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Essays on Empirical Models of Psychological Well-Being and Infant Health

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Essays on Empirical Models of Psychological Well-Being and Infant Health

A Dissertation submitted in partial satisfaction
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by

Yanchao Yang

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ABSTRACT OF THE DISSERTATION

Essays on Empirical Models of Psychological Well-Being and Infant Health

by

Yanchao Yang

Doctor of Philosophy, Graduate Program in Economics
University of California, Riverside, December 2021
Dr. Marcelle Chauvet, Chairperson

This dissertation presents three chapters that provide insights into the public health issues, such as psychological well-being (PWB) and infant health. In Chapter 1, I apply machine learning methods to predict people's psychological well-being using a U.S. large dataset. The main outcome variables used to quantify psychological well-being are: general happiness, satisfaction with financial situation, and satisfaction with job. In order to predict PWB, first, I use K-nearest neighbor (KNN) algorithm to select and rank the importance of predictors. I present that marital status has the highest importance score in predicting one's general happiness. Prestige score of occupation is the most important predictor of satisfaction with jobs. Next, I utilize the Forward Selection algorithm to find the best combination of predictions. Using this selected combination to predict people's PWB, I achieve 70% - 80% classification accuracy when detecting people with low psychological well-being. Lastly, I provide insights that PWB is an important factor that affects people's behavior by investigating how PWB is associated with physical and mental health, risky goods consumption, investment decisions, and working behaviors. I find that happier people have better

health conditions, smoke and drink less, have more confidence in financial institutions, and generally work more hours.

In Chapter 2, I examine the effects of medical marijuana laws(MMLs) on infant health using Vital Statistics Natality data from 1996 to 2016. I exploit the geographic and temporal variation in the implementation of MMLs using a difference-in-differences estimation framework. I find that MMLs are associated with a 0.251 percentage point ($p<0.01$, 3.74% of the mean) increase in the incidence of low birth weight (<2500 grams), and a 0.435 percentage point ($p<0.05$, 4.2% of the mean) increase in the incidence of premature births (<37 weeks). The effects are statistically significant among births of white mothers, and partly significant among births of black mothers. Using an event study design, I show that the effects are persistent and long lasting. This study suggests that there should be a more cautious use of medical marijuana use among pregnant women.

In Chapter 3, we present the evidence on a previously recognized but under-investigated decrease in birth weight in the United States during the first decade and a half of the 21st Century. From 2000 to 2006, mean birth weight for US singletons decreased by 1.53%, and has only partially recovered since 2007. The declines in birth weight occur at all gestational ages, for all races, within all maternal age bins, for both smokers and non-smokers, for vaginal and c-section births and at all quantiles of the birth weight distribution. These trends are of great concerns. We provide some evidence for the declining mean birth weight in the U.S. that could partially explained by changes in gestational length and induction rates.

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Chapter 1

The Economics of Psychological Well-Being: Evidence From the United States Using Machine Learning Methods

1.1 Introduction

Psychological well-being (PWB) is considered an ultimate goal of life. The United States Declaration of Independence of 1776 takes it as a self-evident truth that the pursuit of happiness is an unalienable right, comparable to life and liberty (Frey and Stutzer, 2002). Despite of the dramatic increase in economic growth and personal income in the U.S., the psychological well-being didn't significantly improve (Easterlin, 1974). Even with the rapid growth of economics and PWB literature over the past 50 years, there still remain many open questions in this field.

This paper has two aims. The first is to find the key features to predict people's psychological well-being, and then predict and classify the different state of people's PWB. Second is to study how the extent of PWB may influence economic decisions and behaviors. In detail, this paper uses the large individual-level dataset drawn from the General Social Survey (GSS) that covers a long time span (1972-2018) and includes broad socioeconomic topics in the U.S. The measurements of psychological well-being are people's general happiness, satisfaction with financial situation, and satisfaction with jobs. This paper adopts machine learning approaches, K-Nearest Neighbor (KNN) algorithm and Forward Selection algorithm, to find the most important features that affect PWB. Then use the selected features to predict individual well-being. Then, I use the ordered probit model to see how each feature relates to PWB. Finally, I study how PWB is associated with physical and mental health, consumption activities, working behaviors, and investment behaviors.

This paper is closely related to two strands of the economics of PWB study. The first focuses on how economic policies and the institutional condition affects peoples PWB. Most notably, Easterlin (1974) found a small linkage between happiness and GDP per capita. A more recent study (Helliwell et al., 2012) found similar results for many other countries. Unemployment is another individual attributes that negatively affect PWB (Clark and Oswald, 1994; Winkelmann and Winkelmann, 1998; Grn et al., 2010). Many studies found the racial difference in PWB gap in the U.S.(Deaton and Stone, 2016) and the gap is also shrinking over time (Stevenson and Wolfers, 2009).

The second strand of literature considers PWB as the explanatory variable and checks how happiness affects peoples consumption, investment, human capital, and etc. Oswald et al. (2015) uses experiments to show that happiness increases productivity. Happier people are also more likely to be healthier, (Danner et al., 2001), have better immune systems, less inflammation, and fewer infections (Epel,2009). Unhappiness, on the other hand, is related to risky behaviors such as smoking (Brandon, 1994), drinking, and marijuana use (Magid et al., 2009). Lucas et al. (2003) also found people with higher levels of life satisfaction are less likely to divorce or separate. Cetre et al. (2016) showed that happiness is important in predicting future marriage and fertility.

There are three main shortcomings of the current literature. First, the cross-person comparisons of subjective feelings such as "happy" or "satisfied" are likely to be unreliable because there is no natural scaling to do the comparisons. Second, most of the literature focuses on the impact of one particular factor on PWB, but happiness is jointly determined by many different aspects of life. When people are facing a bundle of choices, they need to know which factors attributes most to their happiness. Yet little study focuses on this question so far. Third, there is no study that provides a reliable method to detect people with low psychological well-being level. People who are unhappy are more likely to have depression, anxiety, and other mental illness. Early intervention could be more effective. Policy makers should focus on investigating people's psychological health and implement early assistance.

To the best of my knowledge, this paper contributes to the literature in the following three ways. First, this is the first paper focusing on the prediction of PWB using machine learning methods, which help to detect individuals who are at a higher risk of depression and guide interventions to assist them. The selected features are common variables in many databases, making it possible for future research to conduct the out-of-sample prediction of PWB. Second, this is the first paper that finds the importance of prestige of occupation on PWB. This finding adds strong evidence to psychological and economic literature that self-esteem and social-value are very crucial. Third, this is the first paper that studies both the prediction of psychological well-being and how PWB is associated with economic activities.

The main results of this paper are as follows. First, I find that marital status is the most important feature that relates to individuals' general happiness. The prestige of occupation, which has long been ignored from the current literature, come out to be significantly crucial to satisfaction with financial situations and jobs. Income is also a strong predictor for PWB. In addition, the KNN algorithm performs well in detecting people who are unhappy or unsatisfied with their jobs. I then use the ordered probit regression model to see how each of those features affect PWB. I find that happier people tend to be those who have no child, with higher income, more prestigious jobs, and married individuals. Lastly, I find that unhappy individuals are more likely to consider suicide if negative events happen in their lives. They are more likely to have an HIV test and generally have 3 more days a year with poor mental health. Unhappy people also smoke and excessively drink more. One the other hand, people who reported as happy have better health, are more confident in the financial institutions, and banking system, which implies a more active potential investment behavior.

The rest of the paper is organized as follows: Section 2 summarizes the related literature. Section 3 describes the details of the dataset. Section 4 introduces the empirical methodologies implemented. In section 5, I present the empirical results. Section 6 shows how PWB relates to economic activities. Section 7 concludes.

1.2 Literature Review

The studies of the relationship between psychological well-being (PWB) and economics began in the 1970s and had drastically grown over the past 50 years. The first strand of the research focus on how economic policies, and the institutional condition affects peoples PWB as well as the formation of PWB. The second body of literature considers PWB as the explanatory variable and study how happiness affects peoples consumption, investment, and human capital, etc,(Magid, Colder, 2009; Edmans, 2012; Chen et al., 2020; Labroo et al., 2009).

Economists have found evidence that PWB is systematically related to both the individual characteristics and socioeconomic characteristics. One of the most prominent studies are done by Easterlin(1974). He found a small linkage between happiness and GDP per capita. Even though the personal income grew over time, people's self-reported happiness doesn't improve. A more recent study(Layard and Sachs 2012) used the Gallup World Poll data and found similar results for many countries. To explain this puzzle, Kapteyn et al. (1997) focused on how the preference changes due to social comparison. Bartel (1981) studied how relative income affects PWB by checking the racial difference in satisfaction with job. Unemployment is another individual attributes that negatively affect PWB (Clark and Oswald,1994; Winkelmann and Winkelmann,1988; Grun et al., 2010). Age is found to be U-shaped related with PWB (Blanchflower and Oswald, 2007). Gender and race are also important indicators for PWB. Many related studies failed to disentangle the confounding impact of the labor market outcomes that substantially exists across different gender and race. Overall, women have higher satisfaction scores for their life and jobs (Clark 1997). Though the gender PWB gap is noted to shrink in many countries(Stevenson and Wolfers,2009). Many studies found the race difference in PWB gap in the U.S. (Deaton and Stone,2016) and the gap is also shrinking over time (Stevenson and Wolfers,2009). Marital status is also related to PWB. Married people usually report higher happiness scores. Divorce has prolonged negative impact on people's happiness. Frey and Stutzer (2006) found the reverse relationship, where it is happier individuals that are more likely to get married. The finding on how education impact PWB is mixed. Di Tella et al. (2001) found that education is monotonically related to happiness scores. But it is difficult to find the net effect of education on happiness because education raises peoples income and other expectations.

Macroeconomics conditions are systematically related to peoples happiness too. People obtain information about the macroeconomic variables regularly from newspapers or social media, which suggests that aggregate economic conditions matters to peoples feeling. Tella et al, (2001) used European data found country-level correlations between happiness and GDP per capita, aggregate unemployment, and inflation. They found large psychic loss due to the recessions. In a later article, they estimated the trade-off between unemployment and inflation using misery index and they found that unemployment have larger negative effects on PWB than inflation. Blanchflower et al,(2014) revisited this topic by using the updated European data and found similar results that the impact of unemployment is 5 times larger than aggregated inflation in lower the well-being.

The literature on the impact of psychological well-being on peoples behaviors and choices has also growing rapidly. Oswald et al., (2015) using experiments by giving people some happy stimulus and they showed that happiness increases productivity. De Neve et al., (2013) found that PWB is a strong predictor of future earnings. Happier people are also more likely to be healthier, (Danner et al., 2001), have better immune systems, less inflammation and fewer infections (Epel,2009). Unhappiness, on the other hand, is related to risky behaviors such as smoking (Brandon,1994), drinking and marijuana use (Magid and Colder,2009). Clark et al., also found people with higher levels of life satisfaction are less likely to divorce or seperate. Cetre et al.(2016) showed that happiness is important in predicting future marriage and fertility.

Individual's psychological well-being is being jointly determined by many different factors. Personality traits, income, education, and the macroeconomic conditions. To the best of my knowledge, this paper is the first one that use the machine learning methods to predict people's PWB. Secondly, I study the association between PWB and people's economic decisions behaviors, which closes the logic loop of why PWB is important to economics and how to predict it.

1.3 Data

1.3.1 Psychological Well-Being

In this paper, I use the data drawn from General Social Survey (GSS), which was conducted by the National Opinion Research Center. GSS data is available between 1972-

2018. The survey was conducted almost every year between 1972-1991 and then every other year between 1993-2018. Every year, GSS interviews around 2000 individuals, which brings up the total number of observations more than 60,000 over the timespan. Questions asked are very broad, including information about the respondents' demographics, financial conditions in their households, their point of view about social, cultural, and political issues. I use the self-reported data as the measurement of psychological well-being. The variables used are the following: respondents' general happiness, satisfaction with financial situation,and job or housework. I focus on these variables because they were available in the 31 survey waves from 1972-2018. The questions being asked are the follows:

> **General happiness:** "Taken all together, how would you say things these days? Would you say that you are very happy, pretty happy, or not too happy? 1) Very happy; 2) Pretty happy; 3) Not too happy."
>
> **Satisfaction with financial situation:** "We are interested in how people are getting along financially these days. So far as you and your family are concerned, would you say that you are pretty well satisfied with your present financial situation, more or less satisfied, or not satisfied at all? 1) Satisfied; 2) More or less; 3)No at all satisfied."
>
> **Satisfaction with Job:** "On the whole, how satisfied are you with the work you do–would you say you are very satisfied, moderately satisfied, a little dissatisfied, or very dissatisfied? 1) Very satisfied; 2) Moderately satisfied; 3) A little dissatisfied; 4) Very dissatisfied."

The raw happiness descriptive statistics are presented in Table 1.1. Overall, there is not a statistical significant difference across gender. People who experienced unemployment and divorce do report higher percentages of unhappy. Income is crucial to PWB. The percentages of "not happy" responses decrease as the income quartiles increases.

Both of the household and personal income are provided by 12 categories in the raw data. In order to convert the categorical income data into continuous variable, I obtained the data from Current Population Survey (CPS) and calculate the mean and standard error for each categories by year. Then randomly assign the value to each respondents by survey year according to normal distribution. I adjust all income variables in 2012 dollars.

Table 1.1: Happiness in the United State:1972-2018

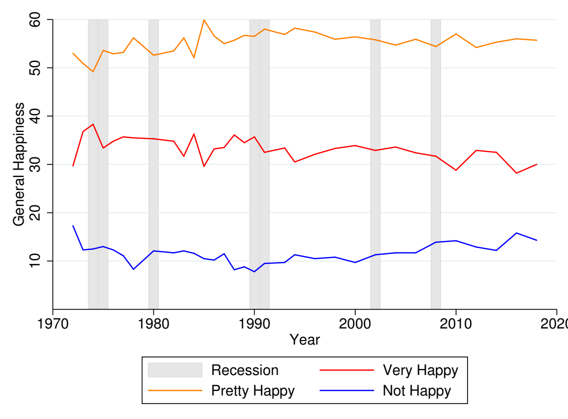
			Marital Status			
Self-Reported Happiness	All (%)	Unemployed (%)	Married (%)		Divorced (%)	
Very Happy	31.34	21.24	40.44		19.62	
Pretty Happy	55.89	54.12	51.91		61.38	
Not Too Happy	12.77	24.64	7.65		19.00	
	Sex		Income Quartiles			
Self-Reported Happiness	Male (%)	Female (%)	1st (Lowest)	2nd	3rd	4th (Highest)
Very Happy	30.70	31.85	22.53	24.23	26.96	33.62
Pretty Happy	56.64	55.29	52.09	55.69	56.34	56.74
Not Too Happy	12.66	12.86	25.38	20.08	16.71	9.64

Note: the above descriptive statistics are based on 60054 observations.

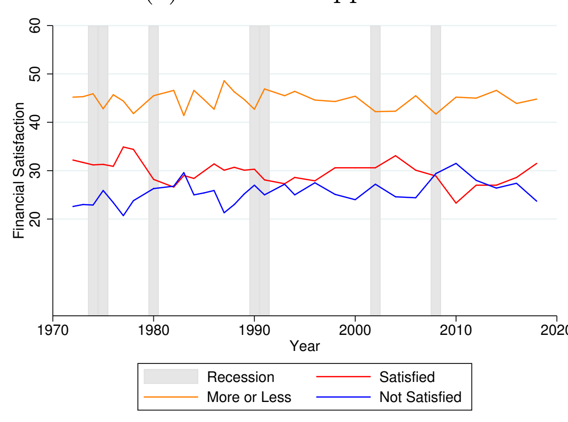
1.3.2 Macroeconomic Data

Tella, MacCulloch and Oswald (2003) have shown that macroeconomic movements have strong effects on people's happiness. To take the macro-level shocks into consideration, I also merge the following macroeconomic variables: annual real gross domestic product per capita, real personal expenditures, unemployment rate, inflation rate, and recession indicators. These variables are drawn from the Federal Reserve Economic Data (FRED) website of the Federal Reserve Bank of St. Louis. All money related variables are chained into 2012 dollars.

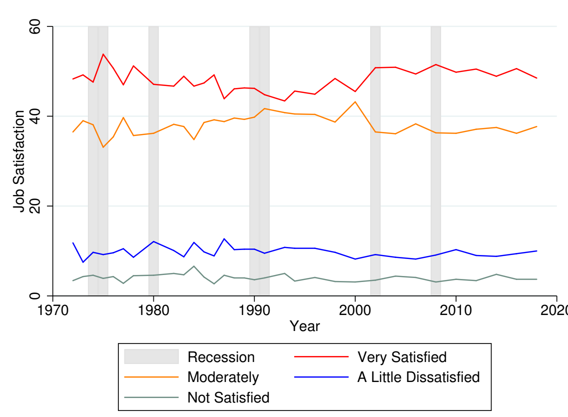
We graph the PWB trends in Figure 1.1. The overall PWB trends are stable, even though the real GDP per capita have grown in the U.S. for those decades. As similar results that Easterlin (1974) found no evidence that the happiness data are trended over time. The shaded areas are the recession time. The trends shows some patterns during the business cycles. With the percent of "not happy" and "not satisfied" respondents increases during the great recessions in 2008.



(a) General Happiness



(b) Satisfaction with Financial Situation



(c) Satisfaction with Job

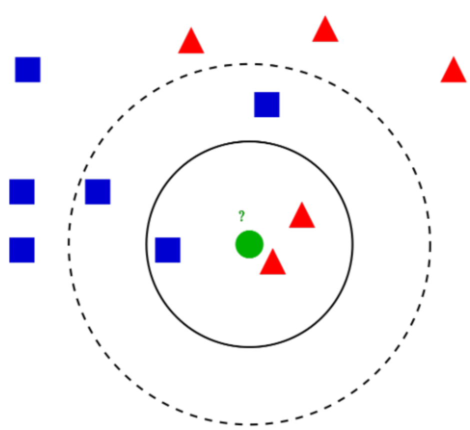
Figure 1.1: Trends in Psychological Well-being

1.4 Empirical Methods

1.4.1 K-Nearest Neighbor(K-NN) Algorithm

K-NN is one of the most fundamental non-parametric algorithms and it has been widely used for classification in public health and clinical studies. Generally, K-NN is used in two different ways: K-NN classification and K-NN regression. In this study, I apply K-NN to classify people's different state of PWB. To determine or classify an instance, K-NN will see what is the majority of the K-nearest neighbors of this instance. For example (in Figure 1.2), there are two red instances and one blue instance out of three nearest neighbors of the green instance. Thus the green instance will be marked as red according to the K-NN prediction. If the prediction was right, it will count as a successful prediction, otherwise a failed prediction.

Figure 1.2: KNN Illustration



From the raw dataset, a 16-parameter vector describes each respondent. "General Happiness", "Satisfaction with the financial situation", "Satisfaction with the job" are three picked parameters as the outputs of the K-NN algorithm, and the rest 13 parameters are used as input data. Each output will be matched with the rest 13 parameters to form a 14-parameter vector, which means I run three subsets in the experiments. This algorithm is based on the distance between a test sample and specified training samples (Peterson,2009). The distance metric is important when implementing KNN. In this paper, I use the Euclidean distance function. Let x_{ij} to represent the input features with n $(i = 1, 2, \ldots, n)$ number of observations and $f(j = 1, 2, \ldots, f)$ number of features. The Euclidean distance between input features x_i and output class x_c is defined as:

$$d(x_i, x_c) = \left(\sum_{i,c=1}^{n} (|x_i - x_c|)^2 \right)^{\frac{1}{2}} \tag{1.1}$$

Since K-NN algorithm relies on distance for classification, I need to normalize the data before implementing a classification algorithm. I normalize the training data by rescaling predictors to [0,1] to improve the classification accuracy. In addition, I assigned weights to the contributions of the neighbors, so that the nearer neighbors contribute more to the average than the more distant ones. This is called weighted nearest neighbor classifier. In this study, I add weights by assigning each neighbor a weight of 1/r, where r is the Euclidean distance to the neighbor.

One of the main drawbacks of K-NN is its sensitivity of outliers or irrelevant features. If I don't remove those outliers and irrelevant features, the classification accuracy can be dramatically degraded. Therefore, it is a kind of algorithm that's very sensitive to irrelevant variables. The accuracy of the classification drops in a great deal if there are irrelevant features in the model. Then how to mitigate the nearest neighbor algorithms sensitivity to irrelevant features? Typically there are three ideas: 1. Use more training instances; 2. Use statistical tests to try to determine which features are useful; 3. Search over feature subsets. In this study, I applied a search algorithm which is "Forward Selection Search" to solve this problem and try to find out the combination of features that give us the best classification rate.

In forward selection, the whole procedure is doing a forward single variable selection which approaches a higher success rate. The first variable selected for an entry into the constructed model is the one with the largest correlation with the dependent variable. Once the variable has been selected, it is evaluated on the basis of certain criteria. The criteria is to see if the prediction accuracy is the highest among all possible combinations. If the first selected variable meets the criterion for inclusion, then the forward selection continues. The procedure stops, when no other variables are left that meet the entry criterion (Walczak and Massart, 2000). During the procedure, if a higher success rate can be obtained, the same process is repeated once again retaining the two selected features and adding a third one, one at a time, until all remaining features have been used. The process is then iteratively repeated until no better combination can be obtained. The result of this procedure is a series of features that represent the best multivariate combination.

Based on these traits, I can use KNN to rank the importance of different features and find how multiple features combined would determine happiness. Unlike probit regression models or linear regression models that many researchers have used to analyze people's happiness (Tella, MacCulloch and Oswald,2003; Jackson,2017), KNN helps us to find the combined features that contribute most to one's psychological well-being. So I can provide a systematic analysis on the determinants of PWB.

1.4.2 Model Performance Evaluation

When the sample is biased towards a certain features in some way, the overall accuracy rate might also be biased. This is why I use the confusion metrics other than overall accuracy to evaluating a machine learning algorithm. By tabulating each of the of predicted and true value, I can evaluate the accuracy rate for each class.

A general way of constructing a confusion matrix is the following: I use TP to denote the true positives, which means when the outcome is positively and is predicted as positive. When a negative outcome is predicted as positive, I denote this case as false positives (FP). Similarly, I define true negatives (TN) as the predicted and actual outcome are all negative. When the actual results are positive but I predict it as negatives, I call it false negatives (FN). Then, I use the following measurements to evaluate the model performances:

$$TPR = \frac{TP}{TP + FN}$$

$$TNR = \frac{FP}{FP + TN}$$

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN}$$

The true positive rate (TPR) measures the proportion of correctly predict the outcome when it is positives which is also referred to as sensitivity or recall. The true negative (TNR) measures the proportion of negative outcomes that are called negatives. In this study, I pay more attention to the true negative rate

$$F_1 - score = \frac{2 \times Precision \times Recall}{Precision + Recall}$$

where

$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN}$$

I also use $F_1 - score$ to calculate the balanced accuracy which is calculated by the weighted harmonic average of precision and recall. I present these results in the confusion matrices.

1.4.3 Ordered Probit Regression

KNN helps to find the most relevant features. To see how each of those features affect people's psychological well-beings, I use the ordered probit model to estimate the association of PWB and each predicting features , where PWB_{ijt} is the measure of psychological well-being j by individual i in year t. $PersonalTraits$ includes a set of variables that include the income, sex, marital status, education, number of children, working status and age. λ_t is the year fixed effects and u_{ijt} is the unobservables.

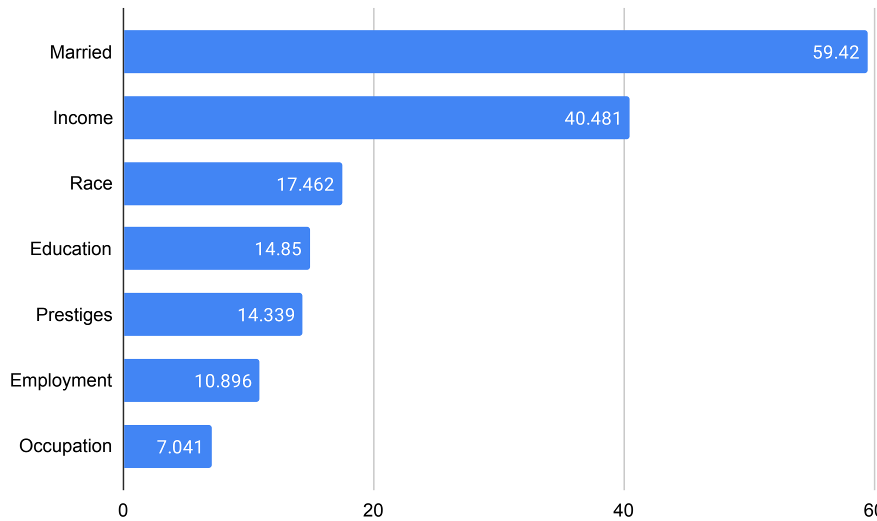
$$PWB_{jit} = \beta_j KeyIndependentVariables_{jit} + \sum \alpha_j PersonalTraits_{jit} + \lambda_t + u_{jit} \quad (1.2)$$

1.5 Empirical Results

1.5.1 Feature Importance Ranking Using KNN

In this section, I use KNN to determine the variables used in classification process by calculating the importance scores of each variable. Figure 1.3 shows that marital status is most important in predicting people's general happiness. Income ranked second. We can notice that the prestige scores of people's occupation is also crucial in predicting happiness. The prestige scores can be understood as people's occupational reputation. For example, physicians, professors in universities, and lawyer have the highest prestige score. As some literature documented, people's happiness is related to self-esteem and the social comparison. So among all job–related variables(employment status and type of occupation), prestige exhibits the higher importance.

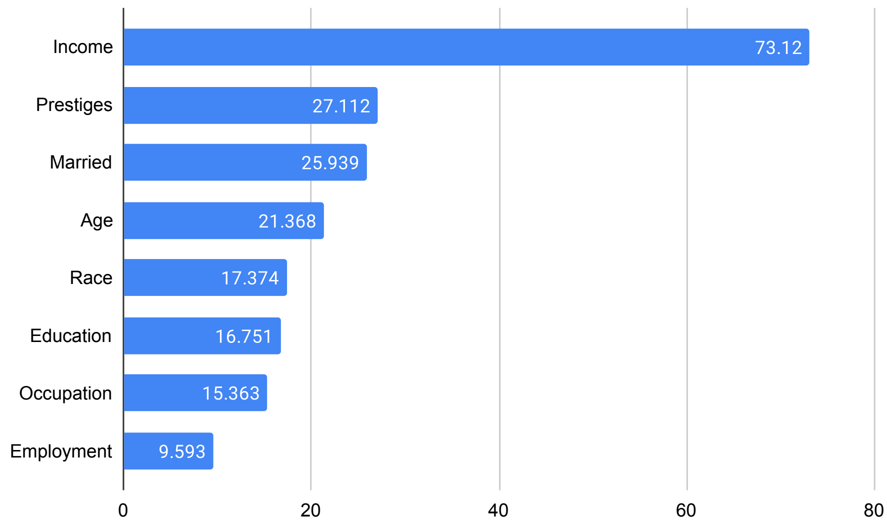
Figure 1.3: The Importance Score for General Happiness



Note: the importance scores are scaled to 100.

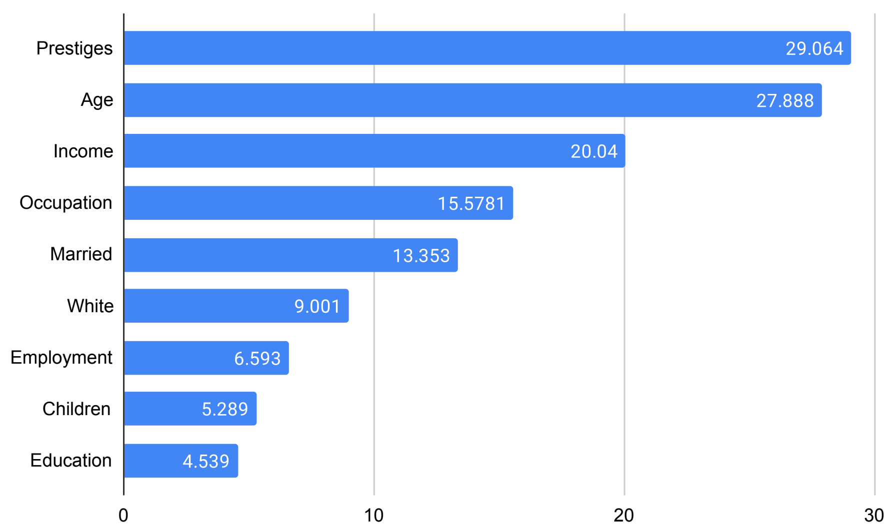
Figure 1.4 shows the importance of ranking of respondents' satisfaction for financial situation. Real income is most important. Next is prestige score. Income and prestige score are also closely related. People with higher prestigious jobs tend to make more money. Marital and age are also crucial predictors. Figure 1.5 presents the importance score for satisfaction for job. Prestiges and age are most important features. The number of children turns out to be important. The balance between work and parenting is always an important topic in social science. Using the probit model, I find that having no child is negatively related to job satisfaction.

Figure 1.4: The Importance Score for Satisfaction for Financial Situation



Note: the importance scores are scaled to 100.

Figure 1.5: The Importance Score for Satisfaction for Job



Note: the importance scores are scaled to 100.

1.5.2 Classification Findings

In this section, I investigate the the performance of KNN algorithm in classifying people's state of general happiness, satisfaction with financial situation and satisfaction with jobs using the selected features. We present the results based on the confusion matrices that clearly show the precision rate and recall rate.

Firstly, I show the results for general happiness. When implementing KNN algorithm, picking the appropriate value of K is very crucial in order to avoid overtraining and oversmoothing. I divide the dataset into training set and testing set to detect these two problems. By experimenting different values of K, I find that the accuracy rate converges at $K = 7$. So the following results are shown for this particular K value. By calculating the feature importance using KNN, I manage to pick the variables that are most relevant to general happiness. The features I use in the classification are the following: the marital status, the real household income, race, the highest years of school, the employment status and the prestige score of their occupation.

As shown in Table 1.2, the KNN algorithm performs best in classifying unhappy respondents, with the rate of 75.9%. Our model performs weakly in predicting "pretty happy" people with the correction rate of only 38.9%. The rate of correctly predicting"very happy" people is 60.9%. People only choose "not happy" when they are really not happy, which is the common issue for self-reported psychological data, especially with 3 possible answers. Most respondents pick the moderate (middle) answer if they don't have strong opinions. Therefore, the prediction using the available features tends to be vague for the "pretty happy" individuals.

Table 1.2: Classification for General Happiness

True	Classified Not Happy	Pretty Happy	Very Happy	Total
Not Happy	4566 75.9%	613 10.19%	837 13.91%	6016 12.34%
Pretty Happy	8033 29.19%	10704 38.90%	8780 31.91%	27517 56.48%
Very Happy	3285 21.63%	2654 17.47%	9251 60.90%	15190 31.18%
Total	15884 32.6%	13971 28.67%	18686 38.73%	48723 100%
Priors	0.3333	0.3333	0.3333	

Note: The first rows of each cell are the number of observations being classified into the corresponding categories. Results are based on weighted KNN

From the perspective of public policy, being able to detect “not happy" individuals is more important. As shown in the existing study, unhappy people are more likely to smoke more (Coan,1973; McKennel,1970; Shiffman,1993; Becona, Vazquez, Lorenzo,1998)), drink more alcohol (Magid, Colder, and et al.,2009), more likely to have mental physical problem (Watson and Pennebaker,1989; Lagdish,1993;Curhan, Sims, and etc.,2014). Our model provides policy-makers with an feasible implementation to target unhappy people and make corresponding policies to promote the overall social welfare.

Next, I present the results for people’s satisfaction with financial situation. The features I use are working status, age, marital status, race, educational level, real household income, religion type, prestige score of their occupation. The value of K is 5. People’s satisfaction with their personal financial situation is an important indicator in predicting their future investment and consumption behaviors. People with higher satisfaction level are generally more likely to consume more and have more investment diversity. Our results

Table 1.3: Classification for Satisfaction with Financial Situation

True	Classified Not at all	More or less	Pretty well	Total
Not at all	9694	1688	1788	13150
	73.72%	12.68%	13.6%	27.02%
More or less	6537	8966	6240	21743
	30.06%	41.24%	28.7%	44.67%
Pretty well	2953	1827	9080	13860
	21.31%	13.18%	65.51%	28.48%
Total	19184	12461	17108	48673
	39.35%	25.56%	35.09%	100.00%
Priors	0.3333	0.3333	0.3333	

Note: The first rows of each cell are the number of observations being classified into the corresponding categories. Results are based on weighted KNN

shows that the KNN algorithm performs best for individuals who are not satisfied with their financial situation at all with recall rate 73.72%. Our model performs weakly for people whose opinion are neutral. The prediction of "pretty well" is 65.51%.

The results for classification for job satisfaction is shown in Table 1.4. The predictors including respondents' working status, age, number of children, marital status, race, education, real household income and occupation. The job satisfaction could be an indicator that predicts people's job quit probabilities. Cote and Morgan(2002) found that the decreases job satisfaction would increases the intentions to quit. The model performs relatively well for individuals who are not satisfied with their job at all.

Overall, the KNN algorithm performs well in classifying people who are unhappy or dissatisfied with their jobs and financial situation. People who are in a less advantaged state of psychological well-being might have more common characteristics, which makes the predictors to be stronger in predicting the outcomes. In the next section, I use probit model

Table 1.4: Classification for Satisfaction with Job

True	Classified Not at all	Moderate	Very satisfied	Total
Not at all	3510 62.9%	1180 21.15%	890 15.95%	5580 14.21%
Moderate	3190 21.1%	7640 50.53%	4290 28.37%	15120 38.52%
Very satisfied	4090 21.27	4950 25.74%	10190 52.99%	19230 48.98
Total	10790 27.02%	13770 34.49	15370 38.49	39257 100%
Priors	0.3333	0.3333	0.3333	

Note: The first rows of each cell are the number of observations being classified into the corresponding categories. Results are based on weighted KNN

to show how each feature affects people's psychological well-beings.

1.5.3 Results of Probit Regression

We use probit regression to see how each feature affect people's psychological well-beings. I find some patterns for these three subjective well-being variables. Panel A of table 1.5 show that people tends to be happier and more satisfied with their financial situation. Having three or more kids would negatively and significantly affect financial satisfaction. In panel B, income is monotonically related to all three outcome variables. Panel C shows that unemployment have large and statistically significant impact on people's well-being. Self-employed people seem happier. Marriage has large impact on people's happiness. The causality link between happy and marriage is bidirectional as documented in literature(Frey and Stutzer,2006;). Getting married makes people happier, more satisfied with their financial situation or jobs. It is likely that happier people are more likely to get married. In all, happier people seems to be those who have no kid, higher income, more prestigious job and married ones.

Table 3: Psychological Well-being and Personal Characteristics: Full Sample Ordered Probit Model

Independent Variable	**General Happiness**	**Satisfaction with financial situation**	**Satisfaction with Job**
Panel A: Number of Children	(1)	(2)	(3)
No child	0.0595***	0.155***	-0.0743***
	(0.0146)	(0.0144)	(0.0168)
One child	-0.0437**	-0.0468***	0.00128
	(0.0143)	(0.0141)	(0.0162)
Two children	0.00305	0.01	0.0182
	(0.0124)	(0.0122)	(0.0143)
Three or more	-0.0119	-0.0844***	0.0354*
	(0.0123)	(0.0121)	(0.0146)
Panel B: Income Quartile			
Second	0.0859***	0.1984***	0.0578**
	(0.0157)	(0.0155)	(0.0187)
Third	0.1972***	0.4925***	0.1358***
	(0.0167)	(0.0165)	(0.0196)
Fourth(Highest)	0.1947***	0.5528***	0.1411***
	(0.0168)	(0.0166)	(0.1958)
Observations	48661	48808	39359
Standard errors in parentheses			
* $p<0.05$	** $p<0.01$	*** $p<0.001$	

Table 1.5: Psychological Well-being and Personal Characteristics: Full Sample Ordered Probit Model,continued

Independent Variable	**General Happiness**	**Satisfaction with financial situation**	**Satisfaction with Job**
Panel C: Working Status	(1)	(2)	(3)
Unemployed	-0.297***	-0.411***	-0.174***
	(0.0226)	(0.023)	(0.0243)
Self-employed	0.0460**	0.0554***	0.292***
	(0.0169)	(0.0166)	(0.0198)
Retired	0.102***	0.164***	
	(0.0194)	(0.0192)	
Keep House	-0.01	0.0710***	
	(0.0171)	(0.0169)	
School	0.180***	0.119**	
	(0.0384)	(0.0379)	
Other	-0.359***	-0.491***	
	(0.0403)	(0.0414)	
Age	0.00294***	0.0147***	0.00979***
	(0.000387)	(0.000384)	(0.00053)
Age squared	0.0000363***	0.000151***	0.000117***
	(0.00000475)	(0.00000471)	(0.00000581)
Prestige Score	0.0031***	0.000151***	0.0112***
	(0.00047)	(0.000464)	(0.000549)
White	0.0423	0.1726***	0.0735**
	(0.0239)	(0.0138)	(0.0264)
Panel D: Marital Status			
Married	0.513***	0.188***	0.114***
	(0.0119)	(0.0116)	(0.0136)
Divorced	-0.0643***	-0.137***	-0.0321
	(0.0165)	(0.0162)	(0.0196)
Separated	-0.405***	-0.235***	-0.0119
	(0.0284)	(0.0287)	(0.0322)
Never married	-0.240***	0.0199	-0.113***
	(0.0155)	(0.0154)	(0.0173)

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

1.6 Extension: Psychological Well-Being and Economic Activities

A large number of studies have found that people who constantly feel happy behave and make decisions fundamentally different from those who are not. I summarize the studies that investigate how happiness affects people's health, consumption activities, working behaviors, and investment behaviors. Due to the availability of the data, I show some evidence using ordinary least squares(OLS) regression and probit regression.

1.6.1 Physical and Mental Health

Research regarding how people's psychological well-being affects physical and mental health mainly falls into the following two parts: how positive psychological well- being affects health and how negative self-feeling affects health. The former have shown evidence that positive affects are associated with lower morbidity, lower level of symptoms and pain, and higher longevity among older community-dwelling individuals (Pressman and Cohen, 2005). Straume and Vitters (2015) also found evidence that happiness is negatively related to sick-leave. Positive affectivity is a strong predictor of good physical health (Billings et al., 2000) but negative affectivity doesn't show evidence to predict health symptoms (Joiner,2001).

On the other hand, people constantly in an unhappy state are found to be related to higher level of stress and poor psychological health, as well as self-reported physical health (Watson and Pennebaker, 1989).

This paper sheds a light on detecting the state of people's psychological well-being

Table 1.6: Happiness and Health

	(1) Health	(2) Suicide if incurable disease	(3) Suicide if bankrupt	(4) Suicide if dishonored family
Happiness	0.408***	-0.134***	-0.091***	-0.097***
	(0.012)	(0.014)	(0.019)	(0.019)
Individual Controls	Yes	Yes	Yes	Yes
Observations	35612	28295	28876	28824

Standard errors in parentheses
* p<0.1 ** p<.05 *** p<.01

	(5) Suicide if tired of living	(6) Ever test HIV	(7) Days of poor mental health
Happiness	-0.107***	-0.099***	-3.271***
	(0.016)	(0.021)	(0.129)
Individual Controls	Yes	Yes	Yes
Observations	28569	11217	8430

Standard errors in parentheses
* p<0.1 ** p<.05 *** p<.01

by using individual traits, making it possible for researchers and policymakers to be able to detect those who tend to be unhappy and precisely provide assistance to them. Column 2-5 of table 1.6 shows unhappy people are more likely to consider suicide when negative events happen in their lives. Happier people have better self-reported health status. As shown in column (1), happier people are less likely to have HIV test and have less days of poor mental feelings. With more data available, policymakers can use our models to target people who are in need of special help and make these studies more cost-efficient.

1.6.2 Consumption Activities

A growing amount of literature has been a focus on how happiness is associated with one's consumption choices. It has been shown in many literature that people's emotions, such as happiness are important predictors in forecasting consumers' choices. A vast literature shows that people in a happy feeling consumes systematically different types of goods from those who are not. For example, people who feel happy are less likely to choose risky options (Isen and Patrick 1983), more likely to make healthier choices (e.g., less alcohol drinking and cigarette consumption). Isen (2001) found that happiness leads to helping and interpersonal understanding which implies increasing in customer satisfaction.

Unhappiness tends to motivate smoking behavior (Brandon,1994). Yet the relationships between smoking and negative affect are more complicated. People who are stressed, angry and unhappy feelings reported smoking more (Coan, 1973; Becon et al., 1999). The study also found more alcohol and marijuana use among unhappy college students (Magid, Colder, and et al.,2009). As shown in table 1.7, I find similar results.

This paper provides a tool to classify the state of people's psychological well-being, which can be a potentially very important instrument for people in business and commercial industry to predict consumers' psychological mental state and take corresponding strategies.

Table 1.7: Happiness and Risky Behavior

	(1) Whether Smoking	(2) Ever quit smoking	(3) Ever drink	(4) Drink too much
Happiness	-0.182***	0.04	-0.097***	-0.068***
	(0.02)	(0.034)	(0.022)	(0.024)
Individual Controls	Yes	Yes	Yes	Yes
Observations	13561	4289	13563	9825

Standard errors in parentheses
* p<0.1 ** p<.05 *** p<.01

1.6.3 Working Behaviors

There is a large literature on productivity and personal happiness level (Siebert and Zubanov 2009). Edmans (2012) found that individuals' satisfaction with jobs is an important predictor of their stock market performance. Increasing job satisfaction increases value-added per hour working in manufacturing by 6.6% (Bckerman and Ilmakunnas, 2010).

Isen (2001) showed that happiness also affects doctor-patient interaction and medical decision making by increasing more understanding between doctors and patients. It is suggested that happiness should be considered in policy decisions as well.

In table 1.8, I show that happier people are likely to work more hours. They are more likely to work anyway even if they get rich.

Table 1.8: Happiness and Working

	(1) Hours worked per week	(2) Work if rich
Happiness	0.289**	0.049***
	(0.14)	(0.016)
Individual Controls	Yes	Yes
Observations	31211	22643
Standard errors in parentheses		
* p<0.1	** p<.05	*** p<.01

1.6.4 Investment Behaviors

Happier people have a different attitude to taking risks than less happy individuals. Labroo and Patrick (2009) have found that people with positive feelings are more likely to adopt for future goals while people in negative moods are more likely to focus on immediate and proximal events. Their finding has some important implications in consumers' invest-

Table 1.9: Happiness and investment behavior

	(1) Whether Own stock	(2) Whether Own Option	(3) Confidence in Financial Institutes
Happiness	-0.023	0.013	0.180***
	(0.043)	(0.068)	(0.011)
Individual controls	Yes	Yes	Yes
Observations	3751	1699	33477

Standard errors in parentheses
* p<0.1 ** p<.05 *** p<.01

ment decision. In economic literature, identifying economic agents' myopia is an important topic. Delis and Mylonidis (2015) found that happiness lowers the probability of investing in risky assets and insurance. Rao, Mei, and Zhu (2016) found evidence that happier people have higher stock market participation potentially due to more trust in capital and optimism. Chuluun and Graham (2015) found a positive correlation between local happiness and firm investment and R&D and the effect is larger for young firms.

The column (3) of 1.9 show that happier people are more confident in financial and banking systems. The investor confidence has long been proved to significantly affect their investment decisions and even the macroeconomic conditions. But few economic studies show the reason why some investors have more confidence. The reasons are complicated and I show one aspect of that.

The state of happiness is crucial and should be an indicator that the financial manager would like to know. But it is not easy to obtain. Our findings help future research in classifying people's psychological well-being state and make the quantification possible.

1.7 Conclusion

This paper shows that using machine learning method and a set of crucial features, I can precisely detect individuals with lower psychological well-being. It also suggests a new way to analyze the determinants of happiness.

I also estimated the ordered probit model to study how each features are associated with PWB. I find that people who are married reported higher level of happiness. Income is also important for all three PWB measurements. Prestige of occupation is another crucial features in predicting happiness and satisfaction and it has been under covered in the current economics of happiness studies.

The impacts of unhappiness are substantial. It is negatively associated with self-reported physical health and mental health. Unhappiness is also positively associated with people's likelihood of risky behaviors, such as smoking and excessive drinking. Happiness, on the other hand, increases people's confidence in financial institutions, productivity and affection towards their career.

In summary, this paper provides a comprehensive study of economics of psychological well-being. Methods developed in this paper have broad applications for economists to analyze the psychological impact on economic decisions and behaviors. This paper also provides policy-makers with efficiently tools to target psychological disadvantaged individuals.

1.8 Appendix

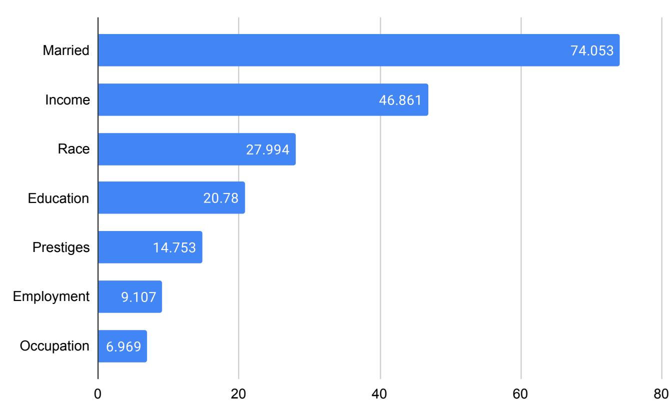
1.8.1 A: Feature Description

Table 1.10: Appendix A: Feature Description

Feature	Type	Details
Age	Numeric	Range between 18-89
Marital Status	Binary	Married or not
Income	Continuous	Adjusted to 2012 dollars
Race	Binary	White or others races
Education	Numeric	Highest years of schooling
Religion	Categorical	Types of Religion
Occupation	Categorical	Types of Occupation
Prestige Score	Numeric	Calculated via type of occupation
Children	Numeric	Number of Children
Working Status	Binary	Currently Employed or not

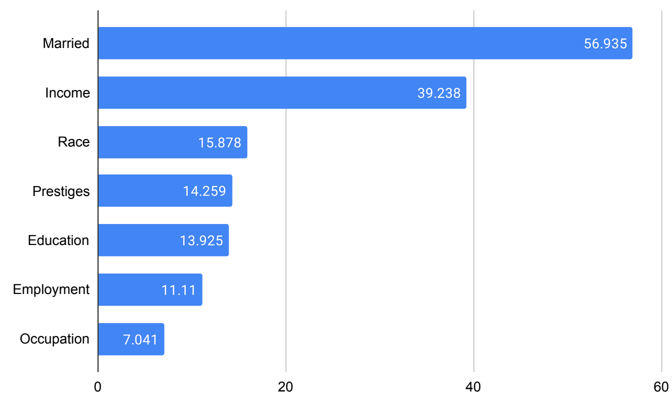
1.8.2 B: Importance Score

Figure 1.6: The Importance Score for General Happiness During Recession



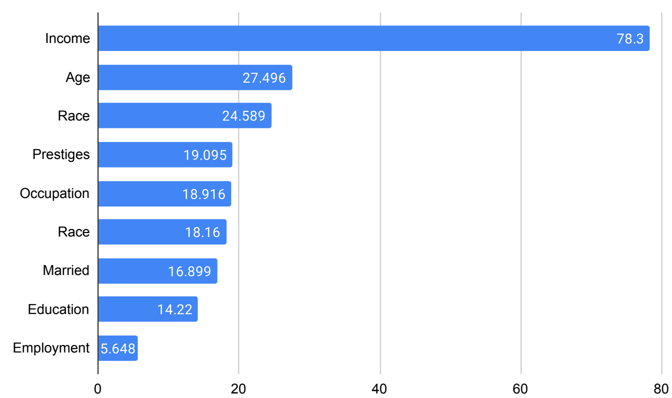
Note: the importance scores are scaled to 100.

Figure 1.7: The Importance Score for General Happiness During Expansion



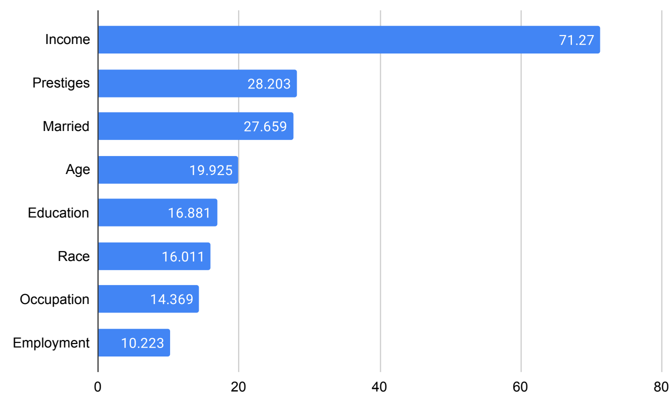
Note: the importance scores are scaled to 100.

Figure 1.8: The Importance Score for Satisfaction for Financial Situation During Recession



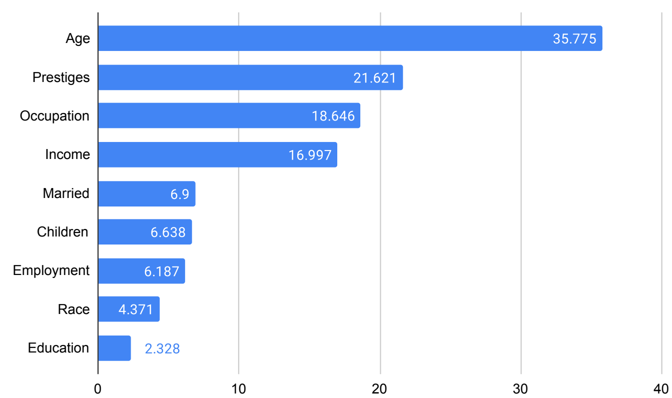
Note: the importance scores are scaled to 100.

Figure 1.9: The Importance Score for Satisfaction for Financial Situation During Expansion



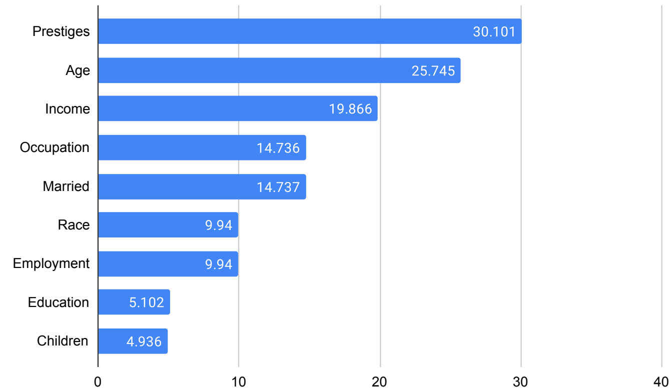
Note: the importance scores are scaled to 100.

Figure 1.10: The Importance Score for Satisfaction for Job During Recession



Note: the importance scores are scaled to 100.

Figure 1.11: The Importance Score for Satisfaction for Job During Expansion



Note: the importance scores are scaled to 100.

C: Classification For General Happiness with Binary Outcomes

Table 1.11: Classification for General Happiness $k = 7$

	Classified		
True	Not Happy	Happy	Total
Not Happy	5132 85.31%	884 14.69%	6016 100%
Happy	15695 36.75%	27012 63.25%	42707 100%
Total	20827 42.75%	27896 57.25%	48723 100%
Priors	0.5	0.5	

Chapter 2

The Effects of Medical Marijuana Laws on Infant Health

2.1 Introduction

With the implementation of marijuana legislation across the United States, marijuana use among reproductive-aged non-pregnant and pregnant women has dramatically increased over the past 15 years (Brown et al. (2017), Rosenberg (2017), Ko et al. (2015)). Previous studies has documented the adverse impact of maternal marijuana use on birth outcomes, such as low birth weight, preterm births, and increased hospitalization of infants (Hatch and Bracken (1986), Linn et al. (1983), Fried et al. (1984), Shi et al. (2021)). As more than 24 states passed medical marijuana laws (MMLs) (Powell et al., 2018) which potentially increased the availability of marijuana, the casual impacts of MMLs on infant health still need to be studied.

Current studies have revealed the advantages and disadvantages of MMLs. Researchers focus on the the direct or indirect impacts of MMLs on (1) risky behaviors: alcohol consumption (Mark Anderson et al., 2013), marijuana use (Mark Anderson et al. (2015), Chu (2014)), hard drug use (Chu, 2015), crime(Gavrilova et al., 2017)); (2) public health: opioid overdose death and addictions (Powell et al. (2018), Shover et al. (2019) Hayes and Brown (2014)), bodyweight (Sabia et al., 2017), suicides (Anderson et al., 2014), birth outcomes (Petrova and Gray, 2021b); (3) labor market outcome (Sabia and Nguyen (2018), Nicholas and Maclean (2019)).The studies of whether MMLs have positive effects on economics and public health are still inconclusive. One major positive impact of MMLs is the implementation of the medical marijuana law relived the opioid overdose crisis in the U.S.(Powell et al. (2018), Shover et al. (2019) Hayes and Brown (2014) Bachhuber et al. (2014)). It is also positively associated with the labor supply of older adults (aged 51 and older) due to better self-assessed health after using medical marijuana. While some studies revealed the unexpected adverse impacts of MMLs. Shover et al. (2019) questioned the findings that support MMLs released the opioid overdose mortality by arguing that medical marijuana is only used by about 2.5% of the U.S. population and used the state-level mortality data showed that there is no significant evidence that MMLs reduced the opioid-related death.

As shown in Figure 1 and Figure 2, the birth weight in the U.S. has declined over the last 3 decades across different mother's age groups and races. Many papers reveal that some policies may directly or indirectly harm infant health. In this paper, I argue that the medical marijuana laws are negatively related to birth weight and gestational age. Previous studies have documented the direct impact of marijuana use on birth outcomes. Linn et al. (1983),Fried et al. (1984), and Hatch and Bracken (1986) found that marijuana use during pregnancy is associated with an increased odds ratio of low birth weight and prematurity. Shi et al. (2021) also found that cannabis use disorder (CUD) has increased dramatically after MMLs and is related to adverse neonatal outcomes. Petrova and Gray (2021a) used the U.S. birth record data to check how MMLs affect birth outcomes. They didn't find any statistically significant impact of MMLs on low birth weight or preterm births. In this paper, I will argue they failed to properly deal with the presence of the endogeneity problem. With a more appropriate empirical strategy, I found robust and significant adverse impacts of MMLs on infant health.

There are some possible channels through which medical marijuana laws can affect infant health. First, it increased women's exposure to marijuana (Shi and Zhong, 2018). Women of reproductive age are more likely to use marijuana. Second, it may send the message that marijuana is "safe". Therefore, increase the maternal use of medical or recreational marijuana to relieve the discomfort during pregnancy. Third, previous studies suggested that marijuana may be substitute for alcohol and cigarettes (Mark Anderson et al., 2013). The MMLs reduce alcohol and cigarettes consumption, which might substantially affect maternal behavior and therefore, affect infant health.

In this study, I use a large population-level individual data collected by the National Vital Statistics System of the National Center for Health Statistics (NCHS) to estimate the causal impact of MMLs on infant health. I use a newly proposed empirical strategy (Freyaldenhoven et al., 2019) to deal with the time-varying unobserved confounder. With the combination of difference-in-differences (DID) methods and 2 stages least square (2SLS) estimation, I found that MMLs increased low birth weight by 0.251 pp ($p<0.01$, 3.74% of the mean). The effects of MMLs on probabilities of premature birth are positive (0.435 pp). Using event study design, I found that the effects of MMLs are persistent on the likelihood of low birth weight and preterm birth. This study suggests that physicians should be more cautious in the use of medical marijuana for women of reproductive age. Guidelines for pregnancy should highlight the adverse impact of marijuana on infant health.

The rest of this paper is organized as follows: Section 2 introduces the background of medical marijuana laws and maternal marijuana use in the United States. Section 3 summarizes the related literature. Section 3 describes the selection of data, sample, and variables. Section 4 introduces the empirical strategies. In section 5, I present the empirical results and Section 6 concludes.

2.2 Background

2.2.1 History of the U.S. Medical Marijuana Law

The history of the use of both medical and recreational marijuana is long and complicated. It is a miniature of the interaction between the social impacts and the drug properties. In the 1850s, marijuana was introduced to the U.S. as a medicine for treating conditions such as pain, nausea, and rheumatism (Wilkie et al., 2016). However, marijuana also has harmful effects, such as addition and other adverse physical and psychological conditions (Budney et al., 2007). State and the federal government enacted laws to prohibit the non-medical use of marijuana in 1914 (also known as the Harrison Act of 1914). In 1937, the use of marijuana is criminalized according to the Marijuana Tax Act passed by the U.S. Congress (Bonnie, Whitebread, 1970). The prohibition of marijuana lasted for 30 years until the initiation of Nixon's War on Drugs in the 1960s. The penalties of marijuana possession and distribution increased to mandatory prison sentences. The War on Drugs lasted for another 4 decades until the Anti-Drug Abuse Act was passed in 1986. The prohibition was reinstated and the penalties of possession and distribution increased (Lee, 2012). In the 1990s, the passage of the Medical Marijuana Law in five states (California in 1996, Alaska, Washington and Oregon in 1998, Maine in 1999) and D.C. relegalized marijuana use for conditions such as AIDS, cancer, and other serious illnesses (Lee, 2012). In the 2000s, states started to reconsider the war on drugs by relaxing prosecution of medical marijuana cases with another eight states passing the MMLs (see Table A1). Currently, twenty-four states are legalizing medical marijuana use(Powell et al., 2018). Seventeen states have fully legalized marijuana use including recreational use. The reasons for the MMLs implementation in these states are equivocal. Some states believe that medical marijuana can replace the use of opioid drugs use to some extend, and therefore offsets the adverse effects of potential addictions and deaths related to opioid overdose (Powell et al., 2018). Some consider the MMLs are paving the way for recreational use of marijuana and can increase the tax revenue (Budney et al., 2007).

2.2.2 Maternal Marijuana Use and Infant Health

As noted from previous studies, marijuana use among reproductive-aged non- pregnant and pregnant women has increased between 2001 to 2013 (Brown et al. (2017), Rosenberg (2017), Ko et al. (2015)). More than 1 in 10 women reported the use of marijuana during the past 12 months (Ko et al., 2015). In 2014, there are 3.9% of pregnant women use reported the use of marijuana, and that of 15.9% for non-pregnant women. (Rosenberg, 2017). Women of younger age (15- 25) are at higher risk of prenatal marijuana use (Brown et al., 2017). Alshaarawy and Anthony (2019) found that among pregnant women, marijuana use tends to ameliorate by the third month of pregnancy. They suggest that marijuana dependence may be a potential reason for marijuana use during the early stages of pregnancy.

2.3 Literature Review

The passage of the Medical Marijuana Laws in the United States is highly debated. Researchers focus on the the direct or indirect impacts of MMLs on (1) risky behaviors (alcohol consumption (Mark Anderson et al., 2013), marijuana use (Mark Anderson et al. (2015), Chu (2014)), hard drug use (Chu, 2015), crime(Gavrilova et al., 2017)); (2) public health (opioid overdose death and addictions (Powell et al. (2018), Shover et al. (2019) Hayes and Brown (2014)), body weight (Sabia et al., 2017), suicides (Anderson et al., 2014), birth outcomes (Petrova and Gray, 2021b)); (3) labor market outcome (Sabia and Nguyen (2018), Nicholas and Maclean (2019)). The studies of whether MMLs have positive effects on economics and public health is still inconclusive. Some have found advantageous impacts of MMLs, some have argue that the MMLs might have unexpectedly adverse impacts . In this paper, I summarize the previous findings in the positive impacts and negative impacts way. Gavrilova et al. (2017) have found MMLs leads to a decrease in violent crime in states near the border of Mexico.

Many researchers argue that the implementation of the medical marijuana law can relive the opioid overdose crisis in the U.S.(Powell et al. (2018), Shover et al. (2019) Hayes and Brown (2014) Bachhuber et al. (2014)). Bachhuber et al. (2014) use state-level death certificate data and simple linear regression methods finding that states with MMLs had a 24.8% lower mean annual opioid overdose mortality rate compared with states without MMLs. However, their findings are subjected to the endogenous problem by directly comparing states with and without medical marijuana laws. In order to solve this endogenous problem, Powell et al. (2018) uses individual level data and difference-in-differences strategy. Instead of using the timing of the enactment of MMLS, they use the date that the medical marijuana dispensaries became legal in states with MMLs. They also found that MMLs have reduced death of opioid overdose and they suggest there should be broader assess to medical marijuana facilitates to substitute addictive opioid pain killers with medical marijuana (Powell et al., 2018). Nicholas and Maclean (2019) use longitudinal data and DID method to check how MMLs affect the labor supply of older adults(age 51 and older). They find that the laws lead to increases in older adult labor supply potentially due to lower pain and better self-assessed health after using medical marijuana. In the public health domain, Sabia et al. (2017) find that MMLs are associated with a 2% to 6% decrease in the probability of obesity. Anderson et al. (2014) show that after MMLs implementation, the suicides among men aged 20-39 years old have fallen. Their findings are consistent with the hypothesis that marijuana helps to release stress and anxiety. Mark Anderson et al. (2013) check the relationship between medical marijuana and alcohol consumption. They found a sharp decline in alcohol consumption implying that marijuana and alcohol are substitutes.

They also find the alcohol-related traffic fatalities decreased by 8-11 percent.

Some studies argue that the MMLs may not have the expected effects or even have adverse impacts. Most notably, Shover et al. (2019) uses the same methods and extended data as Bachhuber et al. (2014)'s analysis. They find a positive association between of MMLs and opioid overdose mortality. They argue that medical marijuana is used by only about 2.5% of the U.S. population which may not have large effects on opioid overdose mortality as previous studies found. Chu (2014) found that MMLs increase illegal marijuana use by showing the marijuana arrests increase by about 15- 20% among adult males.

This study is closely related to maternal marijuana and infant health studies. There are two main streams of these studies. One is how marijuana use affects birth outcomes, such as birth weight and prematurity. The other is how maternal marijuana use affects breastfeeding. HATCH and BRACKEN (1986) use hospital data found that the use of marijuana among white women is associated with an increase in low birth weight (<2500 grams) by the odds ratio of 2.6% and also increases the preterm delivery by 1.9% pp. They didn't find significant adverse effects of marijuana use on non-white women. Similar results was detected by Linn et al. (1983),Fried et al. (1984). Shi et al. (2021) found that cannabis use disorder (CUD) has increased a lot and is related to adverse neonatal outcomes, such as low birth weight, preterm birth, and hospitalization. Ko et al. (2018) further highlighted the behavior channel of how marijuana use would affect birth outcomes. They indicate that marijuana use is associated with the increase use of alcohol and tobacco use during pregnancy and postpartum marijuana use is liked with depressive symptoms. Studies on the impacts of marijuana use on breastfeeding mainly conclude that marijuana use was associated with adverse impact on infant's neuro-development by the transfer of mother's milk ((Ryan et al., 2018), (Bertrand et al., 2018)).

Petrova and Gray (2021a) use the same data set as this paper. They found that MMLs are associated with an increase in birth weight and they didn't find any significant impact of MMLs on low birth weight and preterm births. They construct the treatment as women who are pregnant in the full year of MMLs implementation. However, as previous studies show, there might be a potential long-lasting impact of marijuana use on birth outcomes. Therefore, I construct the treatment as the implementation of MMLs one year before women got pregnant so that there is enough time window for substantial behavior changes.

2.4 Data

The results come from birth record data collected by the National Vital Statistics System of the National Center for Health Statistics (NCHS) for years between 1996-2016. The micro-data are based on information abstracted from birth certificates filed in vital statistics offices of each State and District of Columbia. Birth data for the U.S. are limited to births occurring within the United States to U.S. residents. After 2005, NCHS doesn't provide the state/county level geographic identifiers. However, it is crucial to use geographic information in order to conduct a difference-in-differences strategy. Therefore, I apply for the confidential geographic identifiers through the review of the National Association for Public Health Statistics and Information Systems(NAPHSIS). The birth record natality data provides a variety of individual-level information of all births in the U.S. each year. It has the basic demographic characteristics of parents, such as age, marital status, and educational attainment. The natality data also provides maternal lifestyle and health characteristics information, making it possible to check the underlying mechanism of the impact of MMLs on mothers' lifestyle. Most importantly, the data set have infant health information, such as birth weight, period of gestation, and Apgar score. These variables are the main outcome variables used in this study.

2.4.1 Sample Selection

The time period of the sample in the data analysis is between 1996-2016. I choose 1996 as the start year because California is the first state that implements the MML in 1996. In 2014, there are several other states that passed the MML. Therefore, I choose 2016 as the end year so that the sample includes all the states that enacted the MML during the study period. In the sample, I also drop a few observations with missing information of the mother's education, race, age, and infant's birth. In order to make sure that the analysis is based on all potential live infants, I also drop the observations with birth weight smaller than 500 grams and gestational ages smaller than 26 weeks. I mainly analyze mothers with primary childbearing age between 22-49 since they are potentially more likely to be affected by the MMLs. In addition, we keep the states that adopted the MML leaving the relatively balanced sample for the analysis with the percent treated as 44.21%.

2.4.2 Variables Selection

The main outcome variables include (1) birth weight, indicator for very low birth weight ($<$1500grams), low birth weight($<$2500); (2) gestational age, the indicator for premature birth (<37 weeks), the indicator for very low birth weight (<34 weeks). The individual-level control variables include maternal education level, mother's age categories [1], marital status of mothers, mother's race categories, sex of infant, total birth order, and plurality. I also consider the state and year fixed effects by including the state and year identifiers as control variables. I construct the treatment variable as indicators that equal 1 if the women conceived the baby in the first full year after a medical marijuana law implemented, and 0 otherwise. In order to show the robustness of my results, I also check the regression results using the treatment indicator as zero years after the MMLs were implemented and the second year after the MMLs went into effect. In the event study, I use up to 6 years of leads and lags for the medical marijuana laws.

2.4.3 Descriptive Statistics

Descriptive statistics are reported in Table 1 for years between 1996-2016. I present the statistics for the full sample, the sample of births had no treatment, sample of births that are considered as treated in this study.

[1] I categorize mother's age into the following groups: less than 20; 20-24; 25-34; older than 35.

Table 1: Descriptive Statistics From Birth Records: 1996-2016

	Full Sample		No Treatment	No Treatment	Full Treatment	
	Mean	S.D.	Mean	S.D.	Mean	S.D.
Outcome Variables						
Birthweight (in grams)	3336.977	569.957	3343.292	576.773	3329.262	561.421
Low Birthweight (<2500 grams)	6.709	25.018	6.831	25.228	6.559	24.758
Very Low Birthweight (<1500 grams)	0.889	9.391	0.8928	9.406	0.8435	9.145
Gestational Age (in weeks)	38.83	2.231	38.849	2.275	38.807	2.178
Premature Birth (<37 weeks)	10.321	30.423	10.583	30.762	10.001	30.001
Very Premature Birth (34 weeks)	2.608	15.938	2.713	16.248	2.479	15.549
Maternal Variables						
Mother's Age	30.015	5.041	30.008	4.996	30.033	5.088
Married	0.6245	0.4842	0.703	0.456	0.530	0.499
White	0.7889	0.408	0.7919	0.406	0.788	0.408
Black	0.1045	0.306	0.1226	0.331	0.075	0.264
Years of Schooling	13.668	3.201	13.732	2.983	13.572	3.446
Number of Prenatal Care	11.701	3.885	11.573	3.755	11.856	4.032
Infant Variables						
Total Birth Order	2.634	1.613	2.671	1.651	2.614	1.599
Female	0.488	0.499	0.488	0.499	0.487	0.499
5-Minute Apgar Score	8.895	0.635	8.928	0.611	8.842	0.667
Number of Observations	28983572		16205708		12777864	

Notes: Indicator variables, such as low birthweight, equal to 100 if the value falls under the threshold, equal 0, otherwise.

2.5 Empirical Strategy

2.5.1 Difference-in-Differences Methods

I leverage the differential timing of MMLs adoption, and the comparison of the changes in outcome variables for states with and without MMLs to find the causal impact of medical marijuana laws on infant health. The first approach is the following standard difference-in-differences model:

$$y_{ist} = \beta_0 + \beta_1 MML_{st} + X_{ist}\beta_2 + z_s + v_t + \epsilon_{ist} \tag{2.1}$$

where y_{ist} represents the infant health (birth weight, indicators for low birth weight and very low birth weight, length of gestation, and indicators for premature birth and very premature birth) for an infant i born in year t to a mother residing in state s. The vector MML_{st} represents several indicators for state medical marijuana laws: (1) the dates of MMLs went into effect; (2) the dates when dispensaries are legal(equal to one in the first full year before the women got pregnant). X_{ist} is a vector of individual-level controls; z_s is the state fixed effect (to control for the parallel effects in the outcome variables across states); v_t is the year fixed effect (to control for the trends in the outcome variables over time); and ϵ_{ist} is the error term.

The coefficient of interest in equation (2.1) is β_1. It captures the causal effect of MMLs on infant health if the DiD model follows the assumptions that the infant health outcomes would follow the same trends in the states with MMLs and without MMLs if the MMLs had not been implemented. Researchers usually use the event study methods to detect if there are trends in treated states that differ from those in control states before the adoption of the policies. As shown in the appendix, I found there are pre-event trends that exist using the ordinary least squares (OLS) regression model. To solve this problem, I use a two-stage least square (2SLS) model introduced by Freyaldenhoven et al. (2019) as described in the next section.

2.5.2 Using 2SLS Models to Deal with the Pre-Event Trends

In this study, I am interested in estimating the causal effects β_1 of the medical marijuana laws (MML_{st}) on the infant health outcome (y_{ist}). For the causal effects are valid, MML_{ist} needs to be strictly exogenous. However, I am concerned that there exists a time-varying unobservable η_{ist} that is correlated with both MML_{st} and y_{ist} making the causal effect captured by β_1 being confounded. In the context of this study, the unobservable η_{ist} could be women's attitude towards medical marijuana. Women who accept the use of marijuana are more likely to live in the states that implemented MMLs. A common approach to diagnose is to check whether there present pre-event trends before the policy occurs. As shown in the appendix, the OLS regression model does detect such trends and it is generally believed that the strict exogeneity of MML_{ist} is likely to fail. However, it doesn't necessarily imply that there are no causal effects of the MMLs on infant health. Therefore, the questions fall into: how can we appropriately estimate the causal effects in presence of pre-event trends. In order to solve this problem, Freyaldenhoven et al. (2019) proposed a 2SLS regression to estimate the effects of a policy (in this context MML_{ist}) on the outcome y_{ist} of interests by including a covariate IV_{ist} as an instrument with leads (e.g., $MML_{is,t+1}$). A key underlying assumption is that the dynamic relationship of the instrument IV_{ist} to $MMLst$ mirrors the dynamic relationship of the unobservable η_{ist} to MML_{ist}. Specifically, IV_{ist} is affected by η_{ist} but not by MML_{st}. Given the requirements for the instrumental variable, I use mother's educational level as the instrument because more educated women are likely to be more aware of the harm of marijuana. Meanwhile, maternal educational attainment is independent of the implementation of MMLs. The 2SLS regression model is depicted the following:

$$y_{ist} = \beta_0 + \beta_1 MML_{st} + X_{ist}\beta_2 + \gamma\eta_{ist} + z_s + v_t + \epsilon_{ist} \tag{2.2}$$

I use the closest lead of MML_{ist} as the excluded instrument for mother's educational level IV_{ist}. The results are shown in the following section.

2.6 Results

2.6.1 OLS Results

Panel A of Table 2 shows OLS results from Equation 2.1 using the full sample of the study period. Overall, Table 2 shows that the passage of medical marijuana law is associated with increases the occurrence of low birth weight (<2500 grams) by 0.254 percentage points (p<0.01, 3.5% of the mean). This significant effect is mainly driven by a 0.213 percentage point (p<0.01, 3.53% of the mean) increase for birth to white mothers. The impacts of MMLs on the probability of low birth weight for births to black mothers are also positive but statistically insignificant. Column (3) of Table 2 shows a positive association between the implementation of MMLs and the probability of very low birth weight (<1500 grams).

The effects are modest (0.08 pp increase) in the full sample and the sample of white mothers. Generally, birth weight and gestation are closely related and in the same direction. So I also find the increase in the probability of premature birth (<37 weeks) and very premature birth(<34 weeks) associated with MMLs (shown in columns 5 and 6). The effects are all positive and statistically significant across the full sample, the sample of white mothers, and the sample of black mothers. The effects of MMLs on the continuous birth weight and gestational age variable are negative but statistically insignificant. This may imply that the passage of MMLs mainly affects the most disadvantaged births, instead of the overall distribution.

Table 2: OLS difference-in-differences estimates of the effects of medical marijuana laws on infant health

OLS	(1) Birthweight (g)	(2) Low birthweight (<2500 grams)	(3) Very low birthweight (<1500 grams)	(4) Gestation (weeks)	(5) Premature (<37 weeks)	(6) Very Premature (<34 weeks)
Panel A: Full Sample						
MML	-2.451	0.254***	0.080***	-0.034**	0.530***	0.286***
	(3.202)	(0.083)	(0.018)	(0.016)	(0.102)	(0.041)
Observations	28983572	28983572	28983572	28963686	28963686	28963686
Outcome mean	3336.977	6.709	0.89	38.83	10.321	2.608
Panel B: Birth to White mothers						
MML	-1.479	0.213***	0.070***	-0.029*	0.448***	0.256***
	(2.894)	(0.07)	(0.014)	(0.016)	(0.087)	(0.033)
Observations	22866094	22866094	22866094	22849308	22849308	22849308
Outcome mean	3372.564	6.026	0.769	38.886	9.769	2.37
Panel C: Birth to Black mothers						
MML	3.007	0.197	0.129**	-0.057*	0.686**	0.364**
	(6.057)	(0.212)	(0.05)	(0.03)	(0.312)	(0.137)
Observations	3030789	3030789	3030789	3029640	3029640	3029640
Outcome Mean	3175.365	11.279	1.902	38.466	15.055	4.717

Notes: Standard error in parentheses; * $p<0.1$, ** $p<0.05$, *** $p<0.01$.
All regressions include state and year fixed effects. Individual-level controls are included.
Indicator variables take the value of 100 if the variable is smaller than the threshold, and 0 otherwise.

As discussed above, the event study can show whether there is pre-trend exists and help us to check the strict exogeneity of the policy. As Figure 2.1 shows, the coefficients of the continuous birth weight variable are statistically insignificant. There are also obvious pre-trends that exist for indicator variables (low birth weight and premature). This implies that there exist unobservable time-varying confounders that affect birth outcomes and are also associated with the treatment. Therefore, I use the 2SLS to overcome the endogenous problem. The results are shown in the following section.

Figure 2.1: OLS Event study for birth weight of full sample

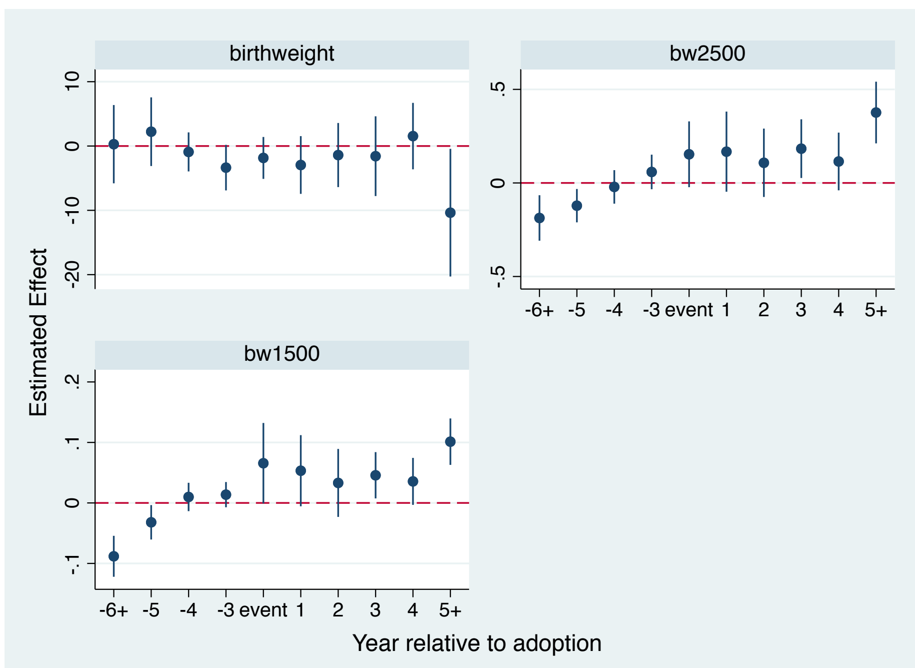
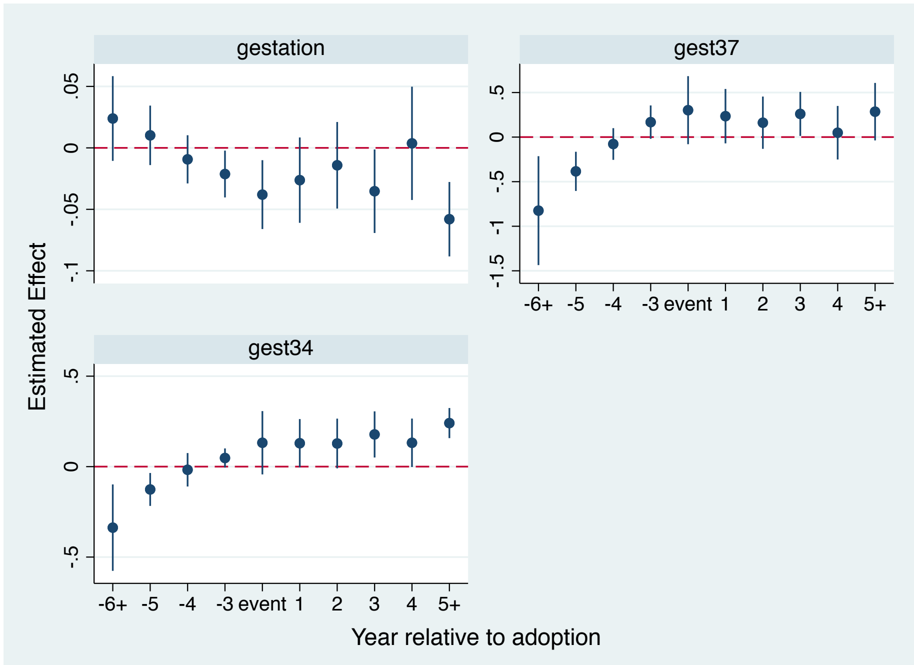


Figure 2.2: OLS Event study for gestational of full sample



2.6.2 2SLS Results

As we can learn from Table 3, the sign of the 2SLS coefficients remains the same as the results of OLS. But the magnitude of these coefficients is smaller with instrument variables, implying that the OLS estimators are upward biased. Column 2 in Table 3 shows that MMLs increased low birth weight by 0.251 pp ($p<0.01$, 3.74% of the mean). The effects of MMLs on probabilities of premature birth is positive (0.435 pp). The most notable difference between the OLS results and 2SLS results is that the coefficients for the prematurity indicators became statistically insignificant for births to white mothers.

Table 3: 2SLS difference-in-differences estimates of the effects of medical marijuana laws on infant health

	(1) Birthweight (g)	(2) Low birthweight (<2500 grams)	(3) Very low birthweight (<1500 grams)	(4) Gestation (weeks)	(5) Premature (<37 weeks)	(6) Very Premature (<34 weeks)
Panel A: Full Sample						
MML	-3.301	0.251***	0.075***	-0.034**	0.435**	0.247**
	(2.195)	(0.084)	(0.025)	(0.014)	(0.213)	(0.101)
Observations	28983572	28983572	28983572	28963686	28963686	28963686
Outcome mean	3336.977	6.709	0.890	38.830	10.321	2.608
Panel B: Birth to White mothers						
MML	-4.869	0.221***	0.054**	-0.032**	0.159	0.125
	(3.301)	(0.066)	(0.027)	(0.013)	(0.294)	(0.151)
Observations	22866094	22866094	22866094	22849308	22849308	22849308
Outcome Mean	3372.564	6.026	0.769	38.886	9.769	2.370
Panel C: Birth to Black mothers						
MML	-2.799	0.794	0.202	-0.129	2.072	0.971
	(45.844)	(4.260)	(0.639)	(0.563)	(11.078)	(4.878)
Observations	3030789	3030789	3030789	3029640	3029640	3029640
Outcome Mean	3175.365	11.279	1.902	38.466	15.055	4.717

Notes: Standard error in parentheses; * $p<0.1$, ** $p<0.05$, *** $p<0.01$.
All regressions include state and year fixed effects. Individual-level controls are included.
Indicator variables take the value of 100 if the variable is smaller than the threshold, and 0 otherwise.

The results of 2SLS event study are shown from Figure 2.3 and Figure 2.4. For the birth weight, the coefficients in the pre-adoption period are all individually and jointly statistically insignificant. The coefficients are estimated to be close to zero in the 5 periods of time leading up to the MMLs adoption. The results access the credibility of the 2SLS difference-in-differences estimates by showing the satisfaction of the parallel trends assumption. The coefficients in the post periods suggest persistent effects on the probability of low birth weight. The coefficients of very low birth weight are also positive but partially persistent, given that in periods 2-4, the coefficients are not statistically significant in $p < 0.01$ level.

Figure 2.4 shows the results for the gestational age. There are still pre-adoption trends for prematurity indicators, but the coefficients are all statistically insignificant. The post-adoption coefficients are all positive (significant in $p<0.01$ level), which suggests persistent and stable post-adoption effects of MMLs.

Figure 2.3: 2SLS Event study for birth weight of full sample

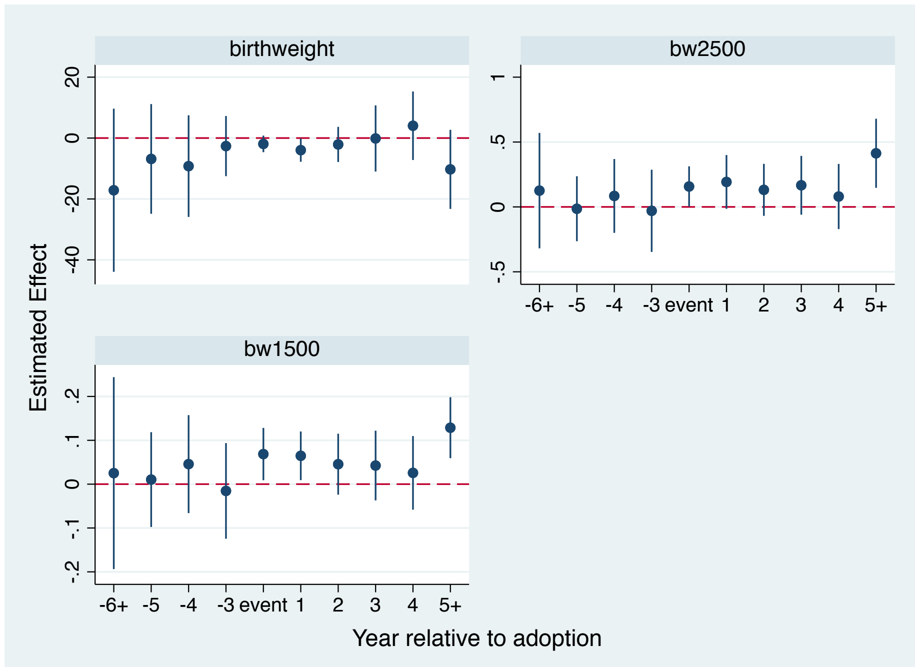
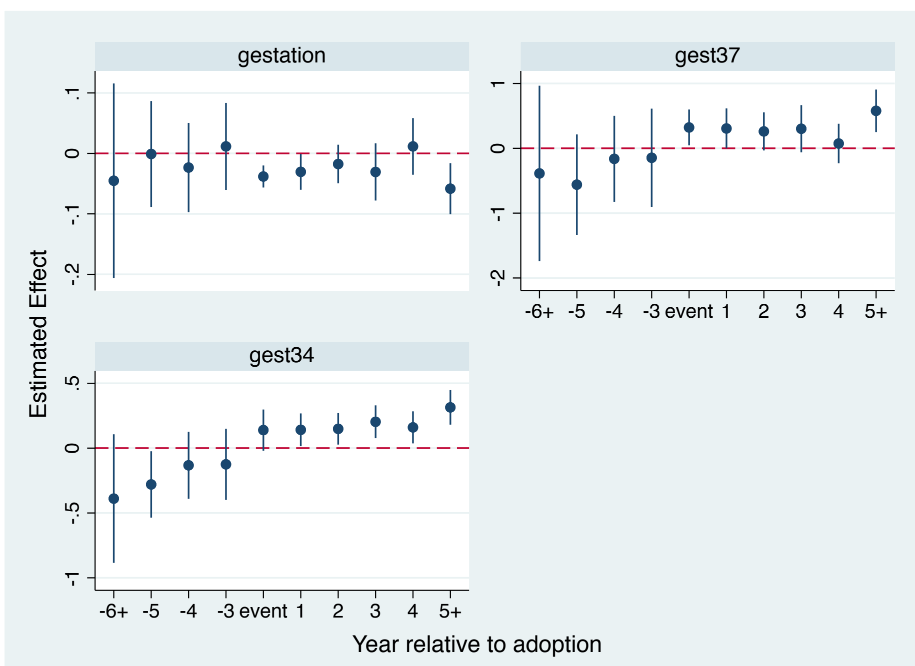


Figure 2.4: 2SLS Event study for gestational of full sample



2.7 Conclusion

This paper suggests that the increases in the probabilities of low birth weight and prematurity birth may be an unintended consequence of medical marijuana laws. The estimates of 2SLS on low birth weight are slightly smaller than the OLS estimates. However, in both cases, the results show that there is the negative impact of MMLs on low birth weight, very low birth weight, and premature birth. One reason that the 2SLS estimates are smaller is that this method teases out the confounding effects of mother's educational level. Mothers who are more educated are more likely to know the harm of marijuana on their offspring and may be more cautious when considering the use of both medical and recreational marijuana. Our findings are consistent with previous finding in the public health area (Linn et al. (1983),Fried et al. (1984). Shi et al. (2021) Shi et al. (2021)).

One limitation of this study is that I am unable to look at whether mothers indeed use marijuana because of the lack of such information in the dataset. What is estimated in this study is the overall impact of medical marijuana laws on infant health. However, with the association of previous public health studies, we can link the channels between the laws and the actual use of marijuana by mothers. As the medical marijuana laws increase the availability of marijuana and potentially send the information that marijuana is safe to women of childbearing age, more women will be exposed to marijuana and will lead to harmful effects on their children. I am also unable to look at the future health of the infant. An increase in marijuana use is associated with early cessation of breastfeeding ((Ryan et al., 2018), (Bertrand et al., 2018)), which is also likely to associate with adverse impact on the future development of infants.

This study suggests that physicians should be more cautious in the use of medical marijuana for women of reproductive age. Guidelines for pregnancy should highlight the adverse impact of marijuana on infant health.

2.8 Appendix

2.8.1 A: Marijuana Legality

2.8.2 Event Study for Birth to White and Black Mothers

Figure 2.5: 2SLS Event study for birthweight of birth to white mothers

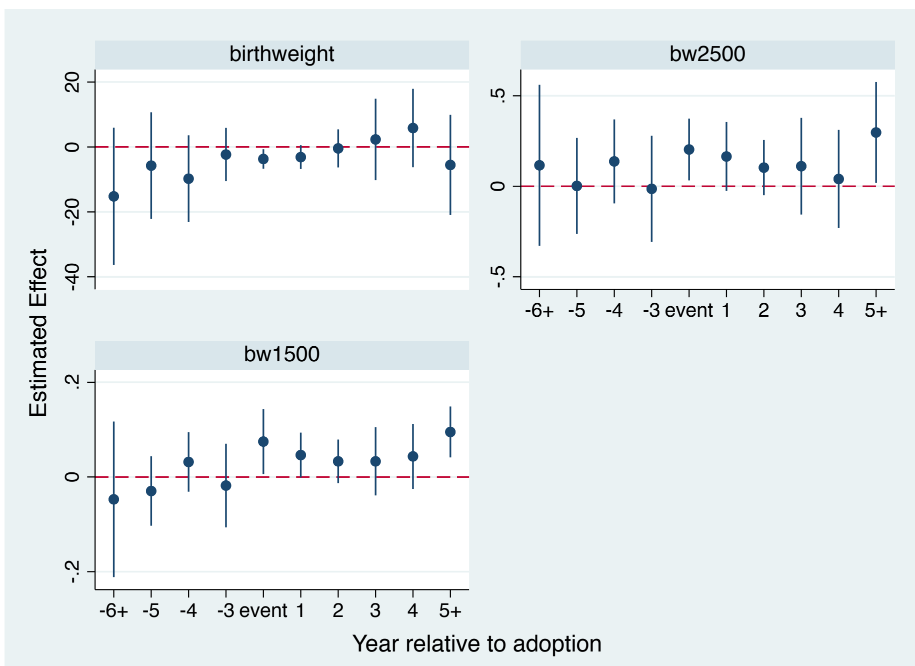


Table 2.1: Marijuana Law Dates During Study Period

State	Medical Marijuana Effective Date	Year Medical Marijuana Dispensary Legalized	Recreational Marijuana Legalized
Alaska	3/4/1999	x	2014
Arizona	11/29/2010	Dec 2012	x
California	11/6/1996	Jan 2004	2016
Colorado	12/28/2000	June 2010	2012
Connecticut	10/1/2012	Aug 2014	x
Delaware	5/13/2011	x	x
Washington DC	7/27/2010	Apr 2013	x
Hawaii	6/16/2000	x	x
Illinois	1/1/2014	x	x
Maine	12/23/1999	Mar 2011	2016
Maryland	10/2/2003	x	x
Massachusetts	1/1/2013	x	2016
Michigan	12/4/2008	x	x
Minnesota	5/30/2014	x	x
Montana	11/2/2004	x	x
Nevada	10/1/2001	Mar 2015	2016
New Hampshire	7/23/2013	x	x
New Jersey	6/1/2010	Dec 2012	x
New Mexico	7/1/2007	July 2009	x
New York	7/5/2014	x	x
Oregon	12/3/1998	Mar 2014	2014
Rhode Island	1/3/2006	Apr 2013	x
Vermont	7/1/2004	June 2013	x
Washington	12/3/1998	x	2012

Note: Information are gathered from National Conference of State Legislatures, and the National Organization for the Reform of Marijuana.
x denotes states didn't pass the law during study period (1996-2016).

Figure 2.6: 2SLS Event study for gestational of birth to white mothers

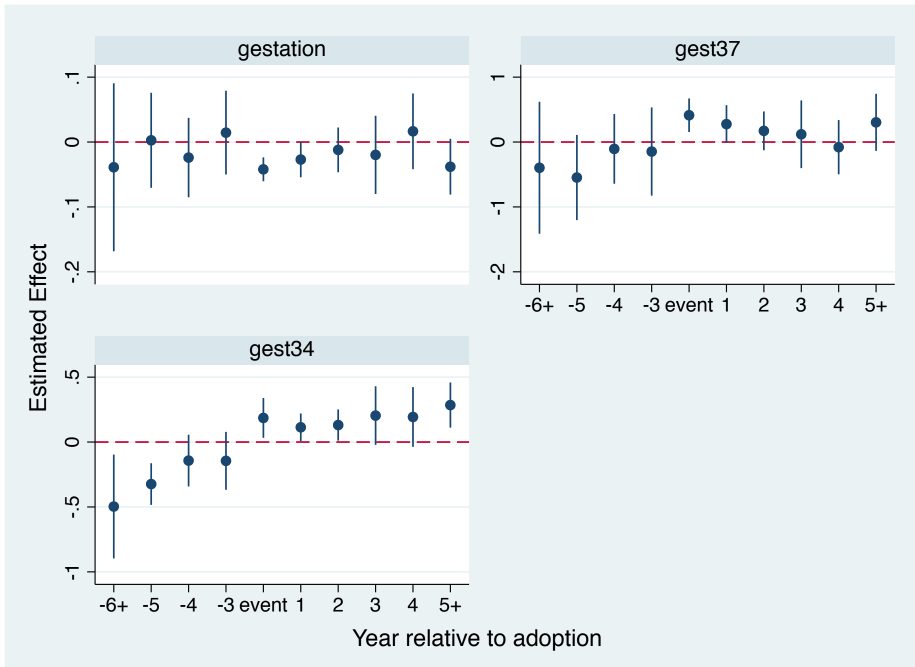


Figure 2.7: 2SLS Event study for birthweight of birth to black mothers

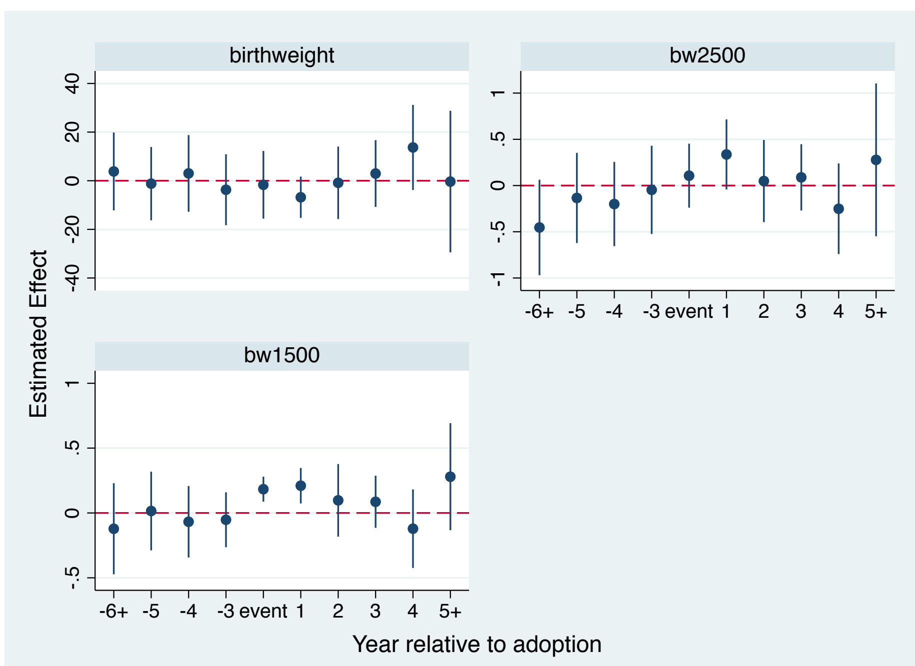
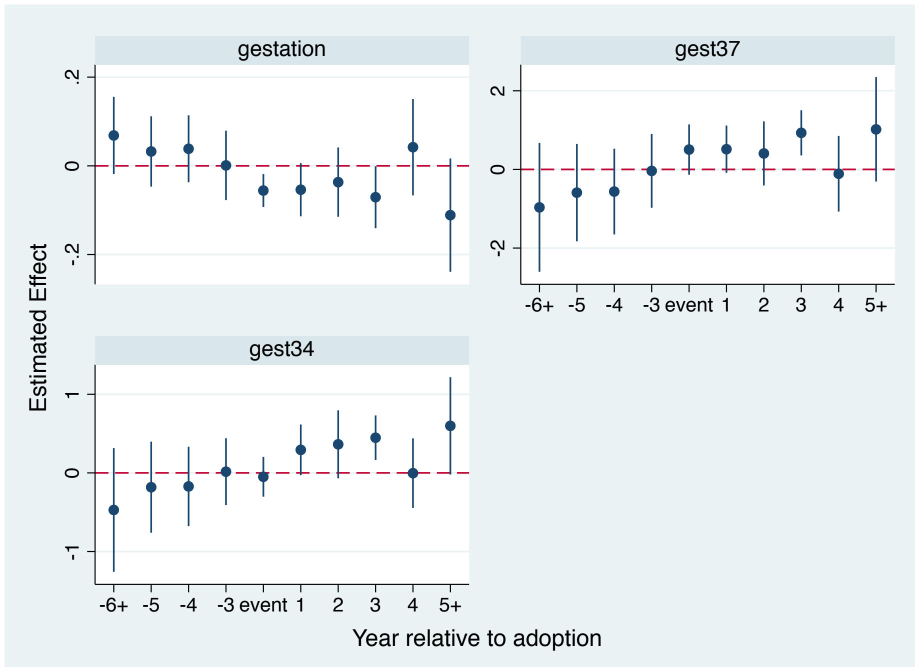


Figure 2.8: 2SLS Event study for gestational of birth to black mothers



Chapter 3

The Puzzling Decline in American Birth Weights with Big Data

– with Joseph Cummins and William Masters

3.1 Introduction

In this paper, we present the evidence on a previously recognized but under-investigated decrease in birth weight in the United States during the first decade and a half of the 21st Century. From 2000 to 2006, mean birth weight for US singletons decreased by 1.53%, and has only partially recovered since 2007. The declines in birth weight occur at all gestational ages, for all races, within all maternal age bins, for both smokers and non-smokers, for vaginal and c-section births and at all quantiles of the birth weight distribution. These trends are of great concerns. Many studies have found evidence that infant birth weight is correlated not only with children's early-life health outcomes, but also with children's health and development into adulthood (Currie and Hyson,1999; Currie and Moretti,2003; Black,2007).

We investigate compositional changes in birth mothers by socioeconomic and health-behavioral groups and show that the changes in birth weight may relate to several or all of changes in child mortality patterns, c-section rates, birth timing, and socioeconomic distribution of mothers. we propose a preliminary but plausible story in which the widespread decreasing in birth weight occurring for all races, within all maternal age bins and at all quantiles of birth weight distribution, is triggered by progressively rising in the rates of induction of labor since 1990 that shifts births across gestational ages. Our results lead us to believe that any single explanation is unlikely to explain the entirety of the decline in birth weight and the failure of mean birth weight to regain pre-2000 levels. We discuss several more and less promising routes for future research.

3.2 Data

Our results come from birth record data collected by the National Vital Statistics System of the National Center for Health Statistics (NCHS). The microdata are based on information abstracted from birth certificates filed in vital statistics offices of each State and District of Columbia. Birth data for the U.S. are limited to births occurring within the United States to U.S. residents.

Sample Selection

We define two samples: a "full" sample and a more restrictive "singleton" sample of children. The full sample includes children born in the U.S. to U.S. citizens or residents with biologically viable birth weight. The "singleton" sample excludes all children born during multiple births (twins, triplets or more), and children born to mothers younger than 15 or older than 45.

We explore heterogeneities in the birth weight trend along several sub-group dimensions. We split the sample by maternal age (15-19, 20-24, 25-29, 30-34, 35-39, 40-45 years) and race/ethnicity (Hispanic, non-Hispanic white, non-Hispanic black, Asian and American Indian) to investigate the consistency of the pattern across demographic groups. Motivated by the biomedical and epidemiology literature, we split on gestational age, which is recorded on birth certificates and is estimated at birth. Birth type (c-section or vaginal) and smoking status of the mother are also recorded on birth certificates and used to define sub-groups for disaggregation.

3.3 Literature Review

The decline in mean infant birth weight in the U.S. has been indicated in many studies in the field of obstetrics and gynecology.

Esplin, Varner and Oken (2013) use data from Intermountain Healthcare system in Utah. They find that even in a population where gestation length did not change, birth weight and fetal growth declined. Decrease in not only gestational length but in fetal growth as well is likely to be contributing to the widely observed recent decrease in birth weight. Catov, Roberts and Xu (2016) use hospital data from 1997 to 2011, finding that birth weight has been decreased since 2000, and reductions were greater in infants born to African-American women. They conjecture that these trends might be explained by accumulation of risk factors such as hypertension and pre-pregnancy obesity. Donahue, Keinman, Gillman and Oken(2010) used data from the U.S. National Center for Health Statistics 1990-2005. They examined trends in birth weight, birth weight for gestational age, large and small for gestational age. They found that in 2005, compared with 1990 the mean birth weight decreased 52 grams in the overall population.

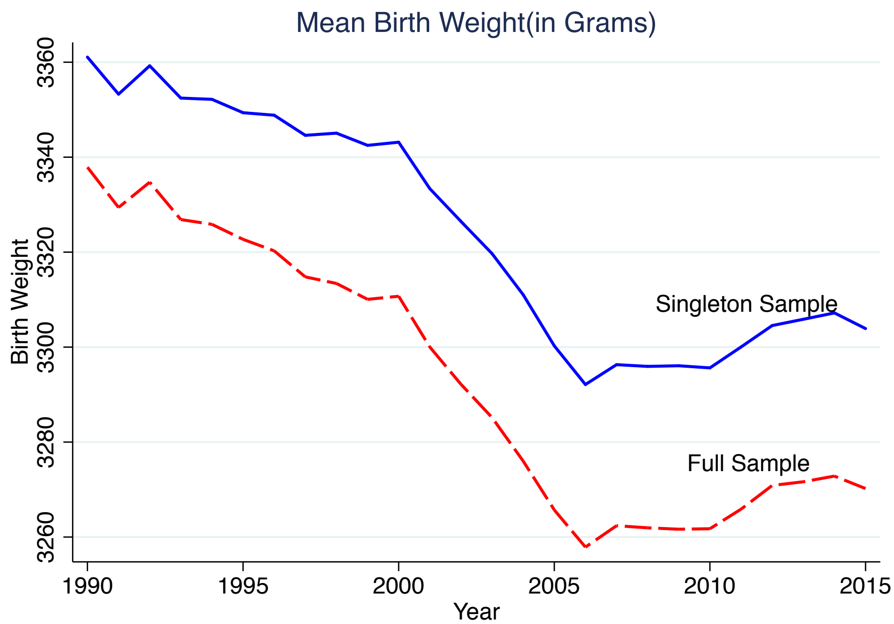
Despite the widely recognized declining in mean birth weight regardless of race or ethnicity, mother's characteristic and delivery route in the U.S., there is no studies so far examining the potential explanation of the declining.

3.4 Documenting Birth Weight by Maternal and Birth Characteristics

The decline trends in American birth weight is observed at all gestational ages, for all maternal races and ethnicities, within all maternal age bins, for both smokers and non-smokers, for vaginal and c-section births and at all quantiles of the birth weight distribution. In this section, we present trends in average annul birth weight by decomposing the change in birth weight by maternal and birth characteristics to provide a round picture of this public-health shock.

Figure 3.1 shows two time-series estimates of mean birth weight from 1990 to 2015. We tracked the birth weight for all infants born in the U.S. after 1990; during the 20th century, the average annual birth weights declined. The dashed line shows mean birth weight for the full sample, and the solid line shows the same for the Singleton sample. The mean birth weight for both the full and the Singleton samples was highest in 1990, at 3337 grams and 3361 grams respectively. It then decreased by 2.4% (full) and 2.05% (singleton) between 1990 and 2006. From 2007 to 2015, the decline in birth weight stopped and slightly reversed, such that by 2014 the mean birth weight recovered around one-third of the loss it suffered between 2000 and 2005. Note that for the rest of this paper, we mainly focus on the "Singleton sample" and the following figures are all graphed among Singleton sample.

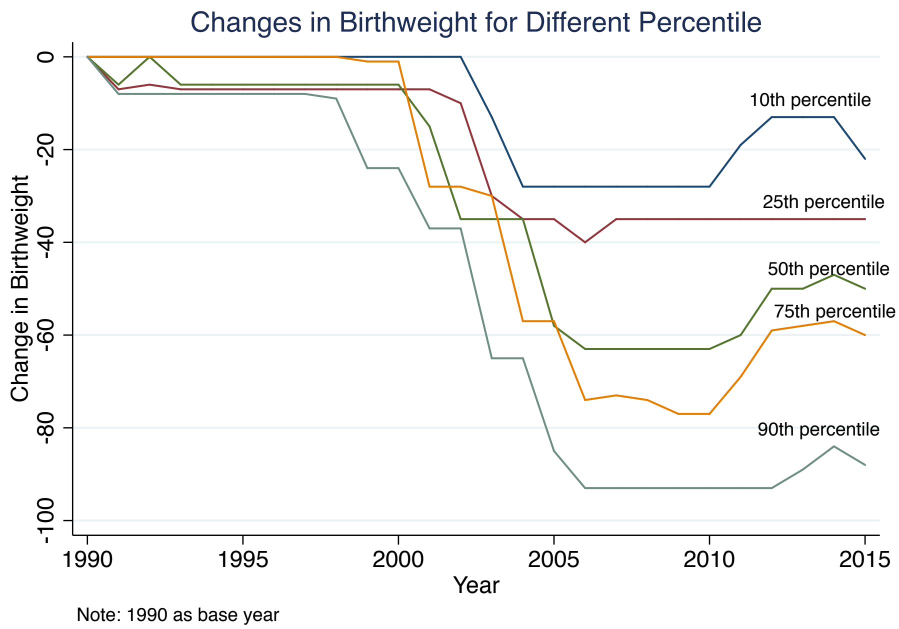
Figure 3.1: Mean birth weight in Grams



The change in birth weight is not only reflected in the means. Figure 3.2 graphs each percentile of the unconditional birth weight distribution in the Singleton sample. There were decreases at every percentile, with the largest decreases coming at the higher end of the birth weight distribution, which suggests that the declining trend is not driven by negative selection of births by more low birth weight survivals. The second plot decomposing the annual average birth weight by child sex, indicating that birth weight decline sharply after

2000 for both sex while the percentage of male infants remained fairly stable at around 51.8% since 1990 until 2015.

Figure 3.2: Changes in birth weight for different percentile



3.4.1 Socioeconomic Composition

One possible explanation for the birth weight decline is purely compositional. The demographics shown in Figures 3.3 and Figure 3.4 provide a more complete picture of mean birth weight time-series plot by disaggregating maternal characteristics (maternal race, ethnics and age). The decrease in birth weight is apparent for all races and all maternal ages.

As is shown in the top line of Figure 3.3, infant birth weights were highest among mothers between the ages of 30 and 34, however the average birth weight for this maternal age group declined from 3414 grams in 2000 to 3353 grams in 2007. The average birth weight among teenage mothers (aged 15-19) was the lowest of all age groups, and the average birth weight for this maternal age group dropped annually by 1.83 percent from 1990 to 2006. Several studies have reported increased risks of low birth weight among children of adolescent mothers (Jolly et al., 2000). It has been suggested that these mothers are themselves still developing and growing, and therefore, the mother and unborn child may compete for the supply of nutrients (Scholl et al.,1994). Therefore, the group of teen mothers should be paid more attention to when we examine declining birth weight trends.

Figure 3.3: Trends in birth weight by mother' age group

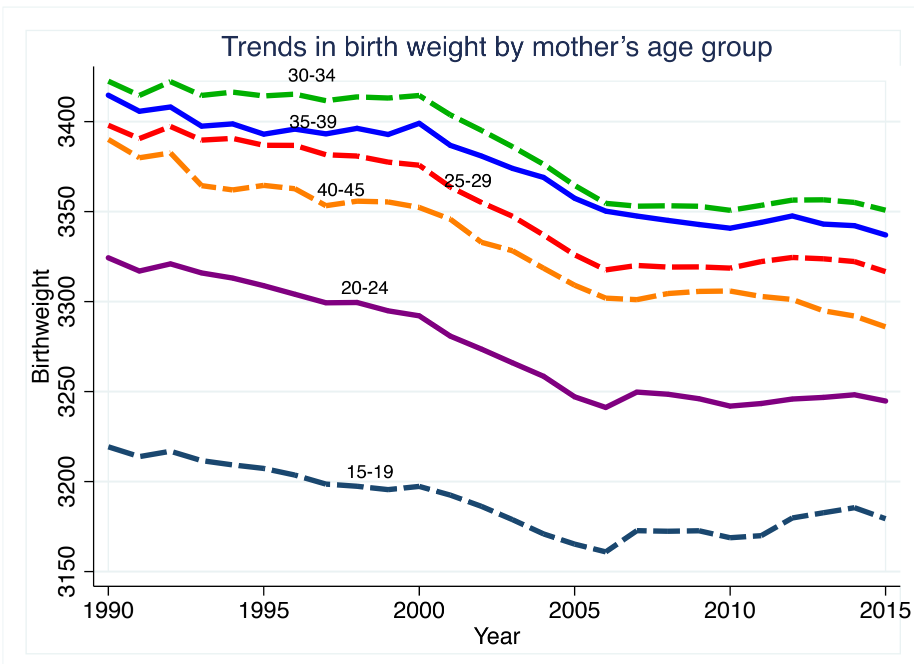
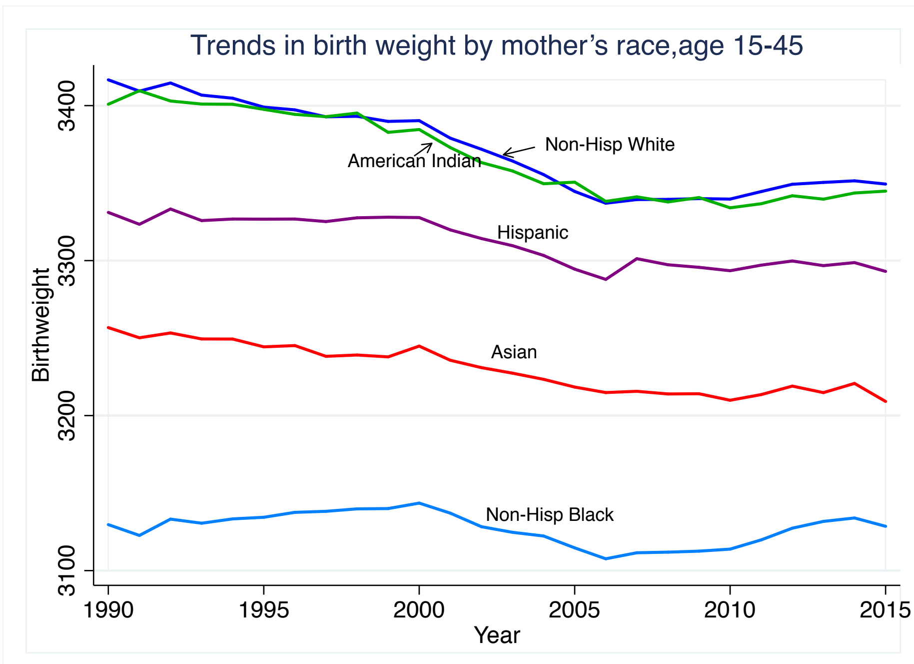


Figure 3.4 presents the estimates of birth weight across maternal racial groups. We separate the estimates for black non-Hispanics, white non-Hispanics, Hispanics, Asians, and American Indians of ages ranging from 15 to 45. The birth weight of non-Hispanic black children was and remains lower than that of other racial groups, and has fallen rapidly,

by approximately 1.14 percent from 1990 to 2006. We note similar patterns of decreasing average birth weights across all racial groups. The top two lines in Figure 3.4 are of interest: it is observed that the slopes of the 1999 to 2006 birth weight estimates for infants of non-Hispanic white and American Indian mothers were steeper (at a decline of 1.63 percent) than for other races (at a decline of 1.37 percent).

Figure 3.4: Trends in birth weight by mother' race



This result accords with the observation of Catov and colleagues (2016) that recent changes in relative birth weight between black and white children may be driven largely by the relative magnitude of birth weight decreases in the two groups (rather than to any improvement in birth weight among minority mothers).

Figures 3.3 and 3.4 provide some evidence that a compositional change across maternal race or age groups is not likely to be the only driver of the aggregate decrease in birth weight. However, racial and age-group composition could still explain part of the trend. Figures 3.5 and 63.6 display characteristics of the mothers who gave birth during the period. As can be seen from Figure 3.5, the fraction of teen mothers (aged15 to 19) fell over time, with an exception of pause from 2001 to 2006. The teenage birth rate increased 5 percent during 2005âĂŞ2007, reversing the 34 percent decline from the peak in 1991 to 2005 (National Vital Statistics Reports, 2007). A similar trend can be seen among the mothers aged 20 to 24. As a result of this, and of the low birth weight among women younger than 24, the rapid decline in overall birth weight could be explained to some extent. The opposite trend is observed among older mothers (aged 25 to 45), with the average birth weight increasing after 2000. It has been suggested that at older ages, women are more likely to have poor health and possibly undiagnosed disease, which could result in poor placentation and low birth weight (Stein, 2000; Balasch, 2012). In addition, women may delay pregnancy for socio-economic reasons, and the biological effect of maternal age on offspring outcomes may be confounded by maternal socio-economic status (Lawlor et al., 2014). Therefore, more careful studies should be conducted while using compositional changes across maternal ages to explain the declining trends in birth weight.

Figure 3.5: Characteristics of mothers by age

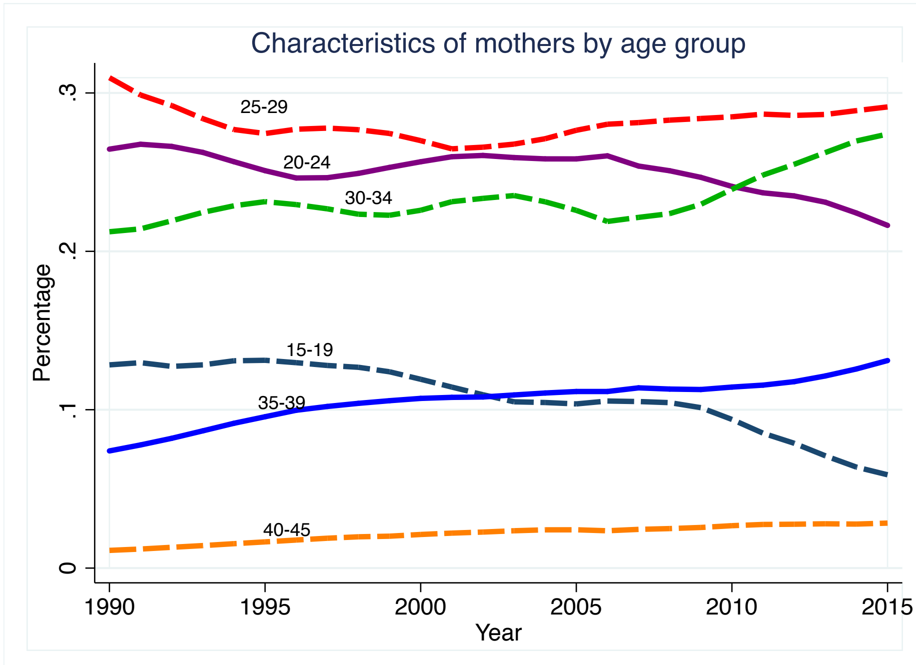


Figure 3.6: Characteristics of mothers by race

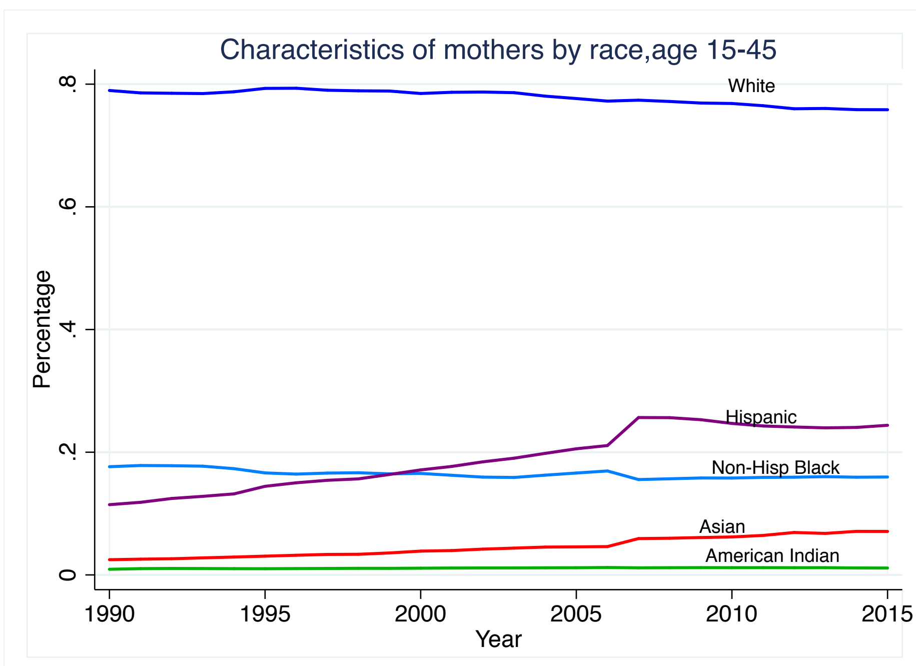


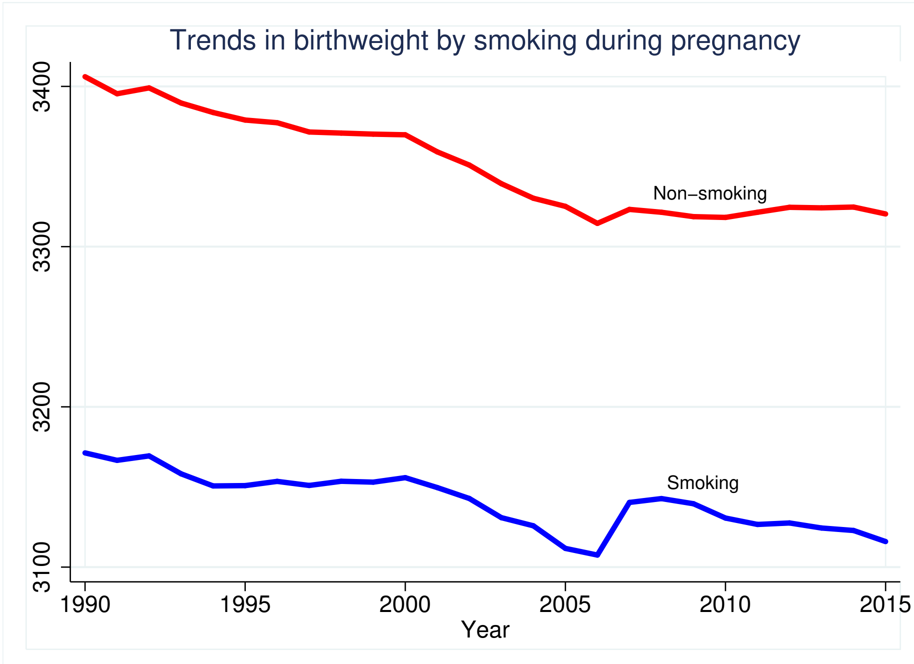
Figure 3.6 presents the percentage of different maternal races. The percentage of White and Black mothers fell annually after 1990, whereas the percentage of Hispanic and Asian mothers increased. Together with the results in Figure 3.5, even though the distribution of socioeconomic composition varies over the period of time, it is unlikely to be the smoking gun for this birth weight shock.

3.4.2 Health and Health Behaviors

Some studies suggested that these trends might be explained by accumulation of risk factors such as smoking behavior, hypertension and pre-pregnancy obesity that disproportionately affect women across different racial groups. (Catov et al., 2016)

Figure 3.7 shows mean birth weight disaggregated by maternal smoking behavior during pregnancy and the fraction of children born to smoking mothers. The same decline (2000-2005) and flattening out (2005-2015) is apparent in both groups. But since mothers who smoke during pregnancy have, on average, children that weigh much less than those whose mothers do not smoke, this decrease in the maternal smoking rate would, ceteris paribus, push average birth weight up over the period. It is also possible that cultural norms regarding smoking have differentially impacted truth-telling on this particular question over time, making the temporal comparison problematic.

Figure 3.7: Trends in birth weight by maternal smoking behavior

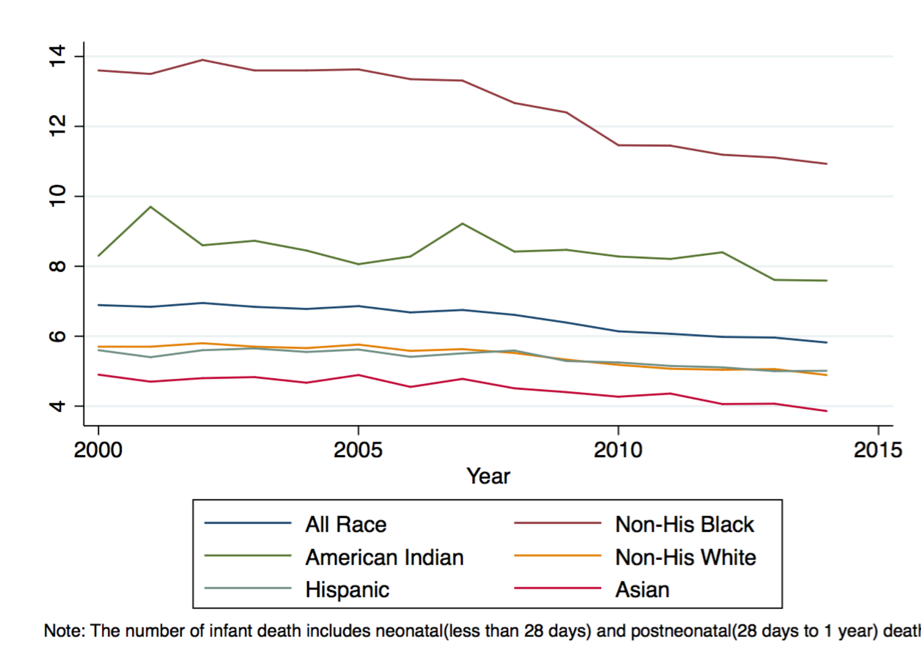


3.4.3 Mortality Selection

Low birth weight is among the three leading causes of infant mortality, along with death congenital malformations and sudden infant death syndrome (National Center for Health Statistics, 2015). Improvements in medical technology may have allowed children who otherwise would have died to survive, thereby reversing or lessening the trend of declining birth weight for living children. An improvement in medical technology that allows children who would have previously died to survive could have an aggregate effect of decreasing birth weight for living children.

Figure 3.8 shows infant mortality rates over the period by maternal racial group. Mortality rates declined for all groups, although the relative rates of decline (and rates relative to the share of children born) differ across groups. In general, mortality rates were lowest among infants of Chinese and Japanese mothers, and highest for non-Hispanic black mothers, who also exhibited the largest decline (approximately 3 percentage points annually) after 2000. We cannot rule out the possibility that some of this change in birth weight was caused by prenatal and perinatal selection effects due to changes in the composition of miscarriage, abortion, and stillbirth.

Figure 3.8: All-cause infant mortality rate (number of infant deaths per 1000 live birth) by racial group

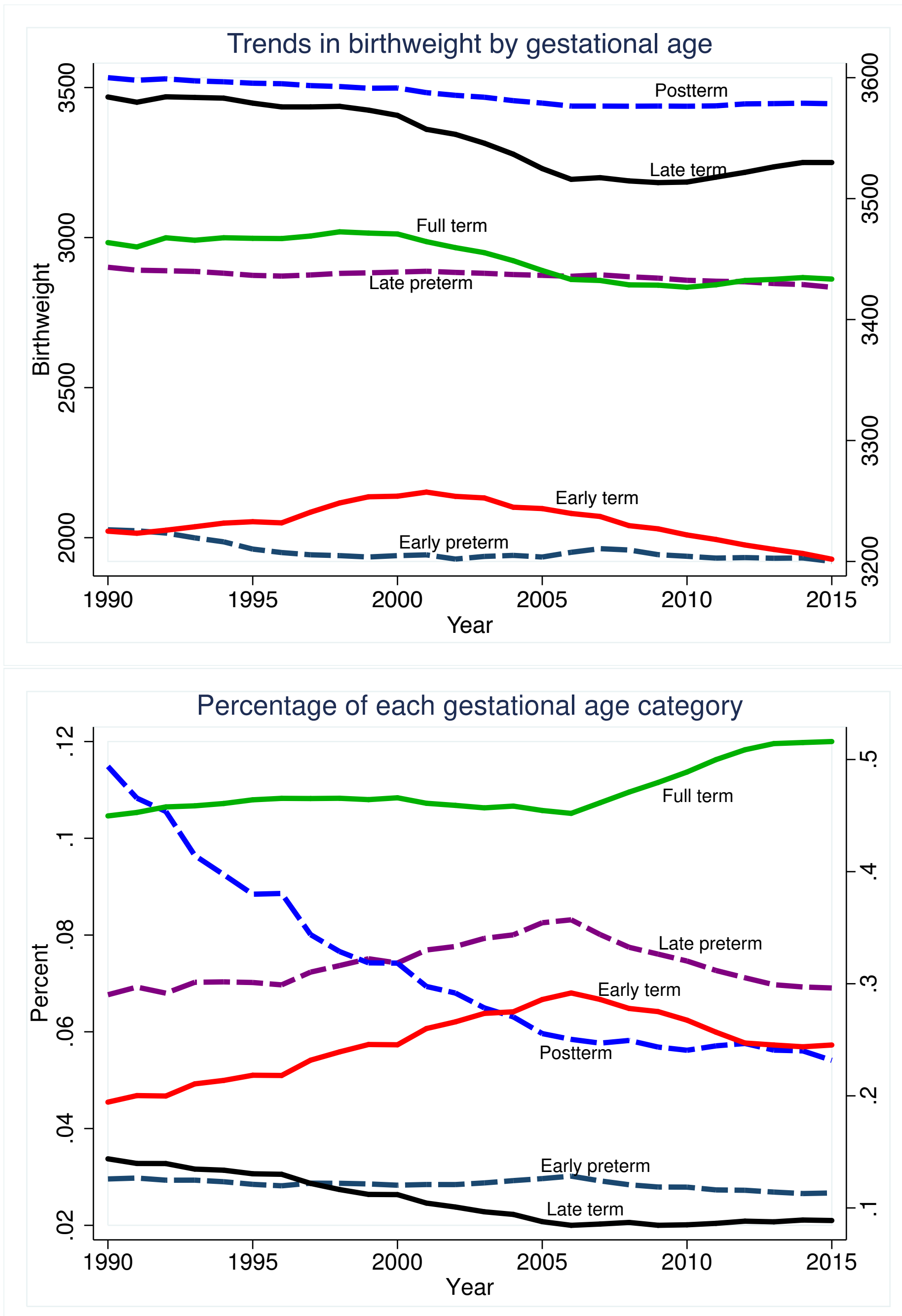


3.5 Accounting for Declining Birth Weights

Taking all of the evidence together, we find it hard to explain these declines in birth weight by neonatal or maternal characteristics. Here, we propose a preliminary but plausible story in which the widespread decreasing in birth weight occurring for all races, within all maternal age bins and at all quantiles of birth weight distribution, is triggered by progressively rising in the rates of induction of labor since 1990 that shifts births across gestational ages. Previous work has focused heavily on induction of labor and C-section as a driver of decreasing birth weight (Hong and Lee, 2014), though it is understood to not be the only factor and their work did not provide a clear channel how these obstetric intervention would play a role in worsening the birth weight. In this section, we present firstly the relationship between trends in birth weight and gestational age, and then decompose the rates of induction of labor across each categories of gestational age.

The shifting in gestational age play a part in the birth weight decreasing can be seen in Figure 3.9 which shows mean birth weight for early pre-term, late pre-term, early-term, full-term, late-term and post-term births, along with the fraction of births for each categories. Children in all gestational length groups, other than early-term, experienced declines in birth weight, with birth weight stabilized post-2005 while the pattern of the trend in early-term birth weight is relatively unique, which experienced slightly increasing since 1996 (3236 grams), reached the highest point in 2001 (3260 grams) and kept declining until 2015 (decreased around 1.8 percent) . While right panel of Figure 9 presents that the gestational length distribution in this population of term births shifted toward shorter gestation duration from 1990 to 2005. However, since 2006, the percentage of full term birth increased 5.8 percentage points with decreasing in the fraction of both early-term and late pre-term birth. These turnaround of gestational age coincides with the stabilized trends in birth weights across maternal and infants characteristics after 2006, lending support the role of gestational age as a driver of the effect in the first part of the decade, the fraction bottomed out in 2005 and has been increasing since without driving a full recovery to 2000-era mean birth weight.

Figure 3.9: Mean birth weight by gestational age and percentage of each gestional age category



Notes: Trends in dash line are shown in the left axis and trends in solid line are shown in the right axis. Early preterm is less than 34 weeks of gestation; late preterm is 34 to 36 weeks; early-term is 37 to 38 weeks;full term is 39 to 40 weeks; late term is 41 weeks; postterm is 42 weeks or more.

As noted by Osterman and Martin (2014), the length of pregnancies in the United states shortened during the 1990s and through 2006. They suggest that the shift in the gestational age distribution has been associated with greater use of Cesarean delivery and induction of labor prior to full-term. Figure 3.10 presents the rates of induction of labor by each categories of gestational age. It is shown that the rate of induction of labor progressively increased from 1990 (9.6%) and almost doubled until 2015(24.2%) for all gestational age. Induction rates for early-term births decreased around 3 percentage points from 2006 to 2012 while those of late pre-term and early pre-term remain quite stable in the 2000s with an exception of increasing after 2013. It is observed that the induction rates for full-term, late-term and post-term constantly increased from 1990 to 2015 (17 percentage points, 23 percentage points and 14 percentage points respectively). The change in induction rates by gestation age can, to some extent, account for shifting births across different gestational age categories. It is likely that infants were forced to grow outside the womb instead of within it. Induction of labor have been evaluated as strategies to decrease the risks of perinatal morbidity and mortality associated with late-term and post-term pregnancies. (ACOG, 2014) As can be seen from Figure 3.11, setting the birth weight as a function of gestational ages by year, the average birth weight is positively related to the mean gestational age. That is to say the falling birth weight was driven mainly by rising induction rate, especially for late-term and post-term pregnancies. The danger would be to kids who were induced unnecessarily and then bottle-fed and/or exposed to infection, whereas they would otherwise have grown for a few more days inside the womb.

Figure 3.10: Induction of labor by gestational age

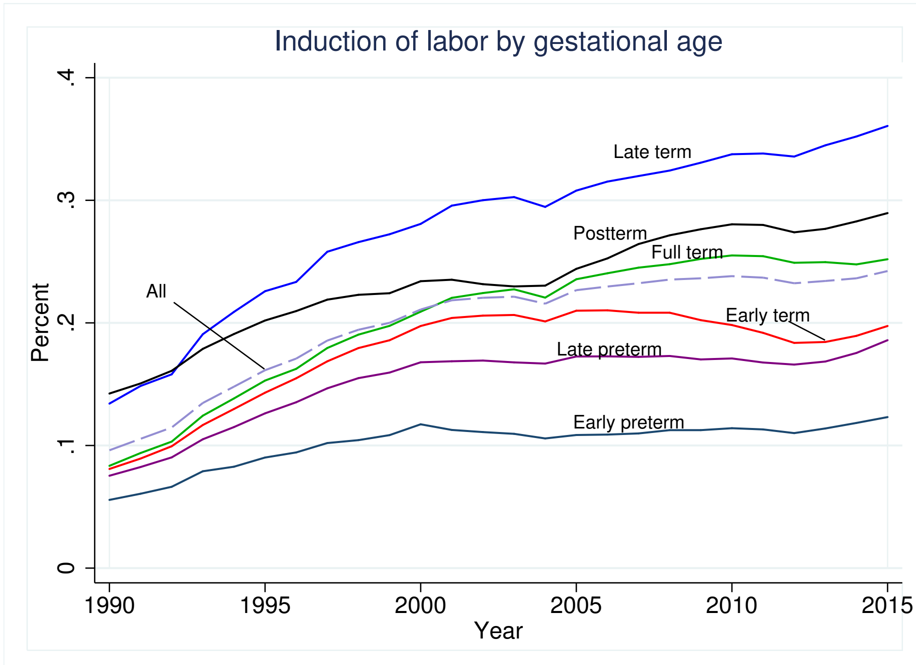
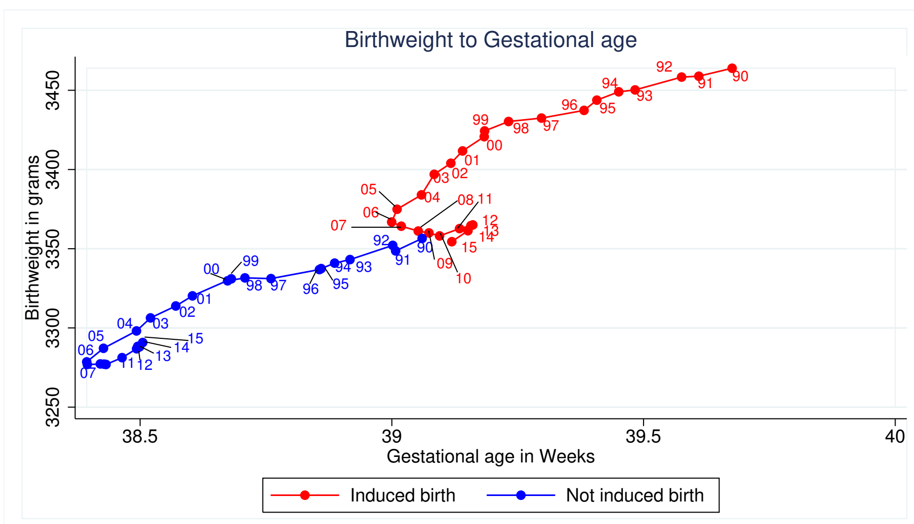


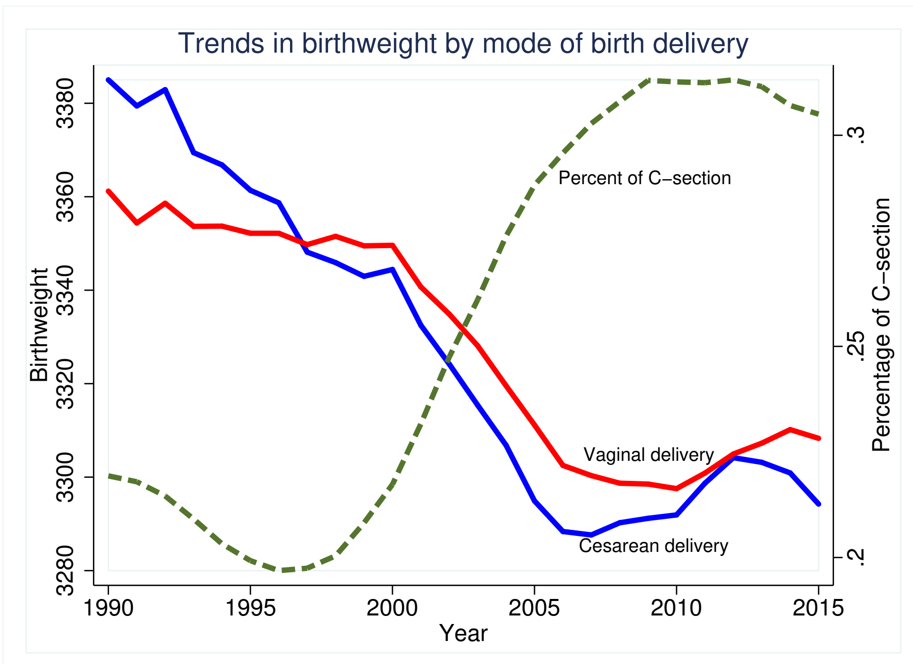
Figure 3.11: Birth weight to gestational age



Another mayor obstetric intervention that is likely to explain the decreasing trends in birth weight is the increasing in the rate of cesarean section after 1996. As shown in Figure

3.12, the cesarean birth rates almost doubled from 1996 to 2011. One in three women who gave birth in the United States did so by cesarean delivery in 2011. The rapid increase in cesarean birth rates without clear evidence of concomitant decreases in maternal or neonatal morbidity or mortality raises significant concern that cesarean delivery is overused. (ACOG, 2016)

Figure 3.12: Trends in birth weight by mode of birth delivery



There are some documents published by the American Congress of Obstetricians and Gynecologists (ACOG) are noteworthy. In July 2009, the ACOG issued a revision of guidelines regarding labor induction. The new guidelines state that the rate of labor induction in the U.S. has more than doubled since 1990. In 2006, more than 22% (roughly 1 out of every 5) of all pregnant women had their labor induced and ACOG recommendations say the gestational age of the fetus should be determined to be at least 39 weeks or, that fetal lung maturity must be established before induction. The ACOGs guidelines played a critical role in changing the trends of obstetric interventions. This indicates that expert opinion and the guidelines from the reputed professional association are critical in doctors choosing medical procedures. Even though the guidelines from professional association is not a compulsory policy intervention, it is likely that the lack of specific guidelines and subsequent uncertainty might contribute to the increasing trends of obstetric interventions and affect the neonatal outcomes.

3.6 Conclusion

We present results on an important, historically anomalous and poorly understood demographic fact: mean birth weight in the U.S. appears to have decreased by 1.53% between 2000 and 2006 and has failed to fully (or even mostly) recover. We address several proposed mechanisms and argue that none of them are likely to fully explain the effect. The effect occurs across the entire birth weight distribution; it is not purely an age- and/or race-based compositional change in mothers; is not solely attributable to maternal smoking rates; and it is unlikely to be only the result of decreased infant mortality. We provide some evidence for the declining mean birth weight in the U.S. that could partially explained by changes in gestational length and induction rates. This decrease in birth weight will likely prove the result of numerous compositional, behavioral and biological causes. We suspect that analyses from economists, demographers, epidemiologists, statisticians and others would all be likely to reveal important aspects of the phenomenon that are buried in the aggregate analysis presented here. We think it deserves their attention.

Conclusions

Chapter 1 of this dissertation shows that using machine learning method and a set of crucial features, I can precisely detect individuals with lower psychological well-being. It also suggests a new way to analyze the determinants of happiness. I also estimated the ordered probit model to study how each features are associated with PWB. I find that people who are married reported higher level of happiness. Income is also important for all three PWB measurements. Prestige of occupation is another crucial features in predicting happiness and satisfaction and it has been under covered in the current economics of happiness studies. The impacts of unhappiness are substantial. It is negatively associated with self-reported physical health and mental health. Unhappiness is also positively associated with people's likelihood of risky behaviors, such as smoking and excessive drinking. Happiness, on the other hand, increases people's confidence in financial institutions, productivity and affection towards their career.In summary, this paper provides a comprehensive study of economics of psychological well-being. Methods developed in this paper have broad applications for economists to analyze the psychological impact on economic decisions and behaviors. This paper also provides policy-makers with efficiently tools to target psychological disadvantaged individuals.

Chapter 2 of this dissertation suggests that the increases in the probabilities of low birth weight and prematurity birth may be an unintended consequence of medical marijuana laws. The estimates of 2SLS on low birth weight are slightly smaller than the OLS estimates. However, in both cases, the results show that there is the negative impact of MMLs on low birth weight, very low birth weight, and premature birth. One reason that the 2SLS estimates are smaller is that this method teases out the confounding effects of mother's educational level. Mothers who are more educated are more likely to know the harm of marijuana on their offspring and may be more cautious when considering the use of both medical and recreational marijuana. Our findings are consistent with previous finding in the public health area (Linn et al. (1983),Fried et al. (1984). Shi et al. (2021) Shi et al. (2021)). One limitation of this study is that I am unable to look at whether mothers indeed use marijuana because of the lack of such information in the dataset. What is estimated in this study is the overall impact of medical marijuana laws on infant health. However, with the association of previous public health studies, we can link the channels between the laws and the actual use of marijuana by mothers. As the medical marijuana laws increase the availability of marijuana and potentially send the information that marijuana is safe to women of childbearing age, more women will be exposed to marijuana and will lead to harmful effects on their children. I am also unable to look at the future health of the infant. An increase in marijuana use is associated with early cessation of breastfeeding ((Ryan et al., 2018), (Bertrand et al., 2018)), which is also likely to associate with adverse impact on the future development of infants. This study suggests that physicians should be more cautious in the use of medical marijuana for women of reproductive age. Guidelines for pregnancy should highlight the adverse impact of marijuana on infant health.

In Chapter 3, we present results on an important, historically anomalous and poorly understood demo- graphic fact: mean birth weight in the U.S. appears to have decreased by 1.53% between 2000 and 2006 and has failed to fully (or even mostly) recover. We address several proposed mechanisms and argue that none of them are likely to fully explain the effect. The effect occurs across the entire birth weight distribution; it is not purely an age- and/or race-based compositional change in mothers; is not solely attributable to maternal smoking rates; and it is unlikely to be only the result of decreased infant mortality. We provide some evidence for the declining mean birth weight in the U.S. that could partially explained by changes in gestational length and induction rates. This decrease in birth weight will likely prove the result of numerous compositional, behavioral and biological causes. We suspect that analyses from economists, demographers, epidemiologists, statisticians and others would all be likely to reveal important aspects of the phenomenon that are buried in the aggregate analysis presented here. We think it deserves their attention.

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