.1620	0.2031
Observations	856	856	856	856	856	856
[Month/year]	[6/2015-12/2019]	[6/2015-12/2019]	[6/2015-12/2019]	[6/2015-12/2019]	[6/2015-12/2019]	[6/2015-12/2019]

Note: Standard errors clustered at the regional level are in parentheses. The units of patients, visits, and expenses are persons, days, and USD (converted from Korean won; 1 USD is about 1,100 Korean won), respectively. Regional control variables, region fixed effects, and month-by-year fixed effects are included in every specification but are not shown for the sake of brevity. DV: dependent variable; Joint significance: p-value for testing the joint significance of corresponding PM level, PM forecast, and their interaction variables. *, **, *** represents statistical significance at 10%, 5%, and 1%, respectively

Finally, we conduct the dummy variable approach to examine the impact of the PM forecast system on respiratory-related hospital utilization in Korea. Note that the data period is now spanned from January 2012 through December 2019. Unlike the results with the actual PM forecast counts, in Table 2.7, we find null impacts from the interaction between the PM_{10} level and the PM_{10} forecast introduction dummy. We find one statistically significant estimate on rhinitis visits, although at the 10% level and with a positive sign. Overall, we understand that the introduction of the PM forecast system itself may not change individuals' respiratory-related hospital utilization particularly because our analysis is conducted at the regional level.

Table 2.7 Effects of Introducing Particulate Matter Forecast on Respiratory-Related Hospital Utilization

Variables	Model 1: Asthma			Model 2: COPD			Model 3: Rhinitis		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$PM_{10} \times PM_{10}\ Forecast$	-125.8	-258.7	-502.8	1.372	6.934	2,377	349.0	472.6*	10,160
	(84.52)	(185.2)	(1,509)	(9.077)	(25.45)	(1,633)	(205.9)	(264.1)	(6,228)
Mean DV	16,313	27,110	738,538	3,248	7,219	540,526	69,035	96,011	1,412,370
R^2	0.751	0.732	0.753	0.555	0.614	0.558	0.915	0.918	0.843
Joint significance	0.0175	0.0178	0.8467	0.0277	0.0002	0.3045	0.1444	0.1765	0.1007
Observations	1,495	1,495	1,495	1,495	1,495	1,495	1,495	1,495	1,495
[Month/year]	[1/2012-12/2019]	[1/2012-12/2019]	[1/2012-12/2019]	[1/2012-12/2019]	[1/2012-12/2019]	[1/2012-12/2019]	[1/2012-12/2019]	[1/2012-12/2019]	[1/2012-12/2019]

Note: Standard errors clustered at the regional level are in parentheses. Each column across models 1-3 represents patients, visits, and expenses of a respiratory disease of interest, respectively. The units of patients, visits, and expenses are persons, days, and USD (converted from Korean won; 1 USD is about 1,100 Korean won), respectively. Regional control variables, region fixed effects, and month-by-year fixed effects are included in every specification but are not shown for the sake of brevity. DV: dependent variable; Joint significance: p-value for testing the joint significance of corresponding PM level, PM forecast, and their interaction variables. *, **, *** represents statistical significance at 10%, 5%, and 1%, respectively

2.4 Discussion

This paper attempts to estimate the effects of the recently introduced PM forecast on respiratory-related hospital utilization in Korea. Although there have been quite higher levels of PM concentration in Korea, Koreans have not been very sensitive to the high PM levels until recently. In this sense, the PM forecast observed by individuals since February 2014 could affect people's cognition of adverse air quality and thus affect respiratory-related hospital utilization.

By using the panel two-way fixed effects model, we find that the adverse impact of higher PM levels can be mitigated conditional on PM forecasts about air quality. In particular, the results are significant for asthma and rhinitis hospital utilization that regional hospital utilization decreases with the higher PM levels in response to an increased number of the PM forecast. On the other hand, we find that COPD hospital use may be largely unresponsive to PM level and forecast. Overall, we interpret the results that the PM level forecast can be effective in reducing the negative health impacts of the higher PM levels through individuals' avoidance behavior and this is in line with the previous studies which examine the health impacts of the higher PM levels interacted with the PM alert (Altindag et al., 2017; Dardati et al., 2021; Kim, 2021; Anderson et al., 2022).

This study would add to the existing literature in that it is the first attempt to examine the impacts of the PM forecast on respiratory-related hospital utilization in Korea. Besides the biological responses to the PM concentration levels, people can now directly perceive health risks given additional information. It would be important to examine how individuals would respond to the identified health risks (i.e., through avoidance behavior) and this has received relatively less attention when examining the health impacts of air pollution.

Our study has several limitations. First, we have not examined the mechanisms as to why only COPD variables are largely unaffected while other respiratory diseases' hospital utilization is reduced upon the higher PM forecast. Also, we implicitly assume that individuals respond to the PM forecast and thus restrain from outdoor activities (i.e., showing avoidance behavior). Finally, we rely on region-month variations in PM levels (and thus PM forecast) and thus losing variations at the daily level. It would be meaningful to evaluate the impact of the high PM level forecast on daily respiratory-related hospital utilization. Ideally, we could construct a quasi-experimental design (i.e., regression discontinuity design) to examine the causal impact of the high PM level forecast more directly, as attempted by Anderson et al. (2022) using the PM alert dimension.

Chapter 3 Tobacco Use and Sleep Duration

3.1 Introduction

Smoking has been a major means of tobacco use and one of the primary causes of preventable diseases such as cardiovascular diseases, respiratory diseases, and a variety of cancers (CDC, 2020). As people become more aware of the health risk of tobacco use, many researchers have examined its adverse impact of it. Of many previous studies, the impact of tobacco use on sleep duration, which is the main interest of this study, has been frequently studied in non-economics fields. Physiologically, tobacco use could influence one's sleep quality via the nicotine channel and excessive use of tobacco may result in sleep disruption.

In this study, I attempt to examine if individuals' tobacco use (smoking or vaping) would influence individuals' sleep duration. To do so, I utilize an instrumental variable (IV) regression of sleep duration on tobacco use, instrumented with tobacco tax policies (i.e., cigarette taxes or e-cigarette tax implementation). In this way, I could construct a causal relationship that individuals' tobacco use, derived from state cigarette or e-cigarette taxes, would influence sleep, possibly through the physiological channel.

Hypothetically, two opposing directions could exist between tobacco use and sleep duration. For example, individuals experiencing sleep disruption may be more likely to smoke or vape. On the other hand, smoking or vaping itself could lead to sleep disruption. Although the extant literature has confirmed the negative association between tobacco use and sleep, one could not distinguish between the two directions above unless one relies on a causality research design.

To my best knowledge, no previous studies, particularly in economics, have attempted to examine the causal relationship that tobacco use (smoking or vaping) affects individuals' sleep.

The current study would be the first to empirically estimate the causal effect of tobacco use on sleep duration using a nationwide public dataset.

Using the Behavioral Risk Factor Surveillance System (BRFSS) database between 2016 and 2018, the empirical results indicate that overall, no smoking or vaping would influence individuals' sleep duration, invalidating the causal direction from tobacco use to sleep. Further analysis of examining the impact of quitting also finds null impacts on sleep. Still, naïve OLS regressions between tobacco use and sleep demonstrate that tobacco use (: smoking, quitting, and vaping) is negatively associated with sleep duration. With some reservations, one could think that tobacco use and sleep are negatively related but the causal direction from tobacco use to sleep duration may not be valid.

This study proceeds as follows. First, the following section introduces and reviews relevant previous studies (: section 3.2). Next, a brief context of tobacco use and policies in the U.S. is provided (: section 3.3) and sections 3.4 and 3.5 demonstrate the data and empirical model to estimate the causal impact of tobacco use on sleep. Section 3.6 presents the empirical results and finally, section 3.7 discusses the major findings and caveats of the current study.

3.2 Literature Review

As cigarette smoking is a major means of tobacco use, many researchers have studied individuals' smoking behavior and its harmful impact on a variety of outcomes. Closer to this study, previous studies show that smoking could have negative impacts on sleep and related diseases such as sleep apnea (Jaehne et al., 2014; Mcnamara et al., 2014; Jaehne et al., 2015; Hsu et al., 2019; Liao et al., 2019; Veronda et al., 2020).

Other than cigarette smoking, vaping (i.e., e-cigarette use) has become increasingly popular these days. As most vapers are adolescents or young adults and given the gateway effect that they may eventually switch to cigarette smoking (Etter, 2018), examining vaping behavior and its impact has been also an important topic among tobacco researchers. A recent study shows that although the prevalence of smoking among adolescents has decreased in the U.S., in return, the vaping prevalence among them demonstrates an increasing trend (Tauras et al., 2020). Similar to the impact of cigarette smoking on sleep, most studies find that vaping would negatively influence one's sleep outcome (Riehm et al., 2019; Brett et al., 2020; Kianersi et al., 2020; Kwon et al., 2020; Wiener et al., 2020; Zvolensky et al., 2020).

Sleep is one of the major determinants of one's time allocation and influenced sleep could have a significant impact on our productivity (Gibson and Shrader, 2018). Researchers show that disrupted sleep could affect individuals' outcomes. Relatedly, Gibson and Shrader (2018) first examine a causal relationship between sleep duration and labor outcomes, using the IV regression model. They find that improved sleep induced by the sunset time difference (= IV) increases weekly earnings by 1.1% and 5% in the short and long runs, respectively. Other studies also explore the impact of sleep on academic outcomes within the IV framework, showing that improved sleep could enhance cognitive or academic outcomes (Giuntella et al., 2017; Heissel and Norris, 2018; Groen and Pabilonia, 2019).

Given the previous studies that demonstrate the negative association between tobacco use and sleep, I am naturally drawn to see if there exists a causal path that tobacco use affects sleep, rather than the opposite direction. To date, however, no previous studies in economics have verified this causal relationship. This study first attempts to estimate the causal impact of tobacco use (smoking or vaping) on sleeping, using the IV design.

3.3 Tobacco Use and Controls in the United States

Given the adverse health impacts of tobacco use, most developed countries have implemented a variety of tobacco control policies. Tobacco control is often divided into the price and non-price policies. Price tobacco policies have been proven to be the most effective in reducing the prevalence of smoking (NCI and WHO, 2016): governments often increase cigarette taxes sharply to incentivize smoking cessation as well as discourage non-smokers from the smoking onset. In the case of non-price tobacco policies, often implemented are the minimum legal purchasing age (MLPA) laws or indoor use bans (i.e., bars, restaurants, and/or worksites)[29] and they vary by state and by either conventional cigarettes or e-cigarettes[30].

The U.S. has experienced a decreasing trend in the prevalence of smoking given the extensive use of tobacco controls such as cigarette tax and smoke-free indoor laws. Importantly, as mentioned earlier, the recent introduction of e-cigarettes has struck the young population (Tauras et al., 2020) and brought a variety of concerns such as a national outbreak of the EVALI[31]. To discourage e-cigarette use, the U.S. state governments recently have implemented vaping-specific laws: e-cigarette tax and vape-free indoor laws[32].

Table 3.1 summarizes the effective dates of state-level tobacco taxes in the U.S. as of 2019. As one can see, most cigarette taxation has been first implemented long ago while

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[29] Oftentimes, it is implemented as “100% smoke-free (or vape-free) laws.” It means that cigarette smoking (or vaping) is completely banned in the targeted area: worksites, bars, or restaurants. In some states, although smoke-free laws (vape-free) have been implemented, cigarette smoking (vaping) could be restrictedly allowed in a designated area or separated space.
[30] In the case of e-cigarettes, all states including the District of Columbia enacted the MLPA laws around 2010 through 2016 (Pesko and Currie, 2019).
[31] The EVALI (e-cigarette or vaping product use-associated lung injury) is defined as the newly identified lung disease allegedly linked to vaping (CDC, 2020). Recently, it has been frequently reported that vaporized marijuana use is related to the development of fatal lung diseases.
[32] Fifteen states to date have adopted comprehensive indoor vaping use bans in public areas, and 25 states have passed laws to require taxation on e-cigarette sales (CDC, 2020).

additional increases have been made continuously by states. On the other hand, e-cigarette taxation has been enacted relatively recently and not all states have an e-cigarette tax policy. In this sense, one may expect that the impact of cigarette taxes on smoking behavior could be marginal, even though the price tobacco policy has been proven the most effective historically. As e-cigarette taxes can be levied in multiple ways (see note in Table 3.1), the current study only examines whether a state has ever implemented the e-cigarette tax in the empirical analysis. Using these state-level variations in tobacco controls, the present study estimates the impact of tobacco use on sleep duration.

Table 3.1 History of Tobacco Taxation in the United States As of 2019

State	Cigarette tax changes (tax amounts after change)	E-cigarette tax implementation
Alabama	5/18/2004 ($0.425), 10/1/2015 ($0.675)	
Alaska	1/1/2005 ($2.00)	
Arizona	11/7/2006 ($2.00)	
Arkansas	3/1/2009 ($1.15)	
California	1/1/1999 ($0.87), 4/1/2017 ($2.87)	4/1/2017[a]
Colorado	1/1/2005 ($0.84)	
Connecticut	7/1/2011 ($3.40), 10/1/2015 ($3.65), 7/1/2016 ($3.90), 12/1/2017 ($4.35)	10/1/2019[b]
Delaware	8/1/2009 ($1.60), 9/1/2017 ($2.10)	1/1/2018[b]
District of Columbia	9/14/2011 ($2.50), 10/1/2014 ($2.90), 10/1/2015 ($2.91), 10/1/2016 ($2.92), 10/1/2018 ($4.94)	10/1/2015[a]
Florida	7/1/2009 ($1.339)	
Georgia	7/1/2003 ($0.37)	
Hawaii	7/1/2011 ($3.20)	
Idaho	7/1/2003 ($0.57)	
Illinois	7/1/2002 ($0.98), 6/24/2012 ($1.98), 7/1/2019 ($2.98)	7/1/2019[a]
Indiana	7/1/2007 ($0.995)	
Iowa	3/15/2007 ($1.36)	
Kansas	1/1/2003 ($0.79), 7/1/2015 ($1.29)	1/1/2017[b]
Kentucky	4/1/2009 ($0.60), 7/1/2018 ($1.10)	
Louisiana	7/1/2002 ($0.36), 7/1/2015 ($0.86), 4/1/2016 ($1.08)	7/1/2015[b]
Maine	9/19/2005 ($2.00)	
Maryland	1/1/2008 ($2.00)	
Massachusetts	7/1/2008 ($2.51), 8/1/2013 ($3.51)	
Michigan	7/1/2004 ($2.00)	

Minnesota	1/1/2011 ($1.23), 7/1/2013 ($2.83), 1/1/2015 ($2.90), 1/1/2016 ($3.00), 1/1/2017 ($3.04)	8/1/2010[a]
Mississippi	5/15/2009 ($0.68)	
Missouri	10/1/1993 ($0.17)	
Montana	1/1/2005 ($1.70)	
Nebraska	10/1/2002 ($0.64)	
Nevada	7/22/2003 ($0.80), 7/1/2015 ($1.80)	
New Hampshire	7/1/2011 ($1.68), 8/1/2013 ($1.78)	
New Jersey	7/1/2009 ($2.70)	9/30/2018[c]
New Mexico	7/1/2010 ($1.66), 7/1/2019 ($2.00)	7/1/2019[c]
New York	7/1/2010 ($4.35)	12/1/2019[c]
North Carolina	9/1/2009 ($0.45)	6/1/2015[b]
North Dakota	6/30/1993 ($0.44)	
Ohio	7/1/2005 ($1.25), 7/1/2015 ($1.60)	10/17/2019[b]
Oklahoma	1/1/2005 ($1.03), 8/23/2018 ($2.03)	
Oregon	1/1/2004 ($1.18), 1/1/2014 ($1.31), 1/1/2016 ($1.32), 1/1/2018 ($1.33)	
Pennsylvania	11/1/2009 ($1.60), 8/1/2016 ($2.60)	7/13/2016[d]
Rhode Island	4/10/2009 ($3.46), 7/1/2012 ($3.50), 7/1/2015 ($3.75), 7/1/2017 ($4.25)	
South Carolina	7/1/2010 ($0.57)	
South Dakota	1/1/2007 ($1.53)	
Tennessee	7/1/2007 ($0.62)	
Texas	1/1/2007 ($1.41)	
Utah	7/1/2010 ($1.70)	
Vermont	7/1/2011 ($2.62), 7/1/2014 ($2.75), 7/1/2015 ($3.08)	7/1/2019[e]
Virginia	7/1/2005 ($0.30)	
Washington	5/1/2010 ($3.025)	10/1/2019[b]
West Virginia	5/1/2003 ($0.55), 7/1/2016 ($1.20)	7/1/2016[b]
Wisconsin	9/1/2009 ($2.52)	7/5/2019[b]
Wyoming	7/1/2003 ($0.60)	

Note: a, b, c, d, and e, respectively, indicate different means of taxation such as per value of wholesale price, per liquid milliliter, percent value of retail sale price, purchase price from the wholesaler, and excise tax by wholesale dealers that is added to the retail price.

3.4 Data

To examine the effect of tobacco use on sleep duration, the current study employs the Behavioral Risk Factor Surveillance System (BRFSS) survey which is administered annually by the Center for Disease Controls (CDC). The BRFSS is the individual level repeated cross-sectional and large-scale public data, surveyed via the landline telephone and cellphone interviews. The BRFSS was designed to survey individuals' health-related behavior and information in the U.S. For example, the BRFSS provides both conventional and e-cigarette use information with a rich set of individual demographic variables such as average sleep duration, health status (i.e., subjective health or mental health), age, income, gender, marital status, educational attainment, race/ethnicity, and working status.

The current study assumes that nicotine as a common factor of tobacco products could distort one's circadian rhythm and there can be heterogeneous effects by types of tobacco products (i.e., conventional cigarettes or e-cigarettes). Also, there may be individuals who use both cigarettes and e-cigarettes or switch to the other product when restraining from one. Hence, I employ the BRFSS data between 2016 and 2018 to incorporate both smoking and vaping information in the empirical analysis[33].

To examine the impact of tobacco use on sleep, several tobacco control policies have been considered instrumental variables: cigarette/e-cigarette taxes, MLPA laws, and indoor use bans. After careful consideration, the present study utilizes cigarette tax amounts and (ever) e-cigarette tax implementation[34]. That is, cigarette tax amounts are manually coded to indicate each state's cigarette tax amounts over time. In the case of e-cigarette policies, each state is marked if it has ever implemented an e-cigarette taxation policy in a given year. This is because e-cigarette taxes are often levied by percent value of wholesale price, retail price, or per milligram of the e-cigarette liquid and this could significantly vary by state.

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[33] This is because the BRFSS starts to survey e-cigarette use-related information in 2016. There was no relevant information in 2019 so I use data between 2016 and 2018.

[34] The MLPA laws for both cigarettes and e-cigarettes have already been effective in most states before the analysis periods. More importantly, the MLPA laws have been proven to be particularly effective among youth or young adults. Further, given the strong collinearity across indoor tobacco use ban policies, I focus on using the traditional taxation policies as instruments. Cigarette taxes are often used as the IV for the endogenous smoking behavior of individuals (Rashad, 2006; Kasteridis and Yen, 2012).

Variables in the analysis sample are defined as follows. First, $Cigarette\ tax$ represents cigarette tax amounts (in USD) for each state in a given year. Note that the tax amounts are adjusted based on the annual average CPI-U index (seasonally adjusted, 1982-1984 = 100). In the case of $E - cigarette\ tax$, it is a dummy variable to indicate if a state has ever implemented e-cigarette taxation in a given year. This is again because of various types of e-cigarette taxation across states.

For tobacco use variables, $Smoke$ and $Vape$ respectively represents if an individual currently smokes or vapes. Importantly, the current smokers are defined among those who have smoked at least 100 cigarettes previously. Also, the current vapers are among those who have ever experienced vaping before (= $Ever\ vape$). $Everyday\ smoke$ and $Someday\ smoke$ are defined as those who have smoked every day and only some days, respectively. Similarly, $Everyday\ vape$ and $Someday\ vape$ are generated. In addition to smoking and vaping status, I further define $Quit$ to represent those who are currently not smoking although having smoked at least 100 cigarettes previously.

$Average\ drink$ represents the average alcoholic drinks consumed on the days of alcohol consumption during the past 30 days[35].

For health information, $Sleep$ represents the average sleeping hours. Note that sleep hours are adjusted to exclude those who have slept more than 10 hours per day[36]. Sleeping more than 10 hours can be seen as “long sleep” or “excessive quantity of sleep (EQS)” if that bothers and/or causes distress during daily life (Ohayon et al., 2013). $Good\ health$ is a dummy variable

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[35] The BRFSS defines one alcoholic drink as a 12-ounce beer, a 5-ounce glass of wine, or a drink with one shot of liquor.

[36] Based on the unadjusted sleep variable, only 1.27% of total observations have more than 10 hours of sleep.

to represent those who feel healthy (subjective health). $Bad\ mental\ days$ count the number of days when individuals felt they have mentally bad health during the past 30 days.

Thirteen age groups (: 5-year gap) and 8 income brackets (i.e., household income from all sources), respectively, are employed as originally defined in the BRFSS database. Also, working status, race/ethnicity, gender, marital status, and educational attainment are controlled for in the analysis. For each annual dataset, the BRFSS contains about 450,000 observations. After data cleaning and processing missing values, the final analysis sample includes 1,346,263 observations at the maximum[37].

Table 3.2 shows the summary statistics for the analysis sample between 2016 and 2018. On average, individuals in the sample experience $1.83 cigarette tax ($0.75 real cigarette tax) per pack of 20 cigarettes. Also, only a few states have ever adopted e-cigarette tax: only 13% of individuals have experienced e-cigarette tax during the analysis period.

The prevalence of smoking and vaping are 15% and 3% in the sample, respectively. About 66% of those who previously smoked at least 100 cigarettes are not currently smoking (i.e., quitters). About 16% of the entire sample have ever experienced vaping before. On average, individuals drink about 1.14 alcoholic beverages on each drinking occasion.

On average, an individual sleeps about 6.97 hours per day between 2016 and 2018 (capped at 10 hours). About 81% of the sample think they have good health. The average monthly bad mental days that an individual in the sample has are about 3.56 days and to its extreme, some individuals may have 30 bad mental days a month.

[37] This varies by variable as each variable of interest generates significantly different missing observations based on its definition.

Age groups are distributed quite evenly in the sample, although there are slightly more older individuals. About half of the sample is employed (including the self-employed). The unemployment rate is about 4%, which is quite close to the natural rate. Income brackets are also distributed quite evenly up to $75,000: about 33% of the sample have an annual household income of more than $75,000. There are slightly more female respondents. About 52% of the sample have married and live with a spouse, and 65% of the sample have at least a college degree.

To depict the sample characteristics regarding variables of main interest, Figure 3.1 is provided to demonstrate trends of average sleep duration, smoking, and vaping in the U.S. between 2012 and 2018, based on the BRFSS database. As one can observe, smoking prevalence shows a little decreasing trend as time goes by. In return, vaping prevalence has slightly increased recently. Sleeping hours have some fluctuations across years but they are quite marginal in magnitude.

Table 3.2 Summary Statistics – The BRFSS Between 2016 and 2018

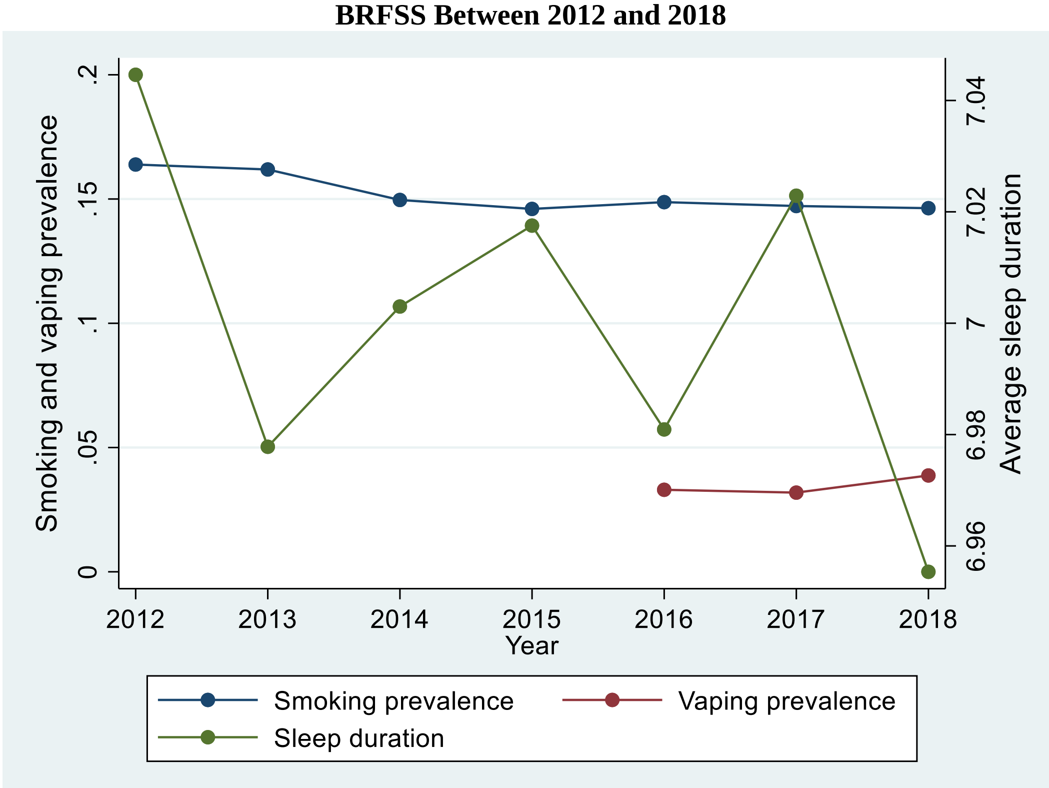
Variables	N	Mean	SD	Min	Max
Tobacco tax					
Cigarette tax, unadjusted ($)	1,346,263	1.83	1.15	0.17	4.94
Cigarette tax ($)	1,346,263	0.75	0.47	0.07	1.97
E-cigarette tax	1,346,263	0.13	0.34	0	1
Tobacco use					
Smoke	1,291,457	0.15	0.35	0	1
Everyday smoke	1,291,457	0.10	0.31	0	1
Someday smoke	1,291,457	0.04	0.20	0	1
Quit	559,892	0.66	0.47	0	1
Ever vape	1,143,110	0.16	0.37	0	1
Vape	1,142,816	0.03	0.18	0	1
Everyday vape	1,142,816	0.01	0.11	0	1
Someday vape	1,142,816	0.02	0.15	0	1
Alcohol consumption					
Average drink (#)	1,261,680	1.14	2.08	0	98

Health information					
Sleep, unadjusted (hours)	930,271	7.05	1.49	1	24
Sleep (hours)	918,420	6.97	1.31	1	10
Good health	1,342,717	0.81	0.39	0	1
Bad mental days	1,324,597	3.56	7.86	0	30
Age group (5-year gap)					
Age 18-24	1,325,386	0.06	0.23	0	1
Age 25-29	1,325,386	0.05	0.22	0	1
Age 30-34	1,325,386	0.06	0.23	0	1
Age 35-39	1,325,386	0.06	0.24	0	1
Age 40-44	1,325,386	0.06	0.23	0	1
Age 45-49	1,325,386	0.07	0.25	0	1
Age 50-54	1,325,386	0.08	0.28	0	1
Age 55-59	1,325,386	0.10	0.30	0	1
Age 60-64	1,325,386	0.11	0.32	0	1
Age 65-69	1,325,386	0.11	0.32	0	1
Age 70-74	1,325,386	0.09	0.29	0	1
Age 75-79	1,325,386	0.07	0.25	0	1
Age 80 or older	1,325,386	0.08	0.27	0	1
Working status					
Employment	1,333,832	0.41	0.49	0	1
Self-employment	1,333,832	0.09	0.28	0	1
Unemployment	1,333,832	0.04	0.20	0	1
Homemaker	1,333,832	0.05	0.22	0	1
Student	1,333,832	0.03	0.16	0	1
Retired	1,333,832	0.30	0.46	0	1
Unable to work	1,333,832	0.08	0.26	0	1
Income brackets					
< $10,000	1,118,501	0.05	0.21	0	1
$10,000 to $15,000	1,118,501	0.05	0.22	0	1
$15,000 to $20,000	1,118,501	0.07	0.26	0	1
$20,000 to $25,000	1,118,501	0.09	0.29	0	1
$25,000 to $35,000	1,118,501	0.11	0.31	0	1
$35,000 to $50,000	1,118,501	0.14	0.35	0	1
$50,000 to $75,000	1,118,501	0.16	0.37	0	1
>= $75,000	1,118,501	0.33	0.47	0	1
Race/ethnicity					
White	1,346,263	0.77	0.42	0	1
Black	1,346,263	0.08	0.27	0	1
Asian	1,346,263	0.02	0.15	0	1
American Indians & Alaska Native	1,346,263	0.02	0.13	0	1
Hispanic	1,346,263	0.07	0.26	0	1
Other race	1,346,263	0.03	0.17	0	1
Gender					

Male	1,344,850	0.44	0.50	0	1
Female	1,344,850	0.56	0.50	0	1
Marital status					
Single	1,336,698	0.16	0.37	0	1
Married	1,336,698	0.52	0.50	0	1
Divorced	1,336,698	0.14	0.34	0	1
Widowed	1,336,698	0.12	0.33	0	1
Separated	1,336,698	0.02	0.14	0	1
De facto	1,336,698	0.03	0.18	0	1
Educational attainment					
Less than high school	1,341,257	0.07	0.26	0	1
High school	1,341,257	0.28	0.45	0	1
College or over	1,341,257	0.65	0.48	0	1

Note: Number of observations across variables varies due to missing values. Cigarette tax is adjusted based on annual average CPI-U (seasonally adjusted, 1982-1984 = 100). N: number of observations; SD: standard deviations; Min: minimum value; Max: maximum value

Figure 3.1 Trends of Average Sleeping Hours, Smoking, and Vaping in the United States – The BRFSS Between 2012 and 2018



Note: E-cigarette use information (i.e., vaping) has been surveyed since 2016. Smoking and vaping prevalence are in percentage. Sleep durations are in hours. Individuals with excessive sleeping hours (i.e., more than 10 hours) are not included in the computation.

3.5 Empirical Model

3.5.1 Empirical Specification

To empirically estimate the causal impact of tobacco use on sleep duration, the current study constructs the individual level and repeated cross-sectional dataset between 2016 and 2018.

Equations (3.1) and (3.2) examine if there exist adverse impacts of tobacco use on sleeping with the instrumental variable (IV) framework as follows:

$$(3.1)\ First\ Stage: Tobacco\ Use_{ist} = \alpha_1 Tobacco\ Control_{st} + X_{ist}\beta_1 + \gamma_{1,s} + \delta_{1,t} + \theta_{1,ist}$$

$$(3.2)\ Second\ Stage: Sleep_{ist} = \alpha_2 \widehat{Tobacco}\ Use_{ist} + X_{ist}\beta_2 + \gamma_{2,s} + \delta_{2,t} + \theta_{2,ist}$$

First, subscript *i* will represent survey participants (i.e., *i* = 1, 2, …, *N*) and *t* will represent the year ranging from 2016 to 2018. s indicates a state where individual *i* lives in year *t*. The dependent variable of interest, sleep duration, is $Sleep_{ist}$ and coded as the number of the average sleep hours for individual *i* in state *s* for year *t*. $Tobacco\ Use_{ist}$ is the endogenous variable that influences sleeping and can be $Smoke$, $Quit$, or $Vape$ for individual *i* in state *s* in year *t*. The instruments for the endogenous $Tobacco\ Use_{ist}$ are tobacco control policies. $Tobacco\ Control_{st}$ can be $Cigarette\ tax$ ($) or $E - cigarette\ tax$ (if ever implemented) for state *s* in year *t*. Then, $\widehat{Tobacco}\ Use_{ist}$ is the first stage predicted value of $Tobacco\ Use_{ist}$ and functions as the main independent variable in the second stage equation (3.2).

To control for other influential factors in terms of individual sleep duration, the current study utilizes a rich set of control variables. X_{ist} is the vector of controls for individual *i* in state *s* for year *t*, which can influence the dependent variable other than $Tobacco\ Use_{ist}$.

α_1 and α_2 are the coefficients of main interest that represent the significance of the IV and identify the causal impact of tobacco use on sleep duration, respectively. $\beta.$ is the vector of coefficients in each equation. $\gamma_{\cdot,s}$ and $\delta_{\cdot,t}$ in each equation represent state and year fixed effects, respectively. Finally, $\theta_{\cdot,ist}$ is the disturbance term in each equation and clustered at the state level.

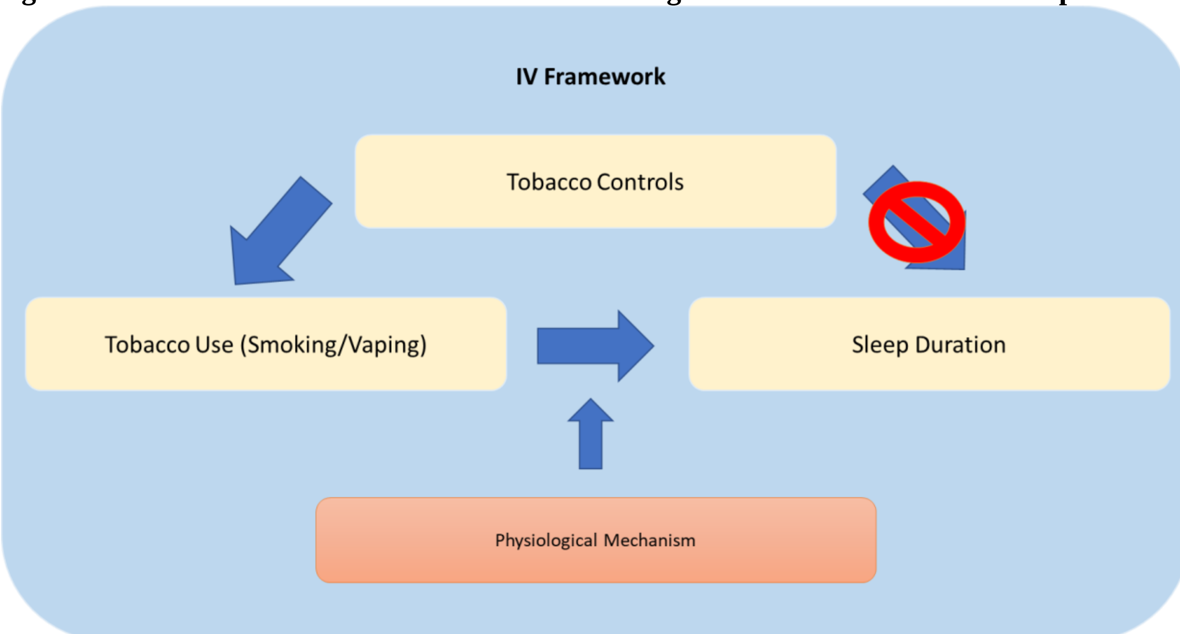
Hypothetically, α_2 could be either positive or negative-valued that individuals' tobacco use induced by tobacco control policies would influence sleep duration. Based on previous studies, the current study expects to see the negative sign that tobacco use would aggravate one's sleep. Of course, in the case that the causal direction from tobacco use to sleep is weak or invalid, one could observe null impacts on sleep.

In comparison with the IV results, the naïve association between tobacco use (: $Smoke$, $Quit$, and $Vape$) and sleep is also explored using the ordinary least squares (OLS) regression. Furthermore, heterogeneous effects across sub-samples are examined by age group, gender, educational attainment, and working status.

3.5.2 Identification

In order to examine the effect of tobacco use on sleep duration, the current study proposes IV regression. Figure 3.2 shows a brief depiction of how the causal mechanism is constructed within the IV framework. As it demonstrates, tobacco controls such as cigarette tax and e-cigarette tax implementation would instrument for endogenous tobacco use of individuals. I assume that physiological mechanism is a potential channel through which tobacco use could affect one's sleep duration. In this setting, one needs to further assume that the IVs do not directly influence the dependent variable, other than through the endogenous variable in the first stage.

Figure 3.2 Schematic of the Instrumental Variable Regression: Tobacco Use and Sleep Duration



Note: Tobacco use variables are the endogenous variables in the IV regression framework. Tobacco controls as instruments are real cigarette tax amounts and (ever) e-cigarette tax implementation across states. Sleep duration is recorded as the average sleeping hours.

Formally, to identify the IV estimate (i.e., α_2), one needs to guarantee that the IV, $Tobacco\ Control_{st}$, satisfies two major identifying conditions. First, the IV should satisfy the *exclusion restriction* that it influences individuals' sleep duration only through the intended endogenous variable, $Tobacco\ Use_{ist}$. Second, the IV should generate sufficient explanatory power in explaining the variation of the endogenous variable in the first stage. Given the nature of the IV, it is unlikely that individuals' sleep duration is directly influenced other than through their tobacco use behavior. Ideally, individual fixed effects based on panel data can better address this issue but I believe that state and year fixed effects should effectively control for unobserved confounders to some extent. One can test for the explanatory power of the IV by examining the first stage F-statistic of the IV. Previous studies often use the rule-of-thumb threshold of 10 for non-weak instruments (Staiger and Stock, 1997; Stock and Yogo, 2005).

Recently, studies show that price tobacco policies such as raising cigarette taxes are no longer as effective as previously believed among smokers in the U.S. (Callison and Kaestner, 2014; Hansen et al., 2017; Kalousova et al., 2020; Kaneko and Noguchi, 2020)[38]. I speculate that this is possibly because cigarette taxes have been implemented for a long time and individuals have become unresponsive to the taxes in recent years. Further, studies often use raw cigarette taxes rather than the ones with price levels adjusted. I employ real cigarette tax amounts in analysis to mitigate this issue to some extent. Nevertheless, in the case that tobacco taxes are less binding in the first stage, one would expect to have the issue of weak IV. Therefore, I provide additional sub-sample analyses as there could exist heterogeneity in response to tobacco taxes across sub-samples.

In addition, in my preferred specification, the other tobacco use behavior is controlled for[39], since the other tobacco use could also affect own sleep duration in the case that individuals use both tobacco products or switch to the other product while restraining from one (e.g., using e-cigarettes as a smoking cessation aid).

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[38] Using the BRFSS database, Pesko et al. (2020) still argue that cigarette and e-cigarette taxes have alleviated smoking and vaping prevalence, respectively. However, the magnitude of the cigarette or e-cigarette tax impacts on the respective prevalence was not that huge (around 0.03-0.08%).

[39] This means controlling for cigarette smoking when examining the impact of vaping on sleep, and vice versa.

3.6 Results

3.6.1 Main Results: The Impact of Smoking, Quitting, and Vaping on Sleep Duration

To estimate the causal impact of tobacco use (smoking, quitting, or vaping) on individuals' sleep duration, the instrumental variable (IV) regression is employed based on the BRFSS database from 2016 through 2018. Note that all specifications include state and year fixed effects in addition to individual-level control variables but they are not shown in the regression tables for the sake of brevity. For each first-stage regression, the Kleibergen-Paap F-statistic is reported to indicate the significance of the IV.

Table 3.3 presents the IV regression of sleep duration on cigarette smoking. First, based on column (1), one can see that cigarette tax as the IV does not appear to predict individuals' smoking status given the marginal F-statistic reported (KP F-statistic = 0.544). Not surprisingly, one finds no impact of cigarette smoking on sleep duration according to column (2). As explained earlier, individuals could use both conventional cigarettes and e-cigarettes and they could also switch between the two tobacco products. Columns (3) and (4) examine the impact of smoking on sleep duration by introducing individuals' vaping status as an additional control. Although it is still limited, cigarette tax now seems to explain individuals' smoking behavior to some extent (KP F-statistic = 3.614). Nevertheless, no statistically significant impact of cigarette smoking on sleep is observed, based on column (4).

Table 3.3 IV Regression of Sleep Duration on Cigarette Smoking – The BRFSS Between 2016 and 2018

Variables	(1) First stage	(2) Second stage	(3) First stage	(4) Second stage
	Smoke	Sleep	Smoke	Sleep
Cigarette tax	-0.00239		-0.00546*	
	(0.00324)		(0.00287)	
Smoke		2.590		1.651
		(7.182)		(2.371)
Vaping controlled	No	No	Yes	Yes
KP F-statistic	0.544		3.614	
Observations	713,302	713,302	604,916	604,916
Number of clusters	51	51	51	51

Note: Robust standard errors are clustered at the state level in parentheses. State and year fixed effects besides other control variables are employed but are not shown for the sake of brevity. KP F-statistic: Kleibergen-Paap F-statistic. *** p<0.01, ** p<0.05, * p<0.1

Table 3.4 demonstrates the IV regression of sleep duration on quitting smoking. Again, columns (3) and (4) represent the IV results with individuals' vaping status. Unlike the results from Table 3.3, one can observe that the first stage regression of column (3) predicts individuals' quitting quite significantly (KP F-statistic = 18.16). In the case of the second stage regression, however, no statistically significant change in sleep is observed by increased quitting.

Table 3.4 IV Regression of Sleep Duration on Quitting Smoking – The BRFSS Between 2016 and 2018

Variables	(1) First stage	(2) Second stage	(3) First stage	(4) Second stage
	Quit	Sleep	Quit	Sleep
Cigarette tax	0.0146**		0.0138***	
	(0.00664)		(0.00324)	
Quit		3.097		2.234
		(2.602)		(1.510)
Vaping controlled	No	No	Yes	Yes
KP F-statistic	4.825		18.16	
Observations	313,579	313,579	266,087	266,087
Number of clusters	51	51	51	51

Note: Robust standard errors are clustered at the state level in parentheses. State and year fixed effects besides other control variables are employed but are not shown for the sake of brevity. KP F-statistic: Kleibergen-Paap F-statistic. *** p<0.01, ** p<0.05, * p<0.1

Finally, Table 3.5 provides the IV regression of sleep duration on vaping. According to column (1), one observes that e-cigarette tax implementation could discourage individuals' vaping to some degree (KP F-statistic = 4.725). However, individuals' vaping status does not appear to affect sleep duration, based on the second stage regression in column (2). No other significant results are found in columns (3) and (4).

Table 3.5 IV Regression of Sleep Duration on Vaping – The BRFSS Between 2016 and 2018

Variables	(1) First stage	(2) Second stage	(3) First stage	(4) Second stage
	Vape	Sleep	Vape	Sleep
E-cigarette tax	-0.00173**		-0.00112	
	(0.000795)		(0.000796)	
Vape		-0.433		-0.222
		(6.760)		(10.98)
Smoking controlled	No	No	Yes	Yes
KP F-statistic	4.725		1.971	
Observations	607,253	607,253	604,916	604,916
Number of clusters	51	51	51	51

Note: Robust standard errors are clustered at the state level in parentheses. State and year fixed effects besides other control variables are employed but are not shown for the sake of brevity. KP F-statistic: Kleibergen-Paap F-statistic. *** p<0.01, ** p<0.05, * p<0.1

Despite the null impacts of tobacco use on sleep from the IV regressions, tobacco use and sleep duration may still be significantly associated with each other as many researchers have pointed out in the extant literature.

To examine this, Table 3.6 displays the OLS regression of sleep duration on tobacco use (smoking, quitting, or, vaping). Across columns (1) through (3), one can find that tobacco use and sleep duration are strongly and negatively correlated with each other (p < 0.01). According to column (1), on average, smoking status is significantly associated with decreased sleep duration, by 0.159 hours (= 9.54 minutes). Note that 9.54 minutes less sleep duration per day can be translated into 1 hour and 6.78 minutes less sleep per week. On the other hand, one can observe that those who quit smoking are associated with increased sleep duration, by 0.124 hours (= 7.44 minutes). Similar to smokers, vapers also appear to sleep less by 0.163 hours (= 9.78 minutes).

Table 3.6 OLS Regression of Sleep Duration on Smoking, Quitting, and Vaping – The BRFSS Between 2016 and 2018

Variables	(1) OLS	(2) OLS	(3) OLS
	Sleep	Sleep	Sleep
Smoke	-0.159***		
	(0.00588)		
Quit		0.124***	
		(0.00572)	
Vape			-0.163***
			(0.0108)
Smoking/vaping controlled	Yes	Yes	Yes
Observations	713,302	313,579	607,253
Number of clusters	51	51	51

Note: Robust standard errors are clustered at the state level in parentheses. State and year fixed effects besides other control variables are employed but are not shown for the sake of brevity. *** p<0.01, ** p<0.05, * p<0.1

3.6.2 Heterogeneity Across Sub-samples: Age Group, Gender, Educational Attainment, and Working Status

Based on the results demonstrated above, the impact of tobacco use on sleep duration appears to be insignificant overall, and often the IVs in the first stage regressions display insignificant explanatory power. That being said, individuals may have heterogeneous tobacco use behavior and sleep patterns according to their demographic characteristics. Hence, the current study further examines the impact of tobacco use on sleep duration across different sub-samples. I focus on the impact of smoking and quitting.

Table 3.7 provides the IV regression of sleep duration on smoking and quitting by age group. Each column represents the second stage regression for each sub-sample. Note that vaping status of individuals is controlled for in every specification. As one can see, individuals from the Age 40-49 and Age 60-69 sub-samples respond to cigarette tax relatively significantly. From column (3), however, one can observe the null impacts of both smoking and quitting on sleep duration. On the other hand, results from the Age 60-69 sub-sample show coefficients that are statistically significant. Although the sign on each coefficient makes sense for the impact of smoking and quitting on sleep, the effect size appears to be a bit large: 4.357 hours less of sleep ($p < 0.05$) and 3.956 hours more of sleep ($p < 0.01$) in response to smoking and quitting behavior, respectively. Other sub-samples seem to be largely unresponsive to cigarette tax in the first stage.

Table 3.7 IV Regression of Sleep Duration on Smoking and Quitting by Age Group – The BRFSS Between 2016 and 2018

Variables	(1) Age 18-29	(2) Age 30-39	(3) Age 40-49	(4) Age 50-59	(5) Age 60-69	(6) Age 70 or older
	Sleep	Sleep	Sleep	Sleep	Sleep	Sleep
Panel A. Cigarette smoking on sleep duration						
Smoke	-5.960	-1.805	-0.124	5.881	-4.357**	-11.24
	(4.304)	(1.360)	(1.543)	(8.227)	(1.841)	(99.14)
Vaping controlled	Yes	Yes	Yes	Yes	Yes	Yes
KP F-statistic	2.690	1.799	9.412	0.784	15.23	0.0197
Observations	58,638	71,859	81,577	119,544	140,447	132,851
Number of clusters	51	51	51	51	51	51
Panel B. Quitting smoking on sleep duration						
Quit	19.70	5.309	1.252	87.55	3.956***	39.14
	(22.02)	(4.728)	(0.967)	(1,308)	(1.118)	(230.5)
Vaping controlled	Yes	Yes	Yes	Yes	Yes	Yes
KP F-statistic	0.607	0.633	8.581	0.00436	21.30	0.0267
Observations	16,255	29,653	32,293	53,380	67,995	66,511
Number of clusters	51	51	51	51	51	51

Note: Robust standard errors are clustered at the state level in parentheses. State and year fixed effects besides other control variables are employed but are not shown for the sake of brevity. KP F-statistic: Kleibergen-Paap F-statistic. Each specification refers to the corresponding second stage result by age group. *** p<0.01, ** p<0.05, * p<0.1

Table 3.8 provides the IV regression of sleep on tobacco use by gender. As one can see, individuals from the female sample respond to cigarette tax significantly. However, based on the second stage regression in column (2), smoking status does not affect individuals' sleep duration in the female sample. Similarly, quitting smoking does not appear to influence sleep duration, although the coefficient is statistically significant at the 10% level.

Table 3.8 IV Regression of Sleep Duration on Smoking and Quitting by Gender – The BRFSS Between 2016 and 2018

Variables	(1) Male	(2) Female
	Sleep	Sleep
Panel A. Cigarette smoking on sleep duration		
Smoke	-1.119	1.113
	(10.86)	(1.366)
Vaping controlled	Yes	Yes
KP F-statistic	0.519	11.21
Observations	275,352	329,564
Number of clusters	51	51
Panel B. Quitting smoking on sleep duration		
Quit	0.866	2.054*
	(7.086)	(1.096)
Vaping controlled	Yes	Yes
KP F-statistic	0.684	13.66
Observations	135,071	131,016
Number of clusters	51	51

Note: Robust standard errors are clustered at the state level in parentheses. State and year fixed effects besides other control variables are employed but are not shown for the sake of brevity. KP F-statistic: Kleibergen-Paap F-statistic. Each specification refers to the corresponding second stage result by gender. *** p<0.01, ** p<0.05, * p<0.1

Table 3.9 now examines the impact of smoking and quitting across different levels of education. In column (3), one finds that individuals with at least a college degree respond to cigarette tax significantly based on the reported F-statistics. However, in this case, as well, no statistically significant impacts of tobacco use are observed.

Table 3.9 IV Regression of Sleep Duration on Smoking and Quitting by Educational Attainment – The BRFSS Between 2016 and 2018

Variables	(1) Less than high school	(2) High school	(3) College or over
	Sleep	Sleep	Sleep
Panel A. Cigarette smoking on sleep duration			
Smoke	-0.726	0.228	1.699
	(2.089)	(4.794)	(1.292)
Vaping controlled	Yes	Yes	Yes
KP F-statistic	3.101	0.152	9.622
Observations	37,948	160,137	406,831
Number of clusters	51	51	51
Panel B. Quitting smoking on sleep duration			
Quit	-0.473	-0.221	1.284
	(2.251)	(5.118)	(1.041)
Vaping controlled	Yes	Yes	Yes
KP F-statistic	0.950	0.0619	14.44
Observations	21,753	83,803	160,531
Number of clusters	51	51	51

Note: Robust standard errors are clustered at the state level in parentheses. State and year fixed effects besides other control variables are employed but are not shown for the sake of brevity. KP F-statistic: Kleibergen-Paap F-statistic. Each specification refers to the corresponding second stage result by educational attainment. *** p<0.01, ** p<0.05, * p<0.1

Finally, Table 3.10 provides the IV regression results by individuals' working status. Across sub-samples, only individuals from the Not-in-labor-force sample tend to respond to cigarette tax in terms of quitting behavior relatively significantly. Based on the second stage regression, individuals who quit smoking appear to sleep 6.061 hours more ($p < 0.05$), on average, which is sizable.

Table 3.10 IV Regression of Sleep Duration on Smoking and Quitting by Working Status – The BRFSS Between 2016 and 2018

Variables	(1) Any employment	(2) Unemployment	(3) Not-in-labor-force
	Sleep	Sleep	Sleep
Panel A. Cigarette smoking on sleep duration			
Smoke	20.86	6.260	-11.19*
	(24.36)	(7.858)	(6.179)
Vaping controlled	Yes	Yes	Yes
KP F-statistic	0.820	0.624	6.333
Observations	323,969	22,023	258,924
Number of clusters	51	51	51
Panel B. Quitting smoking on sleep duration			
Quit	33.42	0.398	6.061**
	(221.9)	(0.842)	(2.782)
Vaping controlled	Yes	Yes	Yes
KP F-statistic	0.0204	6.660	9.255
Observations	127,537	11,740	127,028
Number of clusters	51	51	51

Note: Robust standard errors are clustered at the state level in parentheses. State and year fixed effects besides other control variables are employed but are not shown for the sake of brevity. KP F-statistic: Kleibergen-Paap F-statistic; Any employment: employment or self-employment; Not-in-labor-force: Homemaker, Student, Retired, or Unable to work. Each specification refers to the corresponding second stage result by working status. *** p<0.01, ** p<0.05, * p<0.1

3.7 Discussion

This study attempts to examine the causal effect of tobacco use (: smoking, quitting, and vaping) on sleep duration using the instrumental variable (IV) framework. Using the BRFSS database between 2016 and 2018, the IV estimates demonstrate that overall, tobacco use may not have a causal effect on individuals' sleeping hours, unlike the hypothesis that it would negatively affect one's sleep through the physiological channel. Still, the OLS regression results show that there exist negative associations between tobacco use and sleep, which are in line with the majority of previous studies. Considering these results, one may think that the negative estimates from the naïve OLS regression might have originated from the direction that individuals with sleep disruption tend to use tobacco products and that could further aggravate their sleep quality and quantity.

Essentially, there should be differences in daily available time and thus time allocation depending on tobacco use behavior. The average time spent on smoking one cigarette can take about 6 minutes (Quit & Stay Quit Monday, 2021) and that can be translated into 82.3 minutes per day, given the average number of cigarettes smoked per day (= 13.7 cigarettes) in the sample[40]. Considering the additional time spent on the entire "smoking break", it can take much more time. Possibly, this reduction in daily available time could result in decreased sleep duration.

This study contributes to the existing literature in that it is the first research to examine the causal direction of tobacco use to sleep by leveraging the IV framework. It would be important to identify the causal path as it could allow researchers to link tobacco use and other important outcomes through sleep. Despite the null impacts of tobacco use to sleep, further research is warranted to disentangle the mechanisms behind the observed negative association between tobacco use and sleep.

There are a few caveats in this study. Across specifications, small F-statistics are often observed in the first stage regressions and this could result in biased IV estimates. A major culprit of this small F-statistic would be less-binding tobacco taxes in recent years[41]. Hence, it would be worth examining the same research question based on an earlier data period when

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[40] This figure is, however, somewhat limited because only the 2017 and 2018 BRFSS datasets provide information on the number of cigarettes per day and very few smokers have answered this questionnaire. Still, it is comparable to 14 cigarettes smoked per day among the U.S. daily smokers in 2016 (CDC, 2018).

[41] Relatedly, it has been reported that individuals in high-income countries are less likely to respond to the cigarette price increase in terms of cigarette consumption (NCI and WHO, 2016).

tobacco taxes were effectively discouraging tobacco use. From a policy perspective, a further tax hike at a higher rate may be necessary to incentivize smoking cessation as well as discourage smoking initiation. Another caveat of this study would be that e-cigarette tax implementation as an IV would not be best to predict individuals' vaping behavior. Due to multiple ways of taxing e-cigarettes across states, I have employed the dummy variable approach to have a unified measure of e-cigarette taxation. Alternatively, I could adopt the standardized e-cigarette tax measure developed by Cotti et al. (2020) and that could function as a continuous tax variable that represents the actual e-cigarette excise tax across states (Pesko et al., 2020), thus providing richer e-cigarette tax variation.

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