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Essays on Public Economics

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Abstract

Chapter 1: Health, Health Insurance and Employment: A Dynamic Model

This paper studies the complex feedback loop of health status, health insurance and employment status. Using a discrete choice dynamic programming model where working-age men make employment decisions each period, I model the effect of a health shock on an individual's choice to work full-time, part-time or not work. If he chooses to work, he may not find a job and instead be unemployed. His labor force status, in turn, impacts his probability of health insurance coverage, as well as his subsequent health status. Data from the Panel Study of Income Dynamics from 1999-2015 are used to estimate the model. Counterfactual analyses show that expanding health insurance to all individuals slightly improves overall health but decreases labor force participation. Insurance affects employment decisions through health and expected out-of-pocket medical expenditures. Healthy men obtain more utility from working than not working and have higher wages than unhealthy men. Although there are more healthy individuals with higher wages, this is not enough to offset the negative effect from the increase in medical expenditures. This increase in medical expenditures only occurs for the unhealthy. Thus, the decline in labor force participation is driven by unhealthy men exiting full-time jobs, which provide insurance at higher rates than part-time jobs. This supports the theory that some individuals, particularly unhealthy ones, choose to work to obtain health insurance.

Chapter 2: Consumer Plan Choice in the Florida Medicaid Market

In this paper, I model an individual's health insurance plan decision in the Medicaid market in Florida. Since 2014, most Florida Medicaid recipients have been required to enroll in a Managed Medical Assistance plan that is offered at no cost to the enrollee. All plans must offer the same core benefits but have varying extended benefits and physician networks. Using monthly plan and county specific enrollment data from the Florida Agency on Health Care Administration, I determine what Medicaid enrollees value most in a health insurance plan. I adapt a Berry, Levinsohn and Pakes (BLP 1995) random coefficients discrete choice demand model to a setting without prices and without an outside good. Using a variety of characteristics for plan size, I find that most people prefer to enroll in larger, well-known plans, and that black and Hispanic individuals most prefer large physician networks. In addition, enrollees seem to prefer plans with higher Medicaid report card ratings of ability to keep adults healthy. This characteristic, likely a proxy for plan reputation, has the largest effect in highly impoverished areas where there is a larger network of Medicaid recipients, but a negative effect in areas with lower population densities.

Chapter 3: Close Contests and Future Voter Turnout[1]

Voter turnout is persistent across election cycles, but understanding what factors can change persistent voting behavior and for whom remains unexplored. This paper asks how close state Electoral College contests for presidential elections influence future voting behavior. Specifically, do these close contests differentially affect those who supported losers, winners, or those who did not vote in the previous presidential election. It is likely that after the election, voters update their beliefs on the degree to which they influence on the state and therefore national election. The beliefs depend not only on whether or not one's preferred candidate won the state Electoral College votes but also on the margin by which the candidate won or lost. Using data from the American National Election Studies, we use within state variation in voter turnout and Electoral College closeness from 1948-2012 to analyze individual voting behavior across election cycles. Our findings suggest that those who report not voting in the previous election are 3.5 percentage points more likely to vote than those who did not vote in states where the contest for electoral votes was not close. The results further show that females and low-income individuals who voted for non-victors in states with slim margins of victory were less likely to participate in the subsequent election than those who chose a victor in the previous close contest.

[1] co-authored with Rebecca Lessem, Tepper School of Business, Carnegie Mellon University, and Carly Urban, Montana State University

Contents

Chapter 1

Health, Health Insurance and Employment: A Dynamic Model

1.1 Introduction

In the United States, the majority of working-age individuals obtain health insurance through an employer-sponsored plan, with 59% covered by employer-sponsored plans in 2016 (Long et al. 2016). This is a deviation from the health care systems in most developed countries. Out of all OECD countries, private health insurance takes up the highest share of health spending in the US (OECD 2015). As a result, in the US, access to health insurance is an important determinant of employment decisions. Conceivably, even individuals with health issues that make it difficult to work must continue to work to retain their health insurance. Health insurance is especially important for the unhealthy, as they face higher medical costs.

If an individual stops working, it is costly to return to the labor force, a cost that increases with age, particularly if he faces health problems. If there are psychic benefits of working, then joblessness itself may negatively impact health. This increases the probability that health will worsen as one remains jobless. Evidence of the link between personal health and employment is hard to pinpoint for two reasons: first, labor force participation decisions are inherently different for the healthy and unhealthy, and, second, access to health insurance directly improves health. This paper uses a discrete choice dynamic programming model where working-age men make employment decisions each period to explain not only how health status, health insurance and employment are linked, but also how health insurance policies should be designed to improve both labor force participation and overall health. In this model, health is a state variable that factors into employment status. The employment status each period is a determinant of health for the following period.

The model facilitates the simulation of policy changes through counterfactuals. In the first counterfactual, I explore the impact on employment and health of a policy that expands health insurance to all. In the second counterfactual, I additionally incorporate the cost of insurance to the employee under such a policy. I find, in both counterfactuals, that individuals are slightly healthier overall, but that labor force participation decreases slightly. Insurance improves health, and healthy individuals obtain more utility from working than not working and have slightly higher wages. Insurance also affects utility through expected out-of-pocket medical expenditures. Since labor force participation decreases, the negative effect from increased medical expenditures dominates the effect of improved health. There is a slight decrease in labor force participation among unhealthy men, while labor force participation is unchanged for healthy men. This indicates that the medical expenditures only rise for the unhealthy and are unchanged for the healthy. Specifically, there is a decrease in full-time employment for unhealthy men, while part-time employment remains steady. Since part-time jobs often do not provide health insurance, this supports the theory that some portion of unhealthy individuals only work to obtain health insurance.

The model captures important empirical regularities pertaining to health status and employment. First, the labor force participation rate varies substantially by health status. Using data from the Panel Study of Income Dynamics (PSID) from 1999-2015 for males aged 25-60, we see that healthy individuals begin to drop out of the labor force around age 55, when they are most likely seeking retirement (see Figure 1.1). There are much greater fluctuations in the participation rate for the unhealthy, and around age 45, the rate begins to steadily decline.

Second, while unhealthy and healthy men are equally as likely to have part-time jobs across all ages (see Figure 1.2), unhealthy individuals are employed full-time at much lower rates. Full-time jobs tend to be better paying ($27.55/hr vs. $22.40/hr), and full-time employees have higher rates of insurance (86% insured vs. 66% insured).[1] Thus, health affects wages, probability of insurance and probability of employment, which has a lasting effect throughout the life cycle. This is captured through the dynamic nature of the model.

Finally, the model offers important insights into out-of-pocket medical expenditures. In the data, far more insured individuals incur medical expenses than uninsured individuals (87.2% vs. 56.7%). For those with medical expenses, the average out-of-pocket cost

[1] This is the percent of full-time workers with insurance. It is not necessarily provided by their job. They may have insurance through their spouse or have purchased it.

is also higher for the insured than the uninsured (\$1866 vs. \$1333). Without a model, it is difficult to determine the direction of this relationship - does insurance encourage individuals to seek medical care or do those who frequent the doctor obtain insurance at higher rates?

The most closely related paper is Blau and Gilleskie (2008), who estimate a model for older individuals to examine the role of retiree health insurance on employment. I extend their framework by focusing on a working-age population, rather than a population nearing retirement. By looking at a younger population, I allow individuals to resume working after not working for some period of time. Further, I allow insurance to be stochastic, employment to be a determinant of health, and for individuals to differ in wage type and medical care type.

Specifically, I estimate a discrete choice dynamic programming model for working-age men from 1999-2015. I analyze the relationship between employment status and health status by modeling the effect of a health shock on an individual's choice to work or exit the labor force. His choice to work depends on his observed health, expected wages, expected medical medical expenses and some characteristics. With some probability, he finds a job. This employment status is a determinant of whether he will have insurance in that period. He then observes another health shock and chooses whether to work after observing his health for period 2. His health in period 2 depends on the period 1 employment status, health status and insurance status. The model repeats for T periods. I estimate the model via maximum likelihood.

The rest of the paper is organized as follows: Section 1.2 presents the existing literature to which my work is connected. Section 1.3 details the model, and Section 1.4 describes the data. Section 1.5 outlines the estimation procedure, and Section 1.6 presents the results. Section 1.7 includes the counterfactuals, while Section 1.8 concludes the paper.

1.2 Related Literature

Existing literature captures elements of the relationship between health, employment and health insurance, but fails to fully explain the link between all three. Several studies in developing countries have attempted to isolate the effect of health on income, finding a positive relationship between several measures of health and wages/income (Luft 1975, Bartel and Taubman 1979, Chirikos and Nestel 1981, Mitchell and Burkhauser 1990, Berkovec and Stern 1991, Baldwin et al. 1994, Haveman et al. 1994).

The effects of health on labor force participation are less consistent in the literature, but most research assumes that poor health will decrease labor force participation. Much of the research has been focused on the retirement decision of workers, finding that health, as expected, is an important determinant in retirement (Diamond and Hausman 1984, Sickles and Taubman 1986, Berkovec and Stern 1991, Blau and Gilleskie 2001, French 2005, Bound et al. 2010, French and Jones 2012, Karabarbounis 2016, Blundell et al. 2016). French and Jones (2017) find that, while health is not the primary source of variation in retirement across countries and time, it is important, especially when examining variation within a country. The effect of health on labor force participation across studies varies dramatically for several reasons; e.g. the size of the estimated effect is likely dependent upon age, gender, income, location, family circumstance.

Another crucial aspect of the connection of health, health insurance and the labor market is the relationship between health insurance and health. After reviewing the literature on the topic, Levy and Meltzer (2008) find that health insurance can improve the health of some, but not all, population subgroups, such as infants, children, and individuals with AIDS. They further conclude that health insurance can improve specific measures of health, such as high blood pressure, for a wider population. They find conflicting evidence for other measures of health over broad populations, such as the elderly.

This paper seeks to build on the previous literature by combining health, health insurance and employment into a single dynamic model. Another contribution comes via my focus on the working-age population. Most of the existing literature focuses on retirement decisions but health impacts employment decisions throughout peoples' lives. This is the first paper to explore how all three of these components work together over time for this population.

1.3 Model

In this dynamic discrete choice model, individuals make employment decisions. Each period, after observing a set of payoff shocks specific to each employment decision, an individual chooses whether to work full-time ($j_t = 2$), work part-time ($j_t = 1$) or not work ($j_t = 0$), depending on which choice provides him with the highest utility. If he chooses to work, he will receive a job offer with some probability. This employment status is one determinant of whether he will have insurance in that period. Specifically, I assume that an individual's period 1 health status is the observable, initial state, and model his employment decision in each period following a stochastic payoff shock to the utility function. His choice to work involves maximizing his present utility and his discounted expected future utility, which are functions of his expected wages, expected out-of-pocket medical expenses, previous and current employment states, health and characteristics. If he chooses to work, with some probability he will not find employment and be jobless for that period. This period 1 employment state, health state, age, and a stochastic component, determine his insurance status for that period (1). After he observes a health shock, his period 1 employment status, health state, insurance status and characteristics determine his health state for the following period (2). He then repeats the decision making process, choosing whether to work full-time, part-time or not work in period 2. This process repeats for a finite number of periods, T, when he exits the model.

In the remainder of this section, I describe my model without unobserved heterogeneity to simplify exposition. In Section 1.5, I include heterogeneity over worker type and medical care type. In that section, I also include the possibility that an individual might not obtain his desired employment choice. Below, I characterize the primitives of the model. For the remainder of this section, I suppress the individual subscripts for simplicity.

State space The state space in period t includes the individual's current health status (h_t) and characteristics (X_t) and the previous period employment status (j_{t-1}). The previous period employment state is the observed employment status, after observing the employment shock. Marital status, mar_t, and children, ch_t, are also state variables. To simplify notation, denote Ω_t as the state space in time t consisting of period t health and marital status, children, characteristics and period $t-1$ employment, such that: $\Omega_t = \{j_{t-1}, h_t, \text{mar}_t, \text{ch}_t, X_t\}$.

Timing At the beginning of the period, individual i knows his health status. He observes his utility shocks, $\xi_{j,t}$, which are unique to each employment decision, and then chooses whether to work full-time, part-time or not work, $j_t \in \{2, 1, 0\}$. If he chooses to work, he must search for a job. There is an employment shock, ζ_t, that may cause him to not find a job and instead, be jobless for that period, $j_t = 0$. His insurance status is then determined from his employment status, health status, characteristics and a stochastic component: $n_{j,t}(j_t, h_t, X_t, \varepsilon_t^n)$, where $n_{j,t} \in \{0, 1\}$. The probability of being insured varies depending on employment status. The insurance status in period t factors into his health in period $t+1$. His health status for the next period is a function of his previous period's health status, employment status, insurance status, characteristics, as well as a health shock, ε_t^h: $h_{t+1}(j_t, h_t, n_t, X_{t+1}, \varepsilon_t^h)$. Period $t+1$ marital status and children status are also stochastic and determined prior to the start of period $t+1$. An individual makes his period $t+1$ decision after observing whether he is married and has children.

Utility The utility flow depends on a person's employment status, j_t, previous period employment status, j_{t-1}, health status, h_t, expected medical expenditure, $E[m_t]$, marital status, mar_t, whether he has children, ch_t and characteristics, X_t. Expected wages, $E[w_{j,t}]$, are a function of employment, health and marital status and characteristics. Expected medical expenditures, $E[m_t]$, are a function of health, employment and marital status, characteristics, as well as insurance status, n_t. Wages and medical expenditures both have normally distributed shocks that are not revealed until after the employment decision is made. Current period insurance status is also unknown at the time of the decision, which is a determinant of expected medical expenses. This has to be integrated out and will be explained further in Section 1.5.2. Thus, insurance enters current period utility implicitly through health and medical expenses. As a result, utility is defined as $u(j_t, \Omega_t)$.

Transition probabilities There are transitions over health, insurance, unemployment and marital statuses, and over the presence of children in the household. Although employment is the choice in the model, if an individual chooses to work, he obtains a job with probability π, and he does not find a job with probability $1 - \pi$. This probability depends on employment status in the previous period, the state unemployment rate in that year, age and level of schooling: $\pi = pr(\text{unemp} = 0 | j_{t-1}, X_t, u_t)$, where u_t is the state unemployment rate in time t.

Transitioning to a health status depends on the previous period employment, health, insurance status and current period characteristics. For simplicity, I assume that these transition probabilities are static over time. The probability of being in health status h_{t+1} is denoted to $p^h(h_{t+1}|j_t, h_t, n_t, X_{t+1})$. These values will be explicitly defined in Section 1.5.1.

The probability of being insured, in turn, depends on the employment status that period and characteristics, and a stochastic component. Denote δ_j^τ as the probability that an individual is insured, given employment status j. In Section 1.5.1, I define these probabilities and the full transition probabilities.

Each period, single individuals remain single or get married and married individuals remain married or get divorced. Transitioning to a marital status in period $t+1$ depends solely on marital status in period t. Individuals without children remain childless or have a kid and individuals with children continue to have a child or that child ages out or moves out. Transition probabilities over the presence of a child in the household depend on whether there was a child in the previous period, martial status and personal characteristics. Together, I will denote marital status and whether or not there is a child in the household as 'family status'.

1.3.1 Value Function

In this section, I derive the value function for an individual. Each period, after seeing his payoff shocks, an individual makes a decision to work full-time, part-time or not work. Due to the possibility of unemployment, although working part-time or full-time may provide the highest utility, it is possible that he ends up jobless. This is accounted for in the likelihood function described in detail in Section 1.5.5.

The value function for individual i follows:

$$V_t(j_t, \Omega_t, \xi_{j,t}) = \max_{j_t \in J} v_t(j_t, \Omega_t) + \xi_{j,t}, \tag{1.1}$$

where $v_t(\cdot)$ is the deterministic component and ξ_t is the random component of choice j_t. I assume that these shocks, which are unique for each employment choice, follow an extreme value type I distribution. I further assume that they are unobserved by the econometrician and are random, independent and identically distributed (i.i.d.) across time and employment decision.

The deterministic component of choice j consists of a flow payoff in period t and the discounted expected value of the employment status at the start of period $t+1$. In this model, the flow payoff in period t is the period t utility:

$$v_t(\cdot) = u_j(j_t, \Omega_t) + \beta E\Big[V_{t+1}(j_{t+1}, \Omega_{t+1})\Big] \tag{1.2}$$

Utility depends on expected medical expenses, $E[m_{j,t}]$, and expected wages, $E[w_{j,t}]$, which are both estimated from the state variables, where $w_{j,t}(j_t, h_t, \text{mar}_t, X_t, \text{exper}_t, \eta_t)$ and $m_{j,t}(j_t, h_t, n_t, \text{mar}_t, X_t, \nu_t)$. The decision to work is made before wages and medical expenses are observed for that period, so expected medical expenses enter the utility function rather than realized medical expenses.

There are several sources of uncertainty over what will happen in future periods. They are as follows: obtaining employment, health status, insurance status, family status, wages, out-of-pocket medical expenditure and payoff shocks. I use the properties of extreme value distribution following McFadden (1973) and Rust (1987) to first adjust the value function for the unobserved payoff shocks.

For a given health status and family status, the expected continuation value is given by:

$$\begin{aligned} E\Big[V_{t+1}(j_{t+1}, \Omega_{t+1}, \xi_{j,t}) | h_{t+1}, \text{mar}_{t+1}, \text{ch}_{t+1}\Big] &= E\Big[\max_{j_{t+1}} v_{t+1}(j_{t+1}, \Omega_{t+1}) + \xi_{j,t+1}\Big] \\ &= \log\left[\sum_{j_{t+1}=0}^{2} \exp\Big(v_{t+1}(j_{t+1}, \Omega_{t+1})\Big)\right] + \gamma \end{aligned} \tag{1.3}$$

where γ is Euler's constant ($\gamma \approx 0.58$).

To calculate the unconditional expected value, I then integrate over the transition probabilities on health and family status. Health, marital status and presence of children are discrete variables so:

$$\begin{aligned} & E\big[V_{t+1}(j_{t+1}, \Omega_{t+1}, \xi_{j,t})\big] \\ & \quad = \sum_{h_{t+1}} \sum_{\text{mar}_{t+1}} \sum_{\text{ch}_{t+1}} pr(h_{t+1} = h, \text{mar}_{t+1} = \text{mar}, \text{ch}_{t+1} = \text{ch} | j_t, h_t, n_t, \text{mar}_t, \text{ch}_t, X_{t+1}) \\ & \quad \times E\big[V_{t+1}(j_{t+1}, \Omega_{t+1}, \xi_{j,t}) | h_{t+1} = h, \text{mar}_{t+1} = \text{mar}, \text{ch}_{t+1} = \text{ch}\big] \end{aligned} \tag{1.4}$$

I assume that the payoff shocks are distributed with an extreme value distribution, so the choice probabilities take a logit form. The probability that an individual chooses to work full time in period t, $j_t = 2$, works part-time in period t, $j_t = 1$, or does not work in period t, $j_t = 0$, is:

$$P(j_t | \Omega_t) = \frac{\exp[v_t(j_t, \Omega_t)]}{\sum_{k \in J} \exp[v_t(j_t = k, \Omega_t)]}, \tag{1.5}$$

where $v_t(\cdot)$ is the deterministic component of $V_t(\cdot)$.

1.4 Data

I estimate the model using the Panel Study of Income Dynamics (PSID) data on men from 1999-2015.[2] This study consists of biennial interviews on topics such as employment, income, wealth, expenditures, health, marriage, education, childbearing, etc. Due to the panel design, it is possible to examine changes in an individual's employment status, health expenditures, health insurance coverage and health status over his lifetime.

In 1968, the study began with a nationally representative sample of 5,000 families comprised of 18,000 individuals. The study has evolved beyond the initial 1968 cohort with a 1997 refresher sample of immigrants, as well as the sampling of new family units from split-offs of the initial family unit. A split-off is a person or group of people who moved out of a main family since 1968 to form their own family unit. This could be caused by the aging out of children of an initial family unit or the divorce of a head of household and spouse from the initial cohort, for example. The only families added to the core sample over time were from these split-offs and from the immigrant refresher sample.

The immigrant refresher sample was comprised of individuals who immigrated to the United States after 1968 and who were not married to persons who were living in the United Sates at the time of the original PSID sample. The purpose of this addition was to maintain the national representation of the overall sample.

There are many measures of health status in the PSID, such as health status measures (e.g., work limitations, emotional stress, weight) and specific conditions (e.g., hypertension, diabetes, myocardial infarction). I use "perceived health status" as a measure of health status. This is a score of one to five, with a value of 1 representing excellent health and a value of 5 representing poor health. This is reported for each of the five rounds. Although this is a subjective measure that may have reporting bias, this measure is frequently used, and has been studied, in the literature. Using a longitudinal study of the elderly, Mossey and Shapiro (1982) found that self reported health was actually a better predictor of mortality than more objective measures of health. In addition, studies by

[2] The PSID began in 1968, but did not add questions about medical expenditure until 1999.

Nagi (1969), Maddox and Douglass (1973), LaRue et al. (1979) and Ferraro (1980) found these measures of self reported health to be highly correlated with medically determined measures of health status.

As a measure of employment status, I observe whether individuals are employed part-time, full-time or jobless in each survey period. I denote part-time employment as that constituting less than 35 hours of work per week. I exclude individuals for whom this information is not available. I further classify jobless people as unemployed and out of the labor force[3]. This is necessary for identifying the unemployment transition probabilities. I also create an indicator for whether an individual has insurance, excluding those individuals for whom this information is not available.

After compiling the surveys from 1999 to 2015, the data set consists of 19,066 individuals who participated in one to nine panels. Wage information is only available for the heads of household in the sample. Head of household refers to a husband in a married couple or a single adult of either gender. Due to the design of the survey beginning in 1968, heads of household are predominantly male. Thus, I limit the data set to male head of households.

Wages are defined as hourly wages, either reported directly by the individual or computed within the survey from salary and weekly work hours. I further restrict my data set to exclude the top 2% and bottom 2% of wage earners, so that my wage results are not driven by outlying data. Wages are adjusted using the GDP deflator from the Bureau of Economic Analysis, and are presented in dollars of 2016.

Medical expenditure is the summed total of out-of-pocket doctor, outpatient surgery, dental bills, as well as prescriptions, in-home medical care, special facilities, and other services. I exclude observations with out-of-pocket medical expenses of $9,999,997 or more, as well as those missing medical expenditures. Medical costs are adjusted using the medical care CPI for urban consumers from the Bureau of Labor Statistics and are presented in dollars of 2016.

I further restrict my data set to those for whom I observe employment, health, insur-

[3]Workers are marked as unemployed if they have an unemployment status by the PSID as "only temporarily laid off, sick leave or maternity leave" or "looking for work, unemployed."

ance and personal characteristics. To avoid interpolating missing data, I exclude those who missed surveys. To observe employment and state transitions for identification, I exclude those who only participated in one survey. I further limit the sample to those with residence within the United States, so that unemployment can be measured using state unemployment rates from the Bureau of Labor Statistics.

I define children as an indicator variable for whether there is a child under the age of 17. I do not account for the number of children, assuming that, for men, the number of children in the household does not impact the decision to work as much as the presence of any children.

Education is static and defined as the highest level of educational attainment. The five categories are as follows: no degree, high school diploma, some college, bachelor's degree and some post-graduate work.[4] To prevent capturing Medicare enrollment and schooling decisions, I limit the sample to those aged 25-59. This may result in the exclusion of some survey data for an individual. For example, if a participant is 22 in 1999, he will not be included until the third panel, when he is 26. This results in a final data set of 5,495 men comprising 28,456 surveys.

Table 1.1 includes summary statistics for this reduced sample. We see that approximately 14.4% of the sample is jobless, with 6% unemployed and 8% out of the labor force. The average health status is 2.3, or between "good" and "very good", with a standard deviation of around 1. Approximately 16% of the sample is uninsured. If an individual has medical expenses, they average around $1,800 each period. If he works, the average wage is $28 an hour. Further, the average age at which the enter the panel is 36 and approximately 78% of the sample is married and 52% have children under the age of 18.

1.5 Estimation

I estimate the model via maximum likelihood. I assume that men enter the model at 25 or 26 and exit the model at age 59 or 60, depending on at which age they enter. A time period is defined as 2 years, with individuals exiting the model after 18 periods.

[4] I do not know whether a survey participant has a GED. The value reported by the PSID for someone with a GED is the last grade finished. As a result, those with GEDs are labeled as "no degree".

Although an individual will not be in the model for all 18 periods, he makes decisions today that assume model exit at 18. I use a discount rate of 0.95.

In the first stage, I estimate the transitions for health, marriage, children and unemployment. These transitions are well-identified due to a robust data set that has movement across all state variables.

There are two types of unobserved heterogeneity in this model. There is unobserved heterogeneity over worker type and medical expense type. I assume that there are two types of workers. High productivity workers obtain better paying jobs than low productivity workers. This unobserved heterogeneity enters the wage function as a shifter, as described in Equation 1.12, and shifts wages by a different amount for part-time jobs and full-time jobs. Worker type is unobserved by the econometrician, but observed by the individual. As a result, the probability of being a high type worker is estimated within the model.

I assume that there are two types of individuals with regards to medical expenses: those who frequently incur medical expenses (proactive type) and those who do not (passive type). Although this is correlated with health, health is not the sole determinant of frequency of physician and prescription use. Some individuals are simply more likely to partake in preventative care, take regular prescriptions and go to the doctor when sick. Since I cannot observe whether a person is an active type or a passive type for frequency of medical care, this enters the model as a shifter in medical expenses in Equation 1.7, as well as in the probability function of positive medical expenses. I assume that this affects estimated medical expenses differently for insured and uninsured individuals.

Since proactive type men are more engaged in their health maintenance, it is likely that they obtain insurance at higher rates than passive type individuals in order to reduce out-of-pocket costs. Due to this possible selection bias, medical cost type also enters as a shifter into the insurance transition function, as seen in the following section. Thus, the probability of insurance depends on type.

1.5.1 Health and Health Insurance

Perceived health status is reported each period for each individual. For simplicity, I assume that health takes a value of 0 ("bad") or 1 ("good"). The PSID characterizes self-reported health from one to five, or excellent to poor. I define "good" health (health=1) as ratings of "excellent", "very good" and "good", and "bad" health (health=0) as ratings of "fair" and "poor".

To incorporate insurance, I assume that people who have insurance have a different probability of being healthy in the following period than those who do not have insurance. Those who are insured can seek preventive care to avoid illness and also, obtain treatment (see doctors, take medication, have tests performed) for existing illnesses. Insurance also enters the model through expected medical expenditures, $E[m_t]$, which is a component in the utility function.

I assume that the probability of having health insurance depends on employment status, with the probability varying for non-employed, part-time employed and full-time employed individuals. It also depends on medical care unobserved heterogeneity. Denote δ_j^τ as the probability that an individual is insured, given employment status j, health status, characteristics and medical care type τ: $\delta_j^\tau = pr(n_t = 1|j_t = j, h_t, X_t, \tau)$. Recall that men can be of two medical care types: passive or proactive. Specifically, I expect proactive medical care type men to have a higher probability of insurance than passive medical care type, as they are more engaged in their medical care.

When a person is choosing whether to work, he does not know whether he will have health insurance for that period. In order to estimate the model, the probability of insurance in period t must be taken into account for the expected continuation value in equation 1.4. Recall that the probability of being in health status h_{t+1} is denoted to $p^h(h_{t+1}|j_t, h_t, n_t, X_{t+1})$. Since this depends on health insurance status, the full health transition probabilities are:

$$p^h(h_{t+1}|j_t = j, h_t, n_t, X_{t+1}) = \begin{cases} p^h(h_{t+1}|j_t = j, h_t, n_t = 0, X_{t+1}), & \text{with probability } 1 - \delta_j^\tau \\ p^h(h_{t+1}|j_t = j, h_t, n_t = 1, X_{t+1}), & \text{with probability } \delta_j^\tau \end{cases} \tag{1.6}$$

The health probability in Equation 1.6 that is conditional on insurance status is estimated in the first stage using the data, while the probability of insurance is estimated within the model, since it depends on medical care type.

1.5.2 Medical Expenses

Out-of-pocket medical expenses are a function of an individual's health, employment, family and insurance status, and characteristics. I observe medical expenses over the two year period for each individual and estimate medical expenses using the following regression, where each individual is indexed by i:

$$m_{i,t} = \alpha W_{i,t} + \tau_i^n + \nu_{i,t} \tag{1.7}$$

$W_{i,t}$ consists of highest level of education, health status, employment status, marital status, insurance status and age, and α are the returns to these characteristics. The error terms ν are assumed to be i.i.d. and drawn from a mean 0 normal distribution with variance σ_m.

Unobserved heterogeneity over medical expenses is captured by τ_i^n, where $n = 0, 1$ corresponds to being uninsured or insured, respectively. I assume that some individuals seek out medical care more than others, and that this cannot be entirely captured by health status. As a result, I anticipate that the proactive medical care type individuals are more likely to have regular check-ups, take prescriptions and frequent the doctor when sick. This difference in medical expenses depends on whether or not someone is insured, because the cost of additional medical expenses without insurance is higher than the cost of additional medical expenses with insurance.

Decisions are made over expectations, rather than realized medical expenses. As a result, the choice to work is made prior to observing insurance status, so expected medical expenses are also a function of δ_j^τ, the probability of insurance, defined in Section 1.5.1. Thus, expected medical expenses are equal to:

$$E[m_{i,j,t}] = \begin{cases} \hat{m}_{i,j,t}|n_t = 0, & \text{with probability } 1 - \delta_j^\tau \\ \hat{m}_{i,j,t}|n_t = 1, & \text{with probability } \delta_j^\tau \end{cases} \tag{1.8}$$

Medical expenses are estimated through a two-stage process. First, I find the probability that they are greater than zero, or the probability that an individual has medical expenses. I then estimate the logged out-of-pocket medical costs if an individual incurs medical expenses. This process attempts to account for the large number of zero observations in the data. As in Equation 1.7, the probability of positive medical expenses is a function of health, employment, insurance and insurance status, age and highest level of schooling. Denote the probability of non-zero out-of-pocket medical expenses as p^m. As a result, the updated expected medical expense in Equation 1.8 can further be expanded to be:

$$E[m_{i,j,t}] = \begin{cases} 0, & \text{with probability } 1 - p^m \\ \hat{m}_{i,j,t}|n_t = 0, & \text{with probability } p^m \times (1 - \delta_j^\tau) \\ \hat{m}_{i,j,t}|n_t = 1, & \text{with probability } p^m \times \delta_j^\tau \end{cases} \tag{1.9}$$

The likelihood function, defined in Section 1.5.5,includes the likelihood of a given medical expense draw. Denote $\phi(\cdot)$ as the pdf of the standard normal distribution. The likelihood of a given positive medical expense draw is:

$$\begin{aligned} f_m(m_{i,j,t}|j_t, W_{i,t}, \tau_i) &= \left(\frac{m_{i,j,t} - \hat{m}_{i,j,t}}{\sigma_m} \right) \\ &= \phi\left(\frac{m_{i,j,t} - [(\alpha W_{i,t} - \tau_i^0)|n_t = 0] \times (1 - \delta_j^\tau) - [(\alpha W_{i,t} - \tau_i^1)|n_t = 1] \times \delta_j^\tau}{\sigma_m} \right) \end{aligned} \tag{1.10}$$

Equation 1.10 only enters the likelihood function for an individual with medical expenses greater than zero. The individual likelihood function must be adjusted by the probability that the medical expenses are positive. The probability of zero medical expenses enters into the likelihood function for those without medical expenses. Thus, the period t medical expense component for the individual likelihood function follows:

$$\ell_m(m_i|j_t, W_i, \tau) = \begin{cases} f_m(m_i|j, W_i, \tau_i) \times p^m, & \text{if } m_i > 0 \\ (1 - p^m), & \text{if } m_i = 0 \end{cases} \tag{1.11}$$

1.5.3 Wages

Expected wages are a function of an individual's health status, employment status, family status and characteristics. There is a separate wage process for part-time jobs and for full-time jobs. I observe wages for each individual and estimate wages using the following regression:

$$w^j_{i,j,t} = \beta^j Z_{i,t} + \chi^j_i + \eta^j_{i,j,t} \tag{1.12}$$

In the above equation, $Z_{i,t}$ are individual characteristics at time t and β^j are the static returns to these characteristics specific to a part-time job, $j = 1$, or full-time job, $j = 2$. $Z_{i,t}$ is composed of the current health state, marital status, presence of children, years of experience, age_0,[5] age_0-squared and level of education.

Unobserved heterogeneity over worker type enters the wage function through χ^j_i, where $j = 1, 2$ for part-time and full-time workers, respectively. I assume low productivity workers obtain jobs with lower wages than high productivity workers, with a difference in wages of χ^j. The worker type component is different for part-time jobs and full-time jobs. These parameters, as well as the probability of worker type, are estimated within the model.

Experience accumulates within the model. In period 1, all individuals have zero

[5] Age_0 is the age at which people enter the model.

years of experience. If an individual works in period 1, his experience for period 2 is 1. Experience does not depreciate or reset, but continues accumulating or remains static if an individual chooses to not work for one period. Since people enter the model at different ages, but everyone enters with zero experience, age in the first period (age_0) is also included in the wage function. age_0-squared is included to account for nonlinear returns to age.

Education is an indicator variable with five levels: no degree, a high school diploma, some college, a bachelor's degree, more than a bachelor's degree. I assume $\eta_{i,j,t}$ is drawn from a normal distribution with mean 0 and variance σ_j^2, where $j = 1, 2$ for part-time and full-time employees, respectively. I further assume that the draws are i.i.d. and not observed until after the individual makes his decision to work.

Since the shocks are unobserved by the potential worker until after he chooses to work, I must estimate a wage equation for which he bases his employment decision. I use the results of Equation 1.12 to estimate a wage for each employed individual, $\hat{w_{i,t}}$ at each time period. I compare the observed wages with the estimated wages to estimate the parameter, σ_j^2.

The likelihood function requires the probability of observing a wage given the person has a specific employment status, health status, marital status, characteristics and worker type. Denote $\phi(\cdot)$ as the pdf of the standard normal distribution. Thus, the likelihood of a wage draw is:

$$f_w(w_{i,j,t}^j | j_t, Z_{i,t}, \chi) = \phi\Big(\frac{w_{i,t} - \beta^j Z_{i,t} - \chi_i^j}{\sigma_j}\Big) \tag{1.13}$$

Wages are only observed for individuals who choose to work. Thus, the likelihood of a wage draw only enters the likelihood function, defined in Section 1.5.5, for people who choose $j_t \geq 1$.

1.5.4 Utility Function

The utility function depends on an individual's employment decision, previous period employment decision, expected wage, expected out-of-pocket medical expenses, family characteristics, educational attainment, health, worker type and medical care type. The utility parameters are specific to the employment status. I estimate utility as follows:

$$\begin{aligned} u_j(j_t, \Omega_t, E[w_{j,t}], E[m_{j,t}]) = \alpha_1^j + \alpha_2^j h_t + \alpha_3^j E[m_t] + \alpha_4^j \text{mar}_t + \alpha_5^j \text{ch}_t + \alpha_6^j E[w_t] \\ + \alpha_7^j \mathbb{1}(j_{t-1} = 0)\mathbb{1}(j_t \geq 1) \times \text{age} + \alpha_8^j \mathbb{1}(j_{t-1} = 1)\mathbb{1}(j_t = 2) \times \text{age} \end{aligned} \tag{1.14}$$

For the likelihood function, the choice probabilities in Equation 1.5, are essentially equivalent to estimating a multinomial logit (exactly a multinomial logit for the last period). Since only choices are observed, all coefficients of the utility function cannot be estimated. Only the differences in utilities between options can be identified. For identification, I normalize the utility of not working to be equal to zero. The coefficients for working part-time and full-time are interpreted as the difference in utility from those employment statuses compared to not working.

In Equation 1.14, health affects utility through α_2^j, with utility increasing by α_2^j when an individual is in good health. I anticipate that the coefficients on health will be positive, as healthy people will obtain more utility from working than not. Utility also depends on expected medical expenses, where α_3^j is the return on expected log medical expenses for job j. As explained in Section 1.5.2, medical expenses are estimated through a two step process. Medical expenses only impact utility if they are predicted to be greater than 0. A one unit increase in expected log medical expenses, increases utility by α_3^j. The sign on these coefficients is less clear. Presumably, if an individual has higher expected medical costs, he will need to work more to pay for them, resulting in positive coefficients. Conversely, he may be even unhealthier than what is captured by the intercept making him incapable of working. This would result in negative coefficients.

Marital status and the presence of children in the household, both dummy variables, affect utility by α_4^j and α_5^j, respectively. I expect coefficients on marital status and children to be positive, as marriage and children both increase the likelihood that men work. Expected wages, estimated via Equation 1.12, increase utility by α_6^j for part-time ($j = 1$) and full-time ($j = 2$) employment decisions. A $1 increase in expected wages, increases utility by α_6^j. The coefficients on wages should also be positive, as higher wages should increase the utility from working.

I assume that it is costly to enter the labor force for an individual not employed the previous period, or to find a full-time job if he was employed part-time in the previous period. These costs could include search and matching costs or account for differences in preferences between employed and jobless individuals. If an individual is jobless in period t, he is more likely to be jobless in the following period. This cost enters the utility function through α_7^j and α_8^j. α_7^j is the cost of entering the labor force if an individual is not in the labor force in period $t-1$. This value depends on whether the individual is choosing a full-time or a part-time job. α_8^2 is the fixed cost of choosing a full-time job if the individual was employed part time in period $t-1$. This cost depends on the age of the individual because it is more costly for older individuals to make a change in employment status compared to younger individuals.

I anticipate α_7^j and α_8^j to both be negative since this is a cost. In the data, there is evidence of employment transitions (see Table 1.2), allowing these parameters to be identified. While the vast majority of full-time workers remain employed full-time in the following period, there is significant movement elsewhere. Specifically, many men transition from part-time employment to full-time employment.

1.5.5 Likelihood Function

I estimate the model via maximum likelihood. I calculate the likelihood function for each individual and then integrate over the probability that each individual is of each worker and medical expense type.

The choice probabilities in Equation 1.5 are the probabilities that an individual chooses employment j in time t. Not everyone who wants a job can necessarily obtain one. The model includes a probability of employment, so the likelihood function must account for the possibility of unemployment. Unemployment is observed by the econometrician; jobless individuals in the PSID are characterized as either unemployed or out of the labor force. I classify those who choose employment, but do not obtain a job, as "unemployed". This is in contrast to those who opt not to work, who are classified as "out of the labor force". In the likelihood function, unemployed individuals are considered as working but without a wage. Since I do not know whether they would be employed full-time or part-time, I use the choice probabilities of each scenario.

To adjust the choice probabilities for the probability of employment (or unemployment), we must multiply Equation 1.5 by the likelihood of employment (or unemployment) for the likelihood function. Recall that the probability of employment is denoted π.[6] The employment probabilities are estimated in the first stage of the model using PSID data.

Denote the medical care heterogeneity terms for each individual as τ, where individuals are proactive or passive. Denote the wage heterogeneity terms for each individual as χ, where individuals have high productivity or low productivity. Again, both types of unobserved heterogeneity are individual-specific and unobserved by the econometrician but observed by the individual. Types are static across time, or fixed for each individual across his lifetime.

The probability of having employment status j in time t, conditional on worker and medical care types, follows:

$$l_j(j_t|h_t, \text{mar}_t, \text{ch}_t, \tau, \chi) = \begin{cases} P(j_t|\Omega_t, \tau, \chi), & \text{with probability } \pi \\ P(j_t = 1|\Omega_t, \tau, \chi) & \\ \quad +P(j_t = 2|\Omega_t, \tau, \chi), & \text{with probability } 1 - \pi, \end{cases} \tag{1.15}$$

where $P(j_t|\Omega_t, \tau, \chi)$ is the choice probability from Equation 1.5, now conditional on medical care type, τ, and worker type, χ.

χ enters into the likelihood of a wage draw, while τ enters into the likelihood of a

[6] π is equal to 1 if an individual chooses to not work, $j_t = 0$.

medical draw, as well as the probability of insurance status. The likelihood function for individual i conditional on medical care type and worker type is:

$$L_i(\Theta|\tau,\chi) = \prod_{t=1}^{T} \left[l_j(j_t|h_t, \text{mar}_t, \text{ch}_t, \tau, \chi) f_w(w_{i,j,t}^{j}|j_t, Z_{i,t}, \chi) \ell_m(m_i|j_t, W_i, \tau) \delta_j^{\tau}(j_t, h_t, X_t, \tau) \right], \tag{1.16}$$

where $l_j(j_t|h_t, \text{mar}_t, \text{ch}_t, \tau, \chi)$ is the conditional probability of employment status j_t from Equation 1.15, $f_w(w_{i,j,t}^{j}|j_t, Z_{i,t}, \chi)$ is the conditional likelihood of a wage draw from Equation 1.13 that enters into the likelihood function only if an individual works, $\ell_m(m_i|j_t, W_i, \tau)$ is the conditional likelihood of a medical expense from Equation 1.10 and $\delta_j^{\tau}(j_t, h_t, X_t, \tau)$ is the conditional probability of insurance status.

The above equation is conditional upon medical care type and worker type. I denote p_τ as the probability that an individual is of medical care type τ and p_χ as the probability that an individual is of worker type χ. Both probabilities are estimated within the model. After calculating the likelihood function for all types of workers, I integrate over the probability that workers are of each type. Denote the log likelihood for the full sample as follows:

$$L(\Theta) = \prod_{n=1}^{N} \log \Big(\sum_{\tau} \sum_{\chi} p_\tau p_\chi L_i(\Theta|\tau,\chi) \Big)$$

1.6 Results

In the first stage, I estimate the transitions for health, marriage, children and unemployment. These are estimated from the PSID data and are reported in Appendix 1.C. The probability of health is decreasing in employment, as seen in Table 1.16. Full-time employment decreases the probability of being healthy in the following period more than part-time employment.

In the second stage, I uncover the parameters of the utility function, expected wage equation, expected medical expense equation, insurance transition, and the variances for wages and medical expenses. I also uncover the probability that individuals are of each medical care type and worker type.

The utility parameters are in Table 1.3. The results show that there is a cost to working when not employed in the previous period. This cost increases with age.[7] This cost is highest when switching from jobless to full-time, but also exists when switching from jobless to part-time and part-time to full-time. Older men are even less likely to work than younger men if they did not work in the previous period. This may be capturing early retirement decisions. The results also show for unhealthy individuals, joblessness provides higher utility than working, consistent with initial theory that health concerns impede work.

The expected wage parameters are in Table 1.4. We see that for both part-time and full-time workers, healthiness increases expected wages, with a larger increase in expected wages for part-time workers. This could be capturing the fact that unhealthy men work full-time jobs at a lower rate than healthy men, while they work part-time jobs at the same rate (see Figure 1.2). Wages are increasing in education, with the exception of graduate school for part-time workers. Further, only 14.1% of workers are a high productivity type. 85.9% of workers are low productivity type, with much lower wages: \$17.81 per hour less for part-time workers and \$26.65 per hour less for full-time workers. Thus, there is a small portion of individuals making very high wages, with the rest making significantly less.

The expected medical parameters are in Table 1.5. Jobless individuals have the lowest probability of having out-of-pocket medical expenses. Part-time workers have the highest medical costs out of all workers who have medical costs. This is likely because part-time jobs often do not provide health insurance so the cost of medical care is higher. As expected, the healthy have lower costs, but interestingly, have a slightly higher probability of having medical expenses than the unhealthy. This could be the result of preventative care. Insurance increases the probability of having out-of-pocket medical expenses, but for those with medical expenses, the results are mixed. Approximately 63% of the sample is proactive medical care type.

[7] Recall that age is a value from 1-18, where '1' corresponds to age 25-26 and '18' corresponds to age 59 or 60.

Medical care type is fixed for an individual across his lifetime. Proactive type individuals are more likely to go to seek preventative care, take regular prescriptions and go to the doctor for less severe sicknesses than passive type individuals. Due to this, they are much more likely than passive individuals to be insured, as seen in Table 1.6. They seek out insurance at higher rates in order to lower their cost of treatment since they plan on frequenting the doctor.

Since proactive type individuals are more engaged in their health, they have a higher probability of incurring medical expenses than passive type individuals regardless of insurance status, as seen in Table 1.5. However, if an individual has out-of-pocket medical expenses, the magnitude of the expenses depends, not only on type, but also on insurance status. If medical expenses are incurred, proactive type individuals with insurance have higher expenses than those without. The reverse is true for passive type individuals: those with insurance have lower medical costs than those without, if out-of-pocket medical expenses are incurred.

These results are confirmed with the results of the baseline simulation summarized in Table 1.7. Passive type individuals are less likely to incur medical expenses than proactive type individuals within insurance status. If passive type men incur medical expenses, they are, on average, higher for the uninsured than the insured ($1,343 vs. $912). Of passive type men, the insured are more likely to have out-of-pocket costs than the uninsured. This is because passive medical type men only go to the doctor when they are sick and since it is more costly access medical treatment without insurance, insured passive type men are more likely to seek medical care than uninsured. Although, among passive type individuals, the average positive medical expenses are larger for the insured than the uninsured, since the insured are more likely to incur medical expenses, the average out-of-pocket medical costs across all passive type men are larger for the insured than the uninsured.

Proactive type individuals are more engaged in their health. They are more likely to frequent the doctor for preventative care and minor illnesses, and are also more likely to take regular prescriptions. This type is likely to have insurance (93.2% are insured) because they expect to incur higher medical costs. If they do not have insurance for a period, they presumably still take their prescriptions and may access preventative care. This is reflected in the higher percent of proactive type with medical expenses compared to the passive type (68.10% vs. 60.38%). However, they will wait until they are insured to seek out additional tests and procedures. Thus, if proactive type individuals incur medical expenses, they have much higher medical expenses if they are insured than if they are not insured ($2,450 vs. $674).

Comparing across types, since active medical care type individuals seek out medical care and take regular prescriptions, they are sick less often and their illnesses are less severe. As such, when they do incur medical costs, active type men have lower out-of-pocket medical costs than passive type. Negative health shocks are not as costly for the active type due to these preventative measures.

1.6.1 Model Fit

In the baseline simulation, I assume that individuals live in the same state throughout their life. This is necessary to calculate the probability of employment. I allow the state unemployment rate to change over time, but I assume that individuals reside in the same state as period 1.

Figure 1.3 compares the labor force participation rates from the model and data for part-time and full-time workers. Figure 1.4 looks at the labor force participation rates by health status. This includes full-time and part-time workers. While the model well approximates the participation rate for healthy men over the life cycle, it slightly overestimates the labor force participation rate for the unhealthy, but follows a similar trend.

Figure 1.5 compares the average wages for a high school graduate. Part-time wages are volatile over the life cycle in the data, but the model approximates them fairly well. Wages are compared further in Table 1.8. The model slightly overestimates the wages for part-time and full-time individuals without degrees and slightly underestimates for full-time workers with bachelor's degrees and graduate school, but successfully fits the general trend. It even captures the dip in part-time wages from a bachelor's degree to graduate school.

The model fits medical expenses well, as seen in Table 1.10, which separates the average medical expenses by insurance and health and Table 1.11, which separates the average medical expenses by employment status and health. These are average medical expenses of those with positive out-of-pocket costs (excluding those with zero medical costs). The model slightly overestimates, however, the percent of the uninsured sample with medical expenses, as seen in Table 1.9. It does properly estimate the percent of the insured sample with medical expenses and the insured rate when divided by employment status and health, as seen in Table 1.12.

1.7 Counterfactuals

In this section, I explore how changes in insurance policies impact employment decisions. In the first counterfactual, I simulate a change in health insurance policy where health insurance is expanded to everyone in the model. Compared to the baseline, under this policy, some individuals, specifically the unhealthy, drop of the labor force. This is driven by a decrease in full-time employment, while part-time employment remains steady. A shortcoming of this counterfactual is that it does not account for the cost of implementing this policy. A second counterfactual incorporates the cost of health insurance to employees by reducing wages based on an estimate from Kolstad and Kowalski (2016). I adopt this measure to adjust wages down for those who would not otherwise be insured in the model. This represents a deduction from wages to pay for insurance premiums. I find that labor force participation is slightly lower than it was for the first counterfactual, with unhealthy men choosing joblessness over full-time employment. Again, part-time employment remains steady.

1.7.1 Universal Insurance: No Wage Change

In this first counterfactual, I extend insurance to all individuals. I then compare the results of this policy to the baseline in which insurance is a function of health, employment status and age. Insurance enters the utility function indirectly through three components: health, expected wages and expected medical expenses. Utility of employment is increasing in health and wages and decreasing in logged medical expenses. Although the mechanisms through which insurance impacts health and wages are straightforward, it is less direct for medical expenses.

Individuals are more likely to be healthy if they are insured in the previous period, as seen in Table 1.16. Health is also a function of previous period health, so insurance increases the probability of being healthy directly through insurance each period and indirectly through previous period health. Part-time and full-time utility coefficients on health are positive, so the expansion of health insurance increases the utility of working.

The second component through which insurance affects utility is expected wages. Insurance enters wages indirectly through health. Wages are higher for healthy men than unhealthy men, as seen in Table 1.4. The average wage for healthy working men is \$4.99 higher than for unhealthy men in the baseline model for part-time jobs and \$3.02 for full-time jobs. As mentioned, the probability of good health is higher for the insured. Since the part-time and full-time utility coefficients on expected wages are positive, the expansion of health insurance increases the utility of working through the expected wages. Expanding health insurance increases the utility of working compared to not working through the health and wage channels. Thus, insuring the entire population would increase the labor force participation rate if these were the only two mechanisms; however, insurance also affects the utility function through expected medical expenses.

The relationship between insurance and medical expenses is complicated by the presence of two types of unobserved heterogeneity in medical care. If a passive type individual has insurance, he is more likely to have out-of-pocket medical expenses but if he does have medical expenses, they are lower than if he were uninsured. Table 1.13 captures this relationship. Expanding health insurance increases the percentage of passive medical care type individuals with medical expenses from 69.1% to 70.0%. Although more people have medical expenses, the average medical expense among passive type individuals with medical expenses decreases approximately \$185, or 18%, from \$1,034.10 to \$848.65.

For the utility function, expected medical expenses take into account the probability of medical expenses as well as expected medical expenses if they are incurred. Since insuring the passive medical care type individuals moves these two components in opposite directions, we cannot isolate the directional effect by just examining the sign. However, by examining the overall change in average medical expenses across all low type individuals, we see that the decrease in positive medical expenses outweighs the increase in the percent with medical expenses. As seen in Table 1.13, the overall average medical expenses across the entire sample decreases approximately $121, or 17%, from $714.74 to $593.64, for passive type individuals.

The result of expanding health insurance to proactive medical care type men is more straight-forward, with the probability of medical expenses and expected medical expenses both increasing with insurance. When health insurance is extended to all, more proactive type individuals have medical expenses, with the percent with medical expenses increasing slightly from 90.6% to 90.8%, as seen in Table 1.13. Average medical costs increase for the portion with out-of-pocket expenses by $28, or 1%, from $2,359.78 to $2,387.68. The coefficient on medical expenses is negative so expanding insurance to the proactive medical care type decreases the utility of working.

Although more individuals in the model are proactive medical care type (approximately 63%), the dramatic decrease in out-of-pocket medical expenses for passive type men outweighs the slight increase in medical expenses for proactive type men. As such, the average medical costs for among those who incur out-of-pocket expenses decreases, as does the average expenses among all individuals in the model (including those with zero expenses). Overall, while the percent of people with medical expenses increases from 82.8% to 83.2%, the average medical costs among those with out-of-pocket medical expenses decreases from $1,954.04 to $1,913.32, and the average medical expenses over all individuals decreases from $1,616.87 to $1,591.04 (Table 1.14).

The effects of this policy can be further explored by examining how it separately impacts the healthy and the unhealthy. Although slightly more people are likely to be healthy under this policy (from 88.7% to 89.2%), the remaining unhealthy individuals are worse off than they were without the expansion of health insurance. In Table 1.14, under this policy change, we see that more unhealthy individuals have medical expenses (an increase of 1.3 percentage points) and that average positive medical expenses are slightly higher. This results in an increase of medical expenses across all men from \$1,875.69 to \$1,915.83. The increase in medical expenses for proactive type individuals outweighs the decrease for passive type individuals among the unhealthy. Providing unhealthy proactive type individuals with insurance results in an increase in out-of-pocket expenses, as they access medical care even more frequently. These results are consistent with the finding of the Oregon Health Insurance Experiment that Medicaid increases the volume of physician visits and emergency department visits (Finkelstein et al. 2016).

The reverse is true for the healthy. Among the healthy individuals, the decrease in medical expenses among passive type individuals outweighs the increase in medical costs for the proactive. As such, for the healthy, the average positive out-of-pocket medical costs and the overall out-of-pocket medical costs both decrease. The percent of the healthy population with these expenses remains roughly constant from the baseline to this simulation.

Figure 1.8 summarizes these difference conflicting forces. By including medical care type, I isolate the increase in medical expenditure to proactive type men. For the unhealthy, this increase outweighs the decrease in expenditure for passive men, so that, on average, unhealthy men see an increase in out-of-pocket costs when health insurance is expanded. Due to this, the full-time labor force participation rate declines slightly. This supports the claim that some unhealthy individuals were previously employed for health insurance. Once insurance is guaranteed, they no longer work. Examining this further, Figure 1.9 compares part-time and full-time employment for the unhealthy in the baseline to the policy. The unhealthy are mainly exiting full-time jobs, rather than part-time jobs. These jobs provided health insurance at higher rates. Since they no longer need to work full-time jobs to obtain health insurance, they exit the labor force.

1.7.2 Universal Insurance: Wage Change

In order to incorporate the cost of health insurance, I decrease expected wages for jobs that would not have otherwise given insurance by 10%. This number is adopted from Kolstad and Kowalski (2016)[8] where they model the Massachusetts 2006 health care reform and find that jobs with employee sponsored health insurance (ESHI) pay less than jobs excluding ESHI.

I assume that there is no wage change for jobs that would already have provided health insurance, only jobs forced to implement this policy. Since employment decisions are made prior to observing insurance and utility depends on expected wages, I use the probability of insurance to calculate the flow payoffs for each period from Equation 1.2. For example, current period utility for a specific individual is an average between the utility with this policy and without this policy weighted by the probabilities he does not have and does have insurance, respectively. The discounted expected utility also takes into account the probabilities of insurance.

Since most full-time and part-time employees were already insured in the baseline model (86% and 66%, respectively), this policy does not dramatically reduce wages. The average part-time wage decreases 1.77% and the average full-time wage decreases 0.87%. This change is not large enough to have any significant additional impact on the labor force participation rate beyond the first simulation. With this slight decrease in wages, some unhealthy men drop out of the labor force, as seen in Figures 1.8 and 1.9, slightly more than in the first simulation when there was no wage change. As in the first simulation, the impact is on full-time jobs, rather than part-time.

One reason that adjusting the wages might have relatively no additional effect on the model is that this decrease in wages may be too conservative to affect employment decisions. Although wages are adjusted for jobs without ESHI, wages for jobs with ESHI

[8]Kolstad and Kowalski find that hourly wages are 10% lower for the same individuals when they have ESHI relative to when they do not have ESHI after the reform. This decrease is for wages of employed individuals, rather than average wages among the entire population (including $0 for those who do not work) which they present as their main result. I use a percent decrease, rather than a level decrease, in order to account for heterogeneity across jobs. It is unlikely that the highest wages would be penalized by the same dollar amount as the lowest wages.

are untouched. This does not properly allocate funds to pay for the policy for the jobless. It is possible that all wages will fall in order to cover the expense of this program. This would result in a strong effect on the labor force participation rate, with more men choosing not to work. Further, this counterfactual does not account for any changes in the probability of employment that result from a decrease in the demand for jobs, with the counterfactual assuming the same probability of employment (π) as the baseline model.

1.8 Conclusion

In this paper, I develop a discrete choice dynamic programming model where working-age men make employment decisions each period that impact their future health insurance status and health state. Dynamically, health is a state variable that factors into the employment decision and, in turn, that employment status is a determinant of the following period health. Insurance is stochastic and unobserved at the time the employment decision is made. I assume that there are two types of workers (high productivity and low productivity), as well as two types of individuals with regards to medical care (passive and proactive). I estimate this model using PSID data on men from 1999-2015.

The results show that there is a cost to entering the labor force and switching from part-time to full-time employment. This cost increases with age. Further, healthy men value working full-time over part-time and part-time over not working. I explore two different policy counterfactuals over insurance status: one where insurance is extended to everyone in the model and there is no change in wages and one where wages are reduced for jobs that would not otherwise provide insurance. I find that, on average, health improves and that medical expenses remain fairly constant, with slightly more people incurring medical expenses. However, out-of-pocket medical costs are affected within subgroups. Passive medical care type men see a fall in average positive medical expenses of approximately 17%, while proactive type men see an increase in average positive medical expenses around 1%. The unhealthy also see an increase in out-of-pocket medical expenses, while there is a decease for the healthy population. This is because unhealthy proactive type men see a larger increase in medical expenses that dwarfs the decrease in medical expenses for passive type unhealthy men, while the reverse is true for healthy men. These effects are similar across both counterfactuals.

Due to the increased out-of-pocket medical costs, there is a small decline in the unhealthy labor force participation rates. Specifically, the unhealthy opt out of full-time jobs, while they continue to work at part-time jobs at the same rates. Since full-time jobs provide health insurance at higher rates than part-time jobs, this confirms that some unhealthy individuals were only working in order to obtain insurance. Once insurance is guaranteed, they no longer choose to work.

These results have important policy implications. The Affordable Care Act dramatically changed the way the health insurance market operated in the United States. It enabled individuals to purchase insurance on a marketplace at much lower costs than prior to its implementation. With this, I anticipate that a portion of unhealthy individuals will opt out of working and instead, purchase private insurance.

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1.A Tables

Table 1.1: Summary Statistics for PSID Sample

Variable	Mean	Std. Dev.	Min[1]	Max
employed full-time	0.801	0.399	-	-
employed part-time	0.054	0.227	-	-
unemployed	0.063	0.242	-	-
out of labor force	0.082	0.274	-	-
self-rated health	2.290	1.004	1	5
insured	0.843	0.364	-	-
medical expenses (if > 0)	1,808.443	2,781.673	0.907	63,391.55
wages (if > 0)	27.780	17.597	4.379	126.977
age - first survey	35.919	9.872	25	58
married	0.778	0.416	-	-
children	0.515	0.500	-	-
average number of interviews	5.2			
observations	28,456			
individuals	5,495			

[1] Minimum and maximum are omitted for dummy variables.
Source: PSID 1999-2015, men.

Table 1.2: Employment transitions

	Jobless in t	Part-time in t	Full-time in t
Jobless in $t-1$	61.87%	9.08%	29.05%
Part-time in $t-1$	17.71%	28.75%	53.54%
Full-time in $t-1$	6.65%	3.14%	90.22%

Source: PSID 1999-2015, men.

Table 1.3: Utility Parameter Estimates

	Part-time	Full-time
Healthy	0.802	1.439
	(0.154)	(0.064)
Medical expenses	-0.518	-0.257
	(0.037)	(0.024)
Married	0.490	0.486
	(0.136)	(0.069)
Children	-0.132	0.100
	(0.076)	(0.049)
Wages	0.085	0.057
	(0.008)	(0.003)
Jobless in $t-1 \times$ Age	-0.059	-0.255
	(0.007)	(0.006)
Part-time in $t-1 \times$ Age	-	-0.165
		0.007
Log likelihood	-173,130.581	

Notes: Standard errors in parentheses.

Table 1.4: Wage Parameter Estimates

	Part-time	Full-time
Age_0	1.674	0.814
	(0.253)	(0.077)
Age_0^2	-0.062	-0.036
	(0.013)	(0.004)
Experience	0.684	1.040
	(0.149)	(0.040)
Healthy	4.987	3.024
	(1.336)	(0.328)
Married	3.303	2.548
	(1.031)	(0.234)
No degree	17.221	32.748
	(1.849)	(0.566)
High school	19.043	35.577
	(1.826)	(0.559)
Some college	23.704	38.649
	(1.953)	(0.555)
Bachelor's degree	27.193	44.304
	(2.106)	(0.569)
Graduate school	31.822	46.089
	(2.172)	(0.607)
Low productivity type	-17.806	-26.654
	(1.664)	(0.273)
Probability low productivity type	0.859	
	(0.006)	

Notes: Standard errors in parentheses. Age_0 is the age at which people enter the model. All individuals enter the model with zero experience.

Table 1.5: Medical Parameter Estimates

	$pr(m > 0)$	med
Jobless	-1.182	5.112
	(0.049)	(0.111)
Part-time	-0.958	5.429
	(0.058)	(0.112)
Full-time	-0.764	5.386
	(0.048)	(0.135)
Healthy	0.074	-0.185
	(0.033)	(0.035)
Insurance	0.092	-0.734
	(0.033)	(0.260)
Age	0.047	0.069
	(0.002)	(0.005)
Married	0.588	0.626
	(0.024)	(0.023)
High school	0.179	-0.014
	(0.029)	(0.028)
Some college	0.295	0.057
	(0.033)	(0.029)
Bachelor's degree	0.463	0.138
	(0.043)	(0.032)
Graduate school	0.496	0.209
	(0.052)	(0.036)
Proactive type without insurance	1.017	-1.040
	(0.079)	(0.794)
Proactive type with insurance	1.188	1.354
	(0.032)	(0.074)
Probability proactive type	0.632	
	(0.010)	

Notes: Standard errors in parentheses. The excluded schooling category is "less than a high school diploma". Medical expense coefficients are in logs.

Table 1.6: Insurance Parameter Estimates

Jobless	-0.821
	(0.054)
Part-time	-0.808
	(0.060)
Full-time	-0.335
	(0.048)
Healthy	0.246
	(0.034)
Age	0.062
	(0.003)
Proactive Type	1.525
	(0.035)

Notes: Standard errors in parentheses.

Table 1.7: Model: Medical Expenses by Type and Insurance Status

	% with Medical Expenses		Average Positive Medical Expenses		Average Medical Expenses	
	Uninsured	Insured	Uninsured	Insured	Uninsured	Insured
Passive Type	60.38%	73.28%	1,343.51	912.50	811.21	668.72
Proactive Type	68.10%	92.26%	673.52	2,449.92	458.65	2,260.25

1.A.1 Model Fit

Table 1.8: Model Fit: Average Wages by Highest Level of Education and Employment Status

	Part-Time		Full-Time	
	Data	Model	Data	Model
No Degree	15.91	17.18	18.62	20.35
High School	20.13	20.00	23.25	23.58
Some College	23.37	23.03	27.92	26.55
Bachelors Degree	30.55	28.08	36.16	32.26
Graduate School	27.76	31.65	40.09	34.54

Table 1.9: Model Fit: Percent with Medical Expenses

	Data	Model
Uninsured	56.66%	62.43%
Insured	87.21%	86.65%

Table 1.10: Model Fit: Average Medical Expenses given Medical Expenses Greater than Zero

	Unhealthy		Healthy	
	Data	Model	Data	Model
Uninsured	1,361.92	1,359.51	1,327.53	1,114.38
Insured	2,269.24	2,600.40	1,824.02	2,004.51

Table 1.11: Model Fit: Average Medical Expenses by Employment and Health Status given Medical Expenses Greater than Zero

	Unhealthy		Healthy	
	Data	Model	Data	Model
Jobless	2,126.88	2,431.39	1,604.45	1,727.50
Part-time	2,056.34	2,185.01	1,656.12	1,740.51
Full-time	2,097.74	2,397.98	1,798.44	1,932.64

Table 1.12: Model Fit: Insured Rate by Employment and Health Status

	Unhealthy		Healthy	
	Data	Model	Data	Model
Jobless	75.60%	79.28%	71.12%	81.04%
Part-time	59.89%	59.80%	67.81%	66.54%
Full-time	78.62%	80.22%	88.26%	86.34%

1.A.2 Counterfactuals

Table 1.13: Counterfactual: Medical Expenses by Medical Care Type

	% with Medical Expenses		Average Positive Medical Expenses		Average Medical Expenses	
	Passive	Proactive	Passive	Proactive	Passive	Proactive
Baseline	69.12%	90.63%	1,034.10	2,359.78	714.74	2,138.58
No Wage Change	69.95%	90.79%	848.65	2,387.68	593.64	2,167.84
Wage Change	70.04%	90.78%	849.25	2,400.36	594.82	2,179.08

Table 1.14: Counterfactual: Medical Expenses

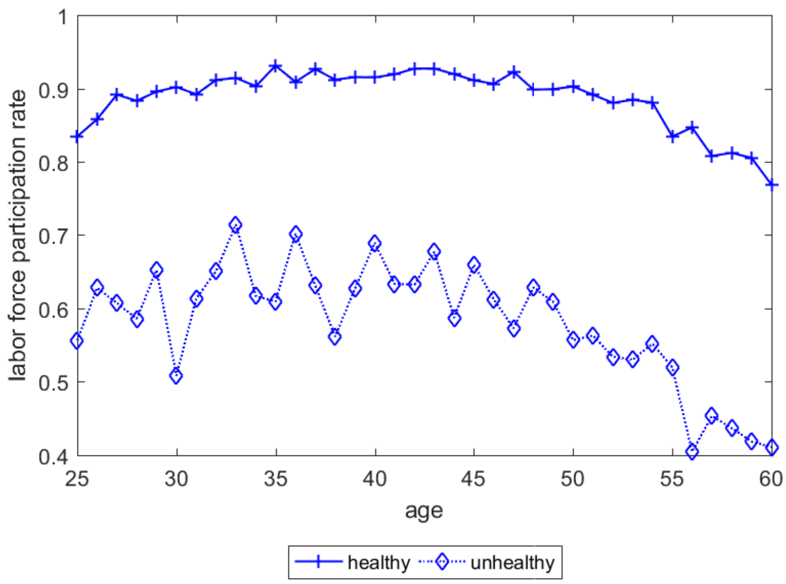
	% with Medical Expenses	Average Positive Medical Expenses	Average Medical Expenses
Baseline	82.75%	1,954.04	1,616.87
No Wage Change	83.16%	1,913.32	1,591.04
Wage Change	83.18%	1,921.81	1,598.60

Table 1.15: Counterfactual: Medical Expenses by Health Status

	% with Medical Expenses		Average Positive Medical Expenses		Average Medical Expenses	
	Unhealthy	Healthy	Unhealthy	Healthy	Unhealthy	Healthy
Baseline	78.18%	83.33%	2,399.06	1,900.65	1,875.69	1,583.78
No Wage Change	79.48%	83.60%	2,410.30	1,856.01	1,915.83	1,551.65
Wage Change	79.21%	83.66%	2,398.61	1,867.35	1,899.99	1,562.24

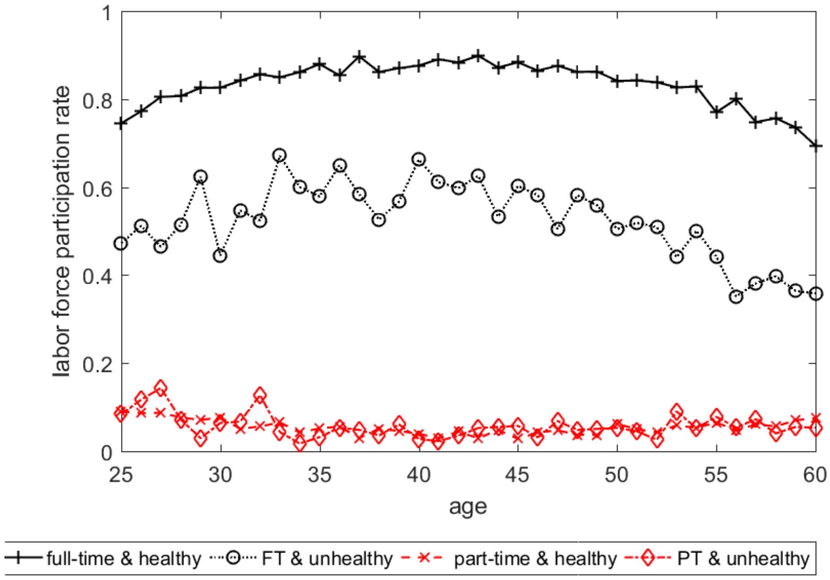
1.B Figures

Figure 1.1: Labor Force Participation by Age and Health Status



Notes: Health is 'perceived health status' and is a binary variable: healthy or unhealthy. The labor force participation rate does not distinguish between part-time and full-time jobs. This is for males 25-64. Source: Panel Study of Income Dynamics 1999-2015.

Figure 1.2: Labor Force Participation by Age and Health Status



Notes: Health is 'perceived health status' and is a binary variable: healthy or unhealthy. The labor force participation rate includes part-time and full-time jobs. Source: Panel Study of Income Dynamics 1999-2015, men.

1.B.1 Model Fit

Figure 1.3: Model Fit: Labor Force Participation by Age and Employment Status

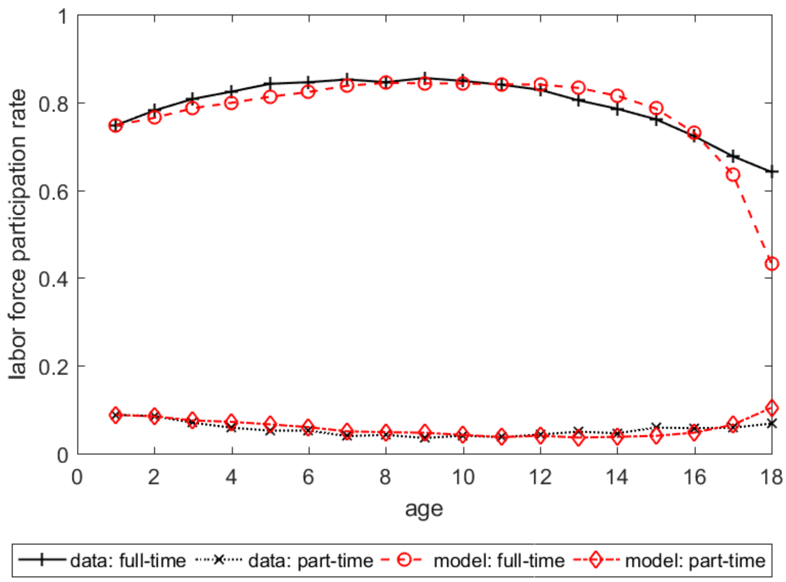


Figure 1.4: Model Fit: Labor Force Participation by Age and Health Status

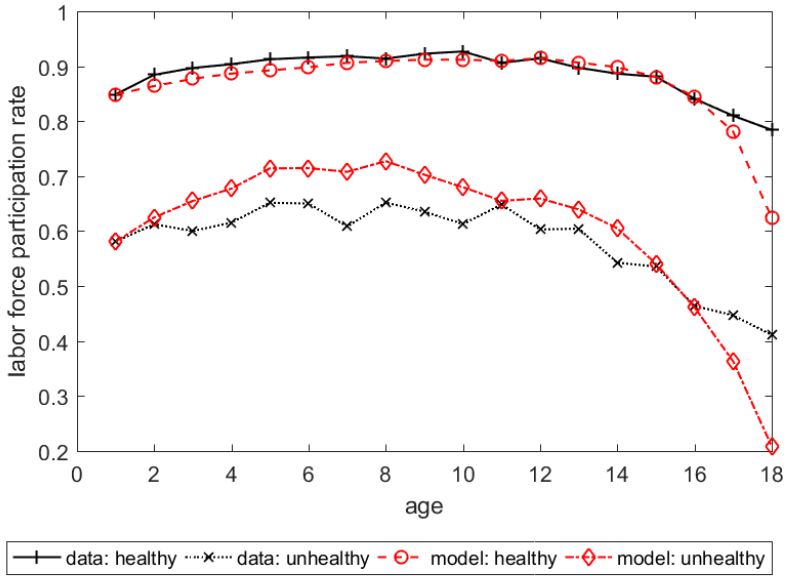
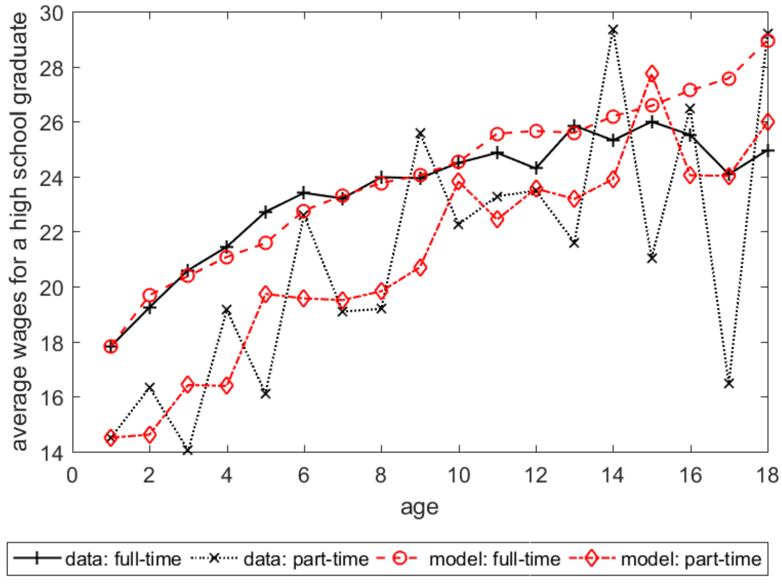


Figure 1.5: Model Fit: Average Wages for High School Graduate by Employment Status



1.B.2 Counterfactuals

Figure 1.6: No Wage Change Counterfactual Results: Labor Force Participation by Age and Health Status

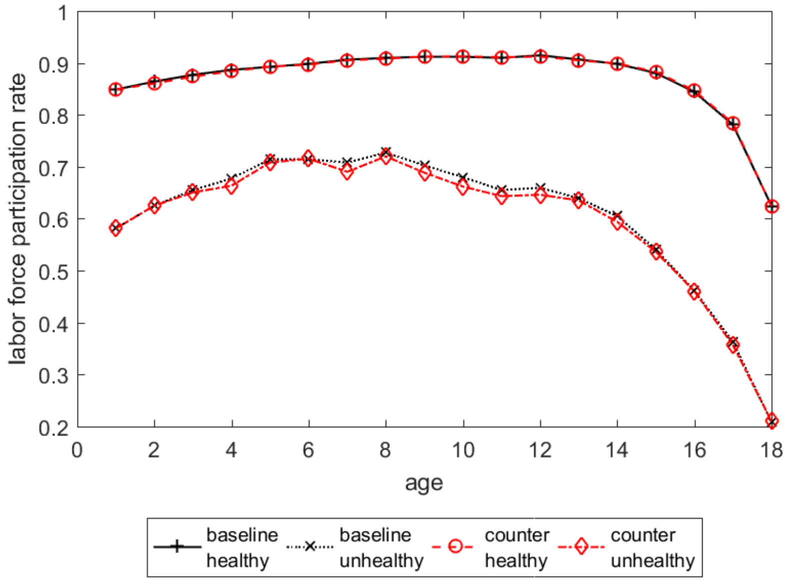


Figure 1.7: No Wage Change Counterfactual Results: Labor Force Participation by Age for Unhealthy

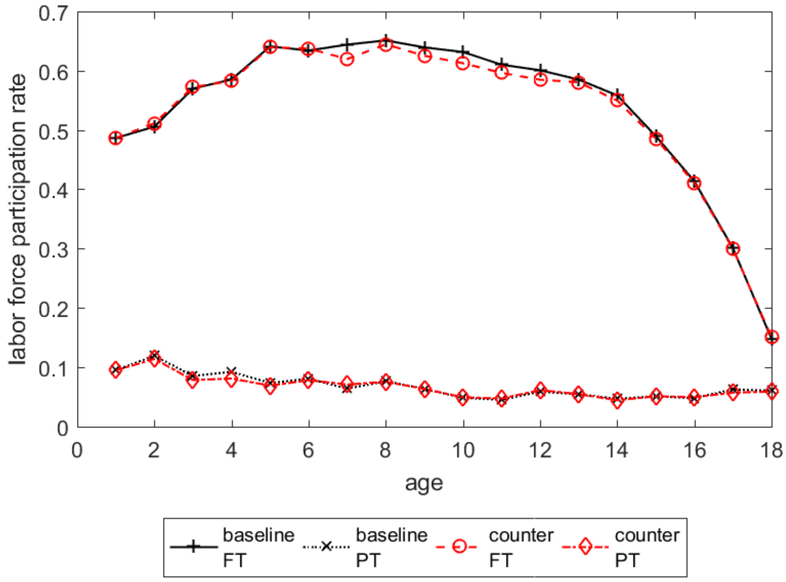


Figure 1.8: Wage Change Counterfactual Results: Labor Force Participation by Age and Health Status

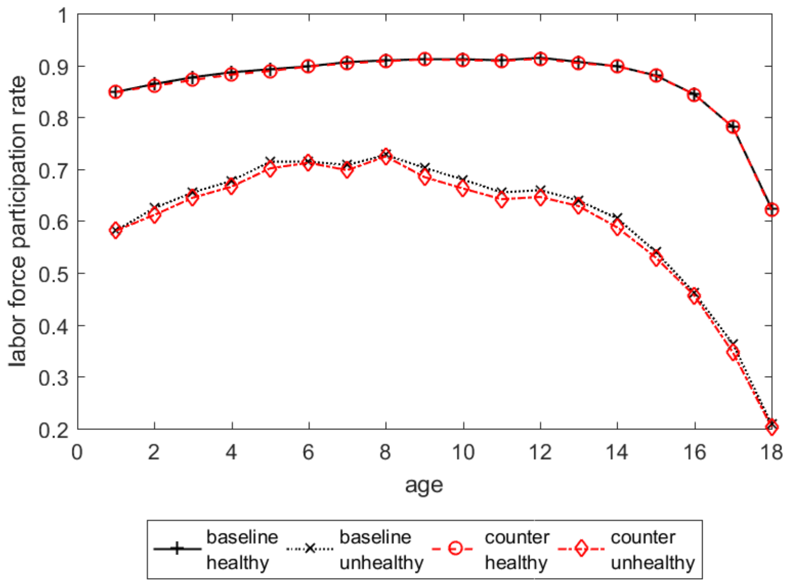
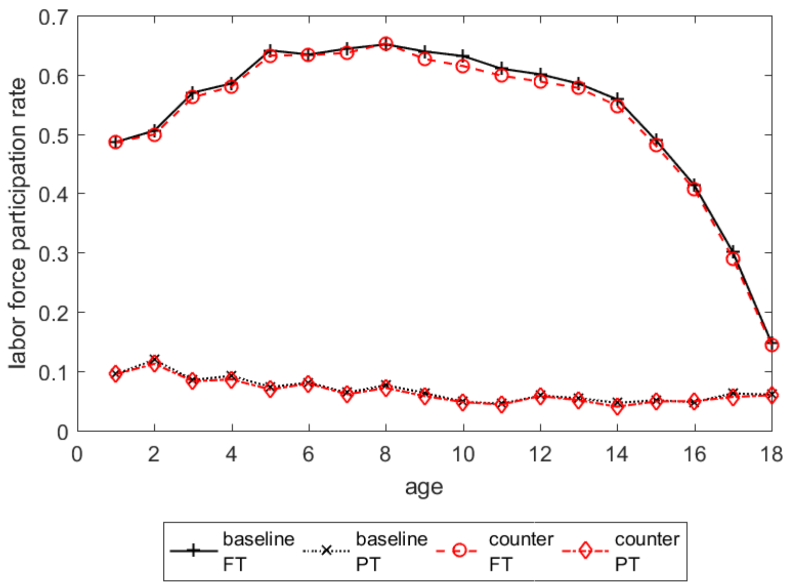


Figure 1.9: Wage Change Counterfactual Results: Labor Force Participation by Age for Unhealthy



1.C First Stage Transitions

This appendix includes the transitions that are estimated in the first stage of the model using the PSID data.

Table 1.16: Probability of good health at t+1

	Health at t+1
Health at t (d)	0.443***
	(0.0114)
Employed full-time at t (d)	-0.0927***
	(0.0117)
Employed part-time at t (d)	-0.0377***
	(0.0128)
Jobless at t (d)	-0.00613
	(0.00698)
Insured at t (d)	0.0274***
	(0.00579)
Age at t+1	-0.00481***
	(0.000383)
High School (d)	0.0314***
	(0.00446)
Some College (d)	0.0395***
	(0.00441)
Bachelor's Degree (d)	0.0588***
	(0.00406)
Graduate School (d)	0.0602***
	(0.00409)
Observations	22961

Marginal effects; Standard errors in parentheses. (d) for discrete change of dummy variable from 0 to 1. $^{*}p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The excluded group is "less than a high school diploma".

Table 1.17: Probability of marriage at t+1

	Married at t+1
married (d)	0.680***
	(0.00643)
Observations	22961

Marginal effects; Standard errors in parentheses
(d) for discrete change of dummy variable from 0 to 1
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 1.18: Probability of child at t+1

	Children at t+1
Children at t (d)	0.794***
	(0.00467)
Married at t+1 (d)	0.465***
	(0.0103)
Age at t+1	-0.0460***
	(0.00117)
Observations	22961

Marginal effects; Standard errors in parentheses
(d) for discrete change of dummy variable from 0 to 1
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 1.19: Probability of unemployment at t+1

	Unemployment at t+1
Unemployment Rate at t+1	0.00724***
	(0.000648)
Employed full-time at t (d)	-0.0467***
	(0.00234)
Employed part-time at t (d)	-0.0570***
	(0.00181)
Jobless at t (d)	-0.471***
	(0.0206)
Age at t+1	-0.000165
	(0.000309)
High School (d)	-0.0247***
	(0.00340)
Some College (d)	-0.0299***
	(0.00324)
Bachelor's Degree (d)	-0.0393***
	(0.00303)
Graduate School (d)	-0.0405***
	(0.00293)
Observations	20979

Marginal effects; Standard errors in parentheses. (d) for discrete change of dummy variable from 0 to 1. *$p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The excluded group is "less than a high school diploma".

Chapter 2

Consumer Plan Choice in the Florida Medicaid Market

2.1 Introduction

In the United States, Medicaid spending rose substantially in recent years. Although the increase in Medicaid spending has been linked to increases in enrollment, and spending growth per enrollee has been low compared to private insurance and Medicare (Clemans-Cope et al., 2016; Congressional Budget Office, 2015; Iglehart and Sommers, 2015; Keehan et al., 2015), state and federal policy-makers have promoted different policies in an effort to stabilize costs. One such policy is Medicaid managed care, which has been implemented in several states including Florida. Florida has seen an average annual growth in Medicaid enrollment of 5.3% from 1991 to 2014.[1] Thus, even though Florida did not expand Medicaid coverage under the Affordable Care Act, the cost of the Medicaid program in Florida has risen dramatically: from $9 billion in 2000 to $22 billion in 2010. Although the federal government pays more than half of that bill, Florida's share amounts to almost one third of the state budget (Allen, 2011).

In 2014, Florida implemented a program with the goal of reducing its rising Medicaid costs, requiring most Medicaid recipients to enroll in an Managed Medical Assistance (MMA) plan. These plans provide the same basic benefits, but offer varied physician networks and extended benefits. Although the goal of the program is to stabilize costs, it is important that this is not achieved at the expense of the consumer, as the plans should provide adequate coverage for all demographic groups and offer desired benefits. Ideally, competition between several plans ensures that the plans appeal to all; however, the set of plans offered varies by county, resulting in different degrees of competition across counties. Some counties may be under-served in the sense that they have demand for a particular plan due to the demographics of the county, but it is not offered. This paper seeks to determine which plan characteristics Medicaid recipients value in an MMA plan, and whether this varies by demographic group. The incorporation of demographics into the analysis helps to explain why, when faced with the same choices, Medicaid recipients may make different decisions depending on the county.

[1] Statistic from Centers from Medicare and Medicaid Services. https://www.cms.gov/research-statistics-data-and-systems/statistics-trends-and-reports/nationalhealthexpenddata/nhe-fact-sheet.html

Specifically, I adapt a Berry, Levinsohn and Pakes (Berry et al. 1995) random coefficients discrete choice demand model to estimate the shares of joiners to the MMA plans offered in each county. I model the Medicaid recipient's choice of joining a plan by examining which factors contribute to an MMA's enrollment share. Unlike other health care decision models and demand models, price does not factor into the decision of the patient, so plan characteristics must be used as proxies for price, inherently determining what patients value in a plan. I further adapt a BLP model by allowing for a different number of products within each county, and by eliminating an outside option. Instead of a typical outside option of not buying a product, I identify one plan per county as the base plan, thereby adjusting all of the plan characteristics to be in reference to this base plan.

The results show that individuals prefer to enroll in larger, well-known plans. One measure of size, the number of primary care physicians covered by a plan within a county, is an important determinant in the share of joiners to a plan in a market, especially for black and Hispanic enrollees. In addition, Medicaid recipients prefer to enroll in HMOs instead of PSNs and prefer plans that are offered in more regions. HMOs tend to be large national firms, or subsidiaries of recognizable large health insurers, so the results for three measures of plan characteristics support the idea that individuals prefer large plans.

The results further show that enrollees also take into account the Medicaid report card rating for keeping adults healthy. Although it is unclear whether Medicaid recipients actually access this information, it is possible that this variable serves as a proxy for plan reputation. This is supported by the fact that this rating is less important for those in lower population density counties and more important in counties with a higher percentage of individuals below the poverty line, where presumably more people are on Medicaid. When interacted with another plan characteristic, lagged log shares (the logged market shares from the previous month), only the interaction term is significant, further supporting this theory. Lastly, lagged log shares are highly significant, with individuals preferring larger plans. However, these results should be cautioned due to possible endogeneity.

Ultimately, the government needs to ensure that it is providing adequate coverage for all demographic groups and not cutting costs at the consumer's expense. This analysis is vital for Medicaid recipients in states beyond Florida, as 73% of Medicaid recipients were covered by private plans in 2015, up from 70% in 2014 and 60% in 2013 (Gottlieb, 2016). Further, insight into non-price characteristics can also be extended to the ACA health exchange, through which nearly 12 million Americans signed up for coverage for 2018.[2]

The paper proceeds as follows. The next section provides a description of the Medicaid industry in Florida, including a history of the pilot program and the implementation of the MMA program. Section 2.3 describes the model and Section 2.4 briefly summarizes the data set. Section 2.5 describes the estimation procedure. Section 2.6 presents results of the different variations of the model estimating the market share of joiners to MMA plans within each county. Section 2.7 provides a brief conclusion.

2.2 Industry Description

2.2.1 Pilot Program

Beginning in 2001, Florida law mandated that most Medicaid participants enroll in a primary care case management program, MediPass, or a Medicaid Health Maintenance Organization (HMO). Under MediPass, medical providers received payment for services directly from the state of Florida via fee-for-service (FFS), billing for each service provided to the patient (Florida Senate: Committee on Health Regulation, 2010). This incentivizes spending over saving, as providers maximize payment by increasing the number of services. Under the HMO payment scheme, providers are prepaid capitation rates, fixed monthly per member fees, and the HMO assumes full financial risk for delivering comprehensive primary and acute care services.

Beginning in 2006, Florida enacted a pilot (Demonstration) program that replaced

[2] Statistic from the Henry J. Kaiser Family Foundation. https://www.kff.org/health-reform/press-release/national-aca-marketplace-signups-dipped-a-modest-3-7-percent-this-year/

the existing payment mechanism in certain Demonstration counties. Under the pilot program, MediPass was eliminated and patients were required to enroll in either a risk-adjusted HMO or a provider service network (PSN). Under the risk-adjusted HMO, the HMOs were paid capitation rates that varied depending on certain risk factors, such as age and illness. PSNs are integrated health care delivery systems that are operated by health care providers or groups of affiliated health care providers (Brown-Woofter 2009).

Under the pilot program, PSNs were paid either through capitation or fee-for-service. The capitation payment scheme operated similarly to that of the HMO, with PSNs receiving fixed monthly per member rates and assuming full financial risk of providing care to those enrolled. Under the FFS payment mechanism, providers were paid by Florida's Agency of Health Care Administration (AHCA) after submitting claims to the PSN for authorization (Florida Senate: Committee on Health Regulation, 2010). If these FFS PSNs received cost savings in a particular time period, they received additional payments, but if they did not achieve cost savings, they were required to repay a portion of the administrative fees. FFS PSNs had less risk than capitation PSNs and HMOs, since they were not responsible for total cost of care and the payments to the providers were not tied to quality performance measures (Harman et al., 2014).

This pilot was initially implemented in Broward and Duval counties on July 1, 2006 and extended to three more rural counties, Baker, Clay and Nassau, on July 1, 2007. Although the Medicaid reform was implemented in July, participants in these counties did not begin enrolling in plans until September of each year (Lemak et al., 2007). The goal of the pilot program was to curb Florida's rising Medicaid costs by altering the providers' incentives from spending to saving.

This Demonstration was found to be financially successful, but at the expense of at least some patients' outcomes. A University of Florida (Harman et al., 2014) study found that the Medicaid pilot program resulted in lower increases in expenditures in these five counties than in the rest of the counties in Florida, using a difference-in-difference approach to compare changes in Demonstration enrollees before and after implementation of the pilot program. VanSant (2014) analyzed quarterly discharge records from 2005 to

2010 and found that the Demonstration increased the number of days to procedure for non-elective admissions at government-owned hospitals in Broward and Duval counties.

Deeming this program a success, Florida granted a three year waiver extension from July 1, 2011 to June 30, 2014 for the Demonstration that was initially slated to end on June 30, 2011. On June 14, 2013, the Centers for Medicare and Medicaid Services approved an amendment to this waiver extension to implement the Managed Medical Assistance (MMA) program. From May 1, 2014 to August 1, 2014, over four waves, the MMA program was implemented, replacing the pilot program in the five Demonstration counties and the MediPass-HMO mechanism in the sixty-two non-Demonstration counties (Florida Agency for Health Care Administration, 2014).

2.2.2 MMA Program

Under the MMA program, MediPass was eliminated and replaced with managed care plans: HMOs and PSNs, similar to the structure of the Demonstration. These managed care plans submitted proposals to Florida, and the state awarded five year contracts, with penalties for early withdrawal of a region and reductions in enrollment. In the bidding process, plans were able to choose in which regions of the state they wished to bid on a contract, with Florida having 11 regions[3] (Florida Agency for Health Care Administration, 2015). Providers contract with managed care plans of their choosing and negotiate mutually agreed upon rates specified in the contracts between provider and plan. Although providers opt to accept a plan, the state requires that plans have a sufficient number of providers in each network. To incentivize providers to accept Medicaid plans, by Florida law, primary care physicians (PCPs) must be paid at or above Medicare rates for similar services, and after two years of continuous operation under MMAs, other

[3] Region 1: Escambia, Okaloosa, Santa Rosa and Walton counties; Region 2: Bay, Calhoun, Franklin, Gadsden, Gulf, Holmes, Jackson, Jefferson, Leon, Liberty, Madison, Taylor, Wakulla and Washington counties; Region 3: Alachua, Bradford, Citrus, Columbia, Dixie, Gilchrist, Hamilton, Hernando, Lafayette, Lake, Levy, Marion, Putnam, Sumter, Suwannee and Union counties; Region 4: Baker, Clay, Duval, Flagler, Nassau, St. Johns and Volusia counties; Region 5: Pasco and Pinellas counties; Region 6: Hardee, Highlands, Hillsborough, Manatee and Polk counties; Region 7: Brevard, Orange, Osceola and Seminole counties; Region 8: Charlotte, Collier, DeSoto, Glades, Hendry, Lee and Sarasota counties; Region 9: Indian River, Martin, Okeechobee, Palm Beach and St. Lucie counties; Region 10: Broward county; and Region 11: Miami-Dade and Monroe counties.

physicians must be paid at or above Medicare rates for similar services.

All MMA plans are paid by the state of Florida risk-adjusted capitation rates that vary by region, age and severity of illness. With the implementation of the MMA program, Florida eliminated the FFS payment scheme for PSNs, so providers were no longer paid by the state for each service provided after billing the plan.

Medicaid recipients required to enroll in an MMA plan receive a letter at least ninety days prior to the enrollment date (Capital Soup, 2013). Although all plans provide the same basic benefits, they differ in the expanded benefits they provide and their network of physicians, pharmacies and hospitals. Participants are encouraged to call a choice counselor, who is employed through the Agency of Health Care Administration, to assist them. The choice counselor tells the Medicaid recipient which plans are available based on the participant's current PCP, specialists, prescriptions and specific extended benefits or services desired. Although counselors may not guide patients to choose one plan over another, they encourage participants to call their current physician to see if she prefers a specific plan.

Selection into a plan is high, with nearly 70% of Medicaid recipients choosing their plan (Kidder, 2015). However, if a recipient does not choose a plan after the enrollment date, she is automatically enrolled in a plan by the Agency of Health Care Administration. The AHCA selects a plan based on whether the individual is eligible for a specialty plan,[4] has a prior Medicaid managed plan that is eligible,[5] is already enrolled in a long term care plan with a sister MMA plan,[6] or has a family member already enrolled in an MMA plan (Florida Agency for Health Care Administration, 2015). After enrolling in a plan, or being selected into a plan by the AHCA, participants have ninety days to change to a different MMA for any reason. After ninety days, they can change plans once a year during open enrollment. Recipients receive a letter that reminds them of the open

[4]If a participant is eligible for a specialty plan, she is automatically enrolled in it by the AHCA unless she chooses to opt out. These specialty plans are for patients with HIV/AIDs, chronic conditions, or serious mental illness.

[5]Some of the plans were available in the Demonstration counties during the pilot program.

[6]Long term care plans (LTCs) are mainly comprised of patients 65 or older who also need nursing facility level of care or 18 years or older who are eligible for Medicaid due to a disability and need nursing facility level of care (Florida Agency for Health Care Administration, 2014).

enrollment period. Any new enrollments or changes in plan go into effect on the first of every month.

Medicaid recipients in MMAs are also required to choose PCPs. Similar to enrollment changes, any PCP changes are effective the first day of the following month. If a participant does not choose a PCP, the managed care plan assigns one based on the enrollee's last PCP, closest PCP, current PCP, language and age (Florida Agency for Health Care Administration, 2015). As previously stated, the AHCA requires that all managed care plans have a sufficient number of providers in each network. The definition of a sufficient number of providers varies greatly by population density. The AHCA requires each participant to have access to a PCP within a thirty minute, or twenty mile, travel distance from her home (Florida Agency for Health Care Administration, 2015). In some of the rural counties, there may only be one PCP within this distance, while in the more urban counties, there may be hundreds.

Broadly, the Medicaid industry in Florida works as follows. First, managed care plans decide for which regions to submit bids. Then, the state chooses with which managed care plans to contract. Physicians decide which plans to accept and negotiate contracts with these plans for payment. Medicaid recipients observe the plan options for their county and opt into one of the available managed care plans.

This paper models the enrollee's choice of a plan, a small piece of this complicated puzzle. Using all the information available to the patient, supplemented with patient characteristics, it attempts to understand the participant's decision process and how it varies depending on participant characteristics.

2.3 Model

I use a static decision model following the methodology introduced by Berry et al. (1995) and the estimation outlined by Nevo (2000). I estimate consumer demand in the Florida Medicaid market using a random-coefficients logit model or a "BLP" model. I assume that patients join a plan at time t. This joining of a plan can be the date of enrollment in Medicaid, the date of the switch from the old payment scheme to the new, or the date of switching into this plan from another plan.

In each county, a consumer has a choice of Medicaid plans indexed by $j = 1, ..., J$.

The total value of plan j to consumer i in market (county-month) m is:

$$u_{ijm} = x_{jm}\beta_i + \xi_{jm} + \varepsilon_{ijm}, \tag{2.1}$$

where x_{jm} is a K-dimensional vector of observable plan characteristics, unique to each plan, ξ_{jm} are unobserved plan characteristics that influence a recipient's choice in plan and that are unique to each plan, ε_{ijm} is the error term, assumed to be i.i.d. and distributed Type I extreme value.

$$\beta_i = \beta + \Pi D_i + \Sigma v_i, \tag{2.2}$$

where Π is a matrix of coefficients that show how plan parameters, such as quantity of in-network PCPs in that county, vary with observed demographics, D_i is a vector of observed demographic variables, such as race and rural residence, v_i are additional unobserved characteristics, such as the patient's level of health or search costs, and Σ is a matrix of unobserved parameters.

Combining Equations 2.1 and 2.2, results in the following:

$$u_{ijm} = \delta_{jm}(x_{jm}, \xi_{jm}; \theta_1) + \mu_{ijm}(x_{jm}, v_i, D_i; \theta_2) + \varepsilon_{ijm}, \tag{2.3}$$

where

$$\delta_{jm} = x_{jm}\beta + \xi_{jm}$$
$$\mu_{ijm} = [x_{jm}](\Pi D_i + \Sigma v_i]),$$

where $\theta_1 = (\beta)$, the linear parameters of the model, and $\theta_2 = (\Pi, \Sigma)$, the nonlinear parameters of the model. δ_{jm} is the mean, which is common to all consumers, while $\mu_{ijm} + \varepsilon_{ijm}$ represent a deviation from the mean of δ, taking into account the effects the individual characteristics in D_i and v_i.

The Medicaid recipient chooses the plan that maximizes her utility:

$$\max_j u_{ijm} \tag{2.4}$$

Alternatively, she can choose to take the outside option, $j = 0$. If she takes the outside option, she receives the following utility:

$$u_{i0m} = x_{0m}\beta + \xi_{0m} + x_{0m}[\pi_0 D_i + \sigma_0 v_{i0}] + \varepsilon_{i0m}, \tag{2.5}$$

where x_{0m} is the utility from the outside option in market m.

In a logit model, β does not have an 'i' subscript in Equation 2.1, so preferences are not consumer-specific but the same for all individuals. Under BLP, β_i is a vector of individual-specific preference coefficients, allowing for variation in demographics and observed and unobserved plan characteristics, such that:

There are several benefits to using BLP over a simpler conditional logit model. The main limitation of a logit model is the independent of irrelevant alternatives assumption, which implies that the relative probability of choosing one alternative instead of another does not depend on whether other alternatives are available and what those are. The problem with the IIA assumption in this setting is twofold. First, the choice set is explicitly different for individuals in different counties. Second, plan characteristics cater to certain demographic groups, so substitution patterns cannot be ignored.

BLP allows for the incorporation of demographics in a more systematic way than logit, which only allows for the inclusion of demographics through interaction terms. Consumers with different characteristics may value contrasting plan features. Rural Medicaid participants may value the number of medical providers more than urban consumers, because they have access to fewer. When choosing between plans that offer 1000 PCPs or 1500

PCPs, an urban consumer may not put much weight on the number of providers. However, for a rural consumer, when deciding between plans with 10 PCPs or 15 PCPs, the number of physicians may strongly impact her decision. Yet, in both cases, the larger plan offers 50% more PCPs.

This will help to explain why across different counties, when faced with the same plan options, consumers choose differently. Medicaid recipients with varying demographics may make different decisions, while those with similar demographics may opt into similar plans.

Additionally, it is expected that if a plan were no longer offered, consumers would choose a similar plan to replace it. Under the traditional logit model, any variation in consumer preference comes in through the error term, ε_{ijm}, which is assumed to be i.i.d. The substitution patterns among plans only depends on market shares of these plans. In random-coefficients logit models, the presence of a structural error term allows for variation in consumer preference based on demographics.

For example, suppose a plan geared towards older people and a plan geared towards children have similar market shares in a county, when a different plan catered towards children closes. Under the logit model, substitution towards both plans would be the same, regardless of characteristics. Substitution patterns only depend on market shares. However, it is intuitive that Medicaid recipients would switch to the plan with more pediatricians and better children services. The random-coefficients logit model accounts for this by having shocks correlated across plans through the structural error term.

The flexible substitution patterns and incorporation of variation in demographic preferences make BLP more suitable for estimating consumer demand in the Florida Medicaid market than conditional logit. The model setup follows.

2.4 Data

The data used in this estimation originate from several sources. To solve the model, I use monthly shares of joiners in each county. In addition, plan characteristics (x_{jm}) and demographic data (used to calculate D_i) for each county are necessary for estimation.

As will be explained in Section 2.5, not all characteristics can be estimated at the same time. As such, I limit my set of characteristics to those that I deem most important: percent of primary care physicians of county maximum (to account for network size), 'keeping adults healthy' star rating (a measure of quality from the Medicaid report card), HMO (a dummy variable for whether the plan is an HMO), number of regions, lagged log shares and an interaction between the Adults' Health star rating and lagged log shares. Summary statistics for these characteristics are located in Table 2.1. These will be defined further below. The county-specific demographic variables that are used are: percent black, percent Hispanic, percent rural and percent in poverty. These will also be explained further below. Summary statistics for the demographics are located in Table 2.2.

In order to calculate the shares of joiners to each plan in each market, I use data generously provided by the Agency on Health Care Administration. The provided data include the number of Medicaid enrollees who joined or exited each MMA plan by month and county from May 2014-March 2016. From the data, I calculate the shares for each plan in each county for every month. To construct the dependent variable, I take the log of the share of joiners in each market.[7] By utilizing the shares of joiners to a plan in a market, rather than the entire market share, I can capture the specific decision to select a plan. If individuals join and exit at plan at equal rates, the market shares will be unchanged, but new enrollment is occurring.

I supplement the provided data with publicly available county-level monthly plan enrollment data.[8] This consists of monthly data on the number of people enrolled in each plan in each county. I use the data to construct a lagged share independent variable that is used in some of the specifications. Specifically, I calculate the monthly market shares for each plan within a county and then take the log of the shares.

From December 2014 to July 2015, the same thirteen MMA plans[9] operated contin-

[7]If a plan has no joiners in a month, I set the number of joiners to 0.1 in order to take the log. This occurs for eleven observations over the seven months.

[8]The enrollment reports can be accessed at the following website: `http://www.fdhc.state.fl.us/medicaid/Finance/data_analytics/enrollment_report/index.shtml`

[9]Amerigroup, Better Health, Coventry, Humana, Integral, Molina, Preferred Medical, Prestige, South Florida Community Care Network, Simply, Sunshine, Staywell, United Healthcare.

uously. For ease of estimation and due to the need for an accurate lagged share term, I restrict my sample to January 2015 to July 2015. The first set of regions were required to switch to the MMA program by May 1, 2014 and the last set were required to switch by August 2014 (Florida Agency for Health Care Administration, 2014). Using data beginning in January has the additional benefit of ensuring that any initial enrollment hiccups have been resolved prior to the beginning of my data.

To proxy a plan network size, I supplement my data with a measure calculated from the number of PCPs (excluding pediatricians) covered by the plan within a county, which were obtained from the health plan websites.[10] These data are publicly available to the Medicaid recipients and all other individuals. Recipients can access this information prior to choosing an MMA.

Using the number of in-network PCPs for each plan in a county, I calculate a measure of physician counts that allows for comparisons across counties: the primary care physicians in a plan as a percentage of the maximum number of primary care physicians in all plans in the county. This method is calculated by taking the number of PCPs under a plan in a county and dividing it by the maximum number offered in all plans in that county. Thus, the largest plan within a county will have a value of 1, while the rest of the plans in that county will have a value between 0 and 1.

Medicaid recipients do not pay towards a premium, have a deductible or have a significant co-payment, so there is no price component to my demand estimation. The maximum co-payment an MMA enrollee can pay under the program is three dollars, but many recipients, such as those enrolled in HMOs, do not even pay this negligible amount. As such, I proxy for the price component of a demand model using different measures of quality. The AHCA publishes a Medicaid report card with ratings for each plan using different quality of care indicators. The ratings are star ratings from one star to five stars.[11] I collected results for the following three categories: keeping kids healthy,

[10] The number of in-network pediatricians does not seem to independently enter the decision process; however, the number of non-pediatrician PCPs and pediatricians are highly correlated at 0.91.

[11] 5 stars- Best: at or above 50% of all Medicaid health plans' scores; 4 stars- Good: better than at least 40% of all Medicaid health plans' scores; 3 stars- Fair: better than at least 25% of all Medicaid health plans' scores; 2 stars- Poor: better than at least 10% of all Medicaid health plans' scores; 1 star- Very Poor: worse than 90% of all Medicaid health plans' scores. The stars are assigned based on the plan's

keeping adults healthy, living with [chronic] illness.

After some analysis, I limited my model to only include the measure of adults' health. Plan characteristics relating to children seem to be less important than those related to adults, especially since I am not including percent of children on Medicaid in a county as a demographic. Also, fewer adults need to reference a measure of living with chronic illness as opposed to one geared towards healthy adults. For these reasons, I exclude the other measures and only include keeping adults healthy in the extended version of my model. Although these ratings are easily accessible on the website, it is unclear how much extended research the participants do prior to selecting an MMA plan. It is possible, however, that the star rating is a proxy for a less observable characteristic, such as plan reputation.

Due to the different organizational structures, I generate a dummy variable for HMOs. I also include a variable with the number of regions in which a plan is offered in order to account for multi-market firms.

I obtain county-level demographics, used to calculate D_i in Equation 2.2, from the U.S. Department of Health and Human Services and from the AHCA.[12] From HHS, I obtained percentages of black and Hispanic individuals in each county, the percentage of individuals in each county living in a 'rural' area, as designated by the HHS, and the percentage of individuals in the county living below the poverty line.

As seen in Table 2.2, approximately 14.5% of individuals in each county are black, with the county with the highest percent of black individuals as 56% and the county with the lowest percent as 2.8%. In an average county, about 12.5% of the population is Hispanic, while the highest Hispanic density county is 65% Hispanic. The population density in Florida varies dramatically from county to county. Broward County has the highest population density, while Jefferson, Lafayette and Liberty Counties have the lowest, with 100% of the population living in a rural area. An average county in the data

score for the specific indicator, with scores as the percentage of members that answered a survey question with a specific response. Source: http://www.floridahealthfinder.gov/HealthPlans/Compare.aspx

[12] To supplement the demographics from the HHS, I calculated the percentage of children on Medicaid in each county using 2015 county totals from the AHCA and county population estimates from the HHS. The results did not seem to depend on the percentage of children in a county so this demographic has been excluded.

has approximately 20% of individuals living below the poverty line, but this varies from 9.5% to 30%.

Although all Medicaid recipients are low income, I expect individuals in a county with a large percentage of low income individuals to act differently than those in a county where being low income is a minority. In the latter situation, there may be more of a stigma about receiving Medicaid benefits, and less of a support system, so it is possible overall enrollment rates are lower. Also, Medicaid recipients may have more information about plan characteristics if they have a larger network of neighbors also on Medicaid.

2.5 Estimation

To estimate the model outlined in Section 2.3, the utility of the outside good must be normalized to zero. Under a typical BLP framework, the outside option is to not purchase a good. This has the effect of equating x_{0m} to zero in Equation 2.5, as the individual chooses to not enroll in any offered plan so utility from the outside option does not depend on plan characteristics.

Estimating the shares of those who opt out of Medicaid is not a viable option. An ideal outside option is the share of the Medicaid eligible population that is uninsured. This population opted out of Medicaid in favor of being uninsured. However, this figure is not quantifiable for several reasons. It is impossible to separate the Medicaid eligible from the uninsured population. In addition, any alleged Florida Medicaid eligibility figures are actually Medicaid enrollment figures, so the exact number of Medicaid eligible individuals in Florida cannot be quantified. As such, I select one plan in each market as the base plan, or outside option, and difference the plan characteristics between all other plans in the market and the base plan. The choice of this outside option will be discussed further in Section 2.5.1.

Thus, x_{0m} is normalized to zero, or more accurately becomes $x_{0m} - x_{0m} = 0$. Equation 2.5, the utility for the outside good, is normalized to zero by setting ξ_{0m}.

Since homogenous changes in plan characteristics will not modify the patient's choice, it is necessary to normalize the utility for the outside option. Thus, the utilities for the

Medicaid plans are relative to that of the outside option, or base plan. As such, δ_{jm} and μ_{ijm} from Equation 2.3, the utility for plan j, must be updated so that the independent variables reflect the difference between the plan characteristics in plan j and in the base plan:

$$\delta_{jm} = (x_{jm} - x_{0m})\beta + \xi_{jm}$$
$$\mu_{ijm} = [x_{jm} - x_{0m}](\Pi D_i + \Sigma v_i]),$$

where Π and Σ are now also relative to the outside option or base plan.

To estimate this adapted BLP model, I construct a GMM estimator following the methods used by Berry (1994) and Nevo (2000).[13] I solve a simultaneous-equations model using a set of instruments, $Z = [z_1, ..., z_N]$, where N is the number of instruments. The following is the set of N moment conditions for the model:

$$E[Z_n \omega(\theta_0)] = 0, \tag{2.6}$$

where $n = 1, ...N$ and θ_0 is the true value of the parameters.

The GMM estimator is obtained through the following objective function:

$$\hat{\theta} = \underset{\theta}{\operatorname{argmax}}\, \omega(\theta)' Z \Phi^{-1} Z' \omega(\theta), \tag{2.7}$$

where Φ^{-1} is a symmetric positive definite weighting matrix and Φ is a consistent estimate of $E[Z'\omega\omega'Z]$. To estimate this model, I replace Φ^{-1} with $[Z'Z]^{-1}$, a consistent estimate of $E[Z'\omega\omega'Z]^{-1}$.

The error term, ω, is defined as follows:

[13] To estimate the model, I modified the code provided by Aviv Nevo and modified by Bronwyn Hall and Eric Rasmusen. The original code was used in support of Nevo (2000).

$$\omega_{jm} = \delta_{jm}(S_m; \theta_2) - (x_{jm} - x_{0m})\beta \equiv \xi_{jm}, \tag{2.8}$$

where ξ_{jm} is defined as the structural error term, assumed to be mean zero. S_m are the observed plan market shares in market (county-month) m. These observed market shares are used to solve this system of equations for each market:

$$s(\delta_m; \theta_2) = S_m \tag{2.9}$$

where $s(\delta_m; \theta_2)$ is the J market shares for market m. For each market and plan, the share is obtained by integrating over the mass of consumers who enter into plan j in market m. This is obtained by minimizing the distance of the predicted market shares and the observed market shares, and by the assumption that the ε_{ijm} are distributed according to Type I extreme value.

To estimate the model, I populate a sample of two hundred individuals with varied demographics and shocks to their taste parameters. I draw the demographics from a uniform distribution based off of the HHS and AHCA parameters, and I draw the shocks from a normal distribution. For each individual, her demographics make up vector D_i and the shocks that determine her taste parameters make up vector v_i of Equation 2.2.

The moment conditions, Equation 2.6, require a set of exogenous variables. I use the set of regressors, supplemented with the average of the values of the same characteristics of other plans offered within the county[14], interactions between regressors and interactions between calculated averages of characteristics of other plans. This results in 15 instrumental variables when there are four regressors and 21 instruments when there are five regressors and therefore, 15 (or 21) moment conditions. Appendix 2.C compares the main results to those using an additional network cost instrument and finds them to be similar.

The regressors are considered exogenous under the assumption that they were all

[14]Nevo (2000) suggests using the sum of the values of the same characteristics of other brands offered within the market. Under Nevo's model, all markets offer all brands. This is not true for the Medicaid consumer market in Florida; not all plans are offered in all counties. To remedy this, I take the mean, rather than the sum.

determined prior to the consumers' valuation of the product characteristics (Nevo 2000). It is reasonable to assume that the physicians negotiate their contracts with the MMA plans prior to accepting patients. Also, it can be assumed that the plans finalize their benefits, since they would be required to provide enrollees with Explanations of Benefits ("EOBs"). Due to the prior determination of the regressors, they can be considered exogenous and included as instrumental variables.[15]

2.5.1 Outside Option

As explained above, for an outside option, I normalize one plan in each market. This plan is known as the base plan. As such, all plan characteristics are the difference between that plan characteristic for plan j in market m and the plan characteristic for plan 0, the base plan, in market m. The summary statistics for the differenced plan characteristics are included in Table 2.3. This differencing is a deviation from the typical BLP methodology, as the outside plan is often the decision not to purchase the good. Thus, all characteristics for plan j are relative to the characteristics of the base plan in that market.

Further, under the Affordable Care Act, all individuals are required to have health insurance during the entire sample period.[16] The ACA also expanded Medicaid in some states, but not in Florida. Although the implementation of the ACA had the effect of reducing the uninsured population and reducing racial and ethnic disparities in coverage, these disparities still exist. Buchmueller et al. (2016) find that the ACA decreased the uninsured rate for Black and Hispanic adults significantly, even in states that did not expand Medicaid coverage, like Florida. It is important to note, however, that even under the ACA, there are still uninsured individuals, especially non-white individuals.

[15] A source of endogeneity remains if observed characteristics are correlated with unobserved components. This would occur if plans chose to invest into either observed or unobserved characteristics, dividing their finite resources into each category. This results in some firms with high observed, low unobserved characteristics and others with low observed, high unobserved characteristics. I estimated the extended specification from Table 2.6 excluding the regressors as instrumental variables, but instead using the average of the values of the same characteristics of other plans offered within the county and interactions between those averages as instruments. The coefficients are nearly identical, but the standard errors are larger, as there are fewer instrumental variables. The consistent results negate the trade-off theory and supports the exogeneity of the regressors. Using the regressors as instruments results in more instruments and allows more parameters to be identified. The baseline model, for example, cannot be estimated with the reduced set of instruments.

[16] President Donald Trump signed the Tax Cuts and Jobs Act of 2017, repealing the mandate in 2019.

An alternative imperfect outside option is the share of individuals enrolled in a fee-for-service (FFS) program. This FFS program is similar to the payment structure of Medipass, the program in use prior to the implementation of the MMA program. Under the FFS program, Medicaid recipients do not enroll in any of the 13 MMA plans.

This is an unsuitable measure of an outside option, because it is not available for all Medicaid recipients. Most participants are required to enroll in an MMA. Only a subset of the population is exempt and allowed to enroll in the FFS program or an MMA plan.[17] An even smaller subset is prevented from enrolling in an MMA and is required to enroll in the FFS program.[18] As such, labeling one plan as a base plan, or outside option, is the best option given the data.

2.5.2 Identification

Identification is attained through the instrumental variables used in the moment conditions in Equation 2.6. Identification follows from sufficient variation in demographics and characteristics coupled with the normalization of the utility from the outside option to zero. Also, variation in the choice set across markets helps to identify the variance of the random shocks (Nevo, 2000).

There is variation in the demographics used and in the plan characteristics. Table 2.2 includes summary statistics for the 67 counties in Florida, showing that there is variation in the population in Florida. The Florida population data are used to generate demographics for twenty individuals in the model. The data are from the U.S. Health and Human Services Area Resource Files. They are county-level population data, with one observation for each county.

There is great variation between counties, with the percent of black and Hispanic

[17] The exempted individuals are the following: 1. Medicaid recipients with other health care coverage, other than Medicare. 2. Recipients eligible for refugee assistance. 3. Recipients who reside in a developmental disability center. 4. Recipients enrolled in a developmental disability center and community based services waiver, or anticipating waiver services. 5. Children in a pediatric extended care center. (Florida Agency for Health Care Administration, 2015)

[18] The following individuals are not eligible to enroll in an MMA plan: 1. Women who are only eligible for family planning services. 2. Women who are only eligible through the breast and cervical cancer services program. 3. Recipients who qualify for emergency Medicaid for immigrants. (Florida Agency for Health Care Administration, 2015)

individuals within a county ranging from 2.8% to 56% and from 1.9% to 65%, respectively, with means of 14.5% and 12.5%. The percentage of the population in poverty ranges from 9.5% to over 30%. The percentage of individuals living in rural areas ranges from 0% in Broward county to 100% in three of Florida's 67 counties.

There is also variation in the plan characteristics of the thirteen MMA plans in operation in Florida. Table 2.1 summarizes the variation in the observed plan characteristics for the 13 plans, or the 267 plan-county observations (for the measure of physician network size), or the 1869 plan-county-date observations (for the lagged log share). All summary statistics include the base plan for each county, which are excluded from the sample for estimation.

To better understand the variation in the data used for estimation, Table 2.3 summarizes the differenced plan characteristics. The table summarizes the differenced characteristics between each plan and the base plan for the 1400 observations in the data set used to estimate the model. The county and plan specific measure of physician network size, the percent of PCPs of county maximum, is created from the physician counts obtained from the MMA plans' websites. The raw value can take a minimum value of 0 and a maximum value of 1. Thus, the differenced value ranges from -0.818 to 1, with a mean of 0.242 and a standard deviation of 0.402.

HMO and Number of Regions are both plan-specific variables. HMO is a dummy variable for whether the plan is an HMO, so this takes on a value of 0 or 1. The differenced values take on values of -1, 0 or 1, with an average of -0.25. The number of regions in which a plan is offered varies from 1 to 9, with a differenced value ranging from -8 to 0 with a mean of -3.

Adults' Health is a plan-specific star rating that can vary from 1 to 5, but in the data set, only varies from 2 to 4 with an average of 3. The differenced value ranges from -2 to 1, with an average of 0.29.

Lagged log share can vary from -4 to -0.4, with an average of -1.7. The differenced values vary from -6.9 to 7.5, with an average value of 0.58 and a standard deviation of 2.5. Thus, the differenced values used to estimate the model vary substantially either across plans, across plans and county or across plans, counties and months.

2.6 Results

I seek to determine which characteristics are most valued to a Medicaid recipient when choosing an MMA plan, and additionally, how this value changes by demographics. I look at four main demographics: Black, Hispanic, Rural and Poverty, and a variety of plan characteristics that depend on the specification. In order for the model to be identified, not all characteristics can be estimated at the same time. I used machine learning (LASSO) to narrow down the set of possible characteristics and then further narrowed down the results after comparing many specifications. Additionally, all of the interactions with demographics cannot be evaluated concurrently due to limitations from the moment conditions, so I only test those I believe to be relevant.

The set of instruments used for these main results consists of the plan characteristics, average of the values of the same characteristics of other plans offered within the county, and interactions of the plan characteristics. Appendix 2.C includes results using different sets of instruments.

In the baseline specification, I include four plan characteristics: percent of primary care physicians of county maximum, adults' health (star rating), HMO (a dummy variable for whether the plan is an HMO) and number of regions. Table 2.4 compares the results from the simple logit specification and the BLP specification.[19] The results for the logit model are obtained from an ordinary least squares regression of $\ln(s_{jm}) - \ln(s_{j0})$ on plan characteristics and interactions between product characteristics and demographics. The estimation procedure for the BLP model is described in Section 2.5.

As seen in Table 2.4, the results are consistent between the logit model and the BLP model, although the magnitudes are larger in the BLP model.In the logit model, the coefficients (except for physician network size) are biased towards zero, which is corrected in the BLP model. It is also important to reiterate, as explained in Section 2.5, that the

[19]In the BLP specification, I find that the demographic for black is not significant when interacted with any of the plan characteristics and rather, weakens the statistical significance of other coefficients. As such, I do not include any race demographics in the first specification, only an ethnic demographic for Hispanic.

logit model produces restrictive substitution patterns, while the BLP allows for flexible substitution patters and for unobserved product characteristics to enter.

In both models, all coefficients are statistically significant at the 5% level, except for poverty and Adults' Health, which is narrowly insignificant at 5% in both models. The results show that individuals join plans with higher percentages of PCPs, and that this effect is highly pronounced for Hispanic individuals. This plan characteristic captures the size of the network, with enrollees preferring plans with larger networks. Individuals also join plans with higher Adults' Health ratings, that are HMOs and that are offered in more regions, which is another measure of network size, even if that network is not necessarily accessible to the individual. The effect for Adults' Health star rating is negative for those in rural areas and positive and seven times the mean for areas in poverty. As mentioned previously, it is not obvious how many enrollees access this information prior to choosing a plan. This star rating may serve as a proxy for plan reputation. As such, in rural areas, this negative effect may be the result of a smaller network of individuals on Medicaid. Perhaps the patients simply are uninformed about a plan's reputation, since they do not have many neighbors with whom to discuss their options. This also explains the opposite effect seen in areas of poverty. In locations where we expect more people to be on Medicaid, the reputation of a plan would be more well-known.

In the model, recipients are more likely to choose an HMO than a PSN. Although this information is publicly available, it is unlikely that a consumer researches the organizational structure of the firm that manages the MMA plan. It is more likely that the organizational structure serves as a proxy for other factors. The HMOs are often nation-wide firms that may offer private insurance in addition to Medicaid, while PSNs are owned by physicians and physician groups. Perhaps enrollees choose a plan based on name recognition and trust a plan that provides national coverage over one that they do not know.

Table 2.5 summarizes the BLP results further, including the "Standard Deviations," or the effects of the unobserved demographics. The effects are insignificant, suggesting that most of the heterogeneity is explained by the observed demographics. The rest of the results in this section are for different specifications of the BLP model.

Table 2.6 adds lagged logged shares to the specification in Table 2.5. These are the log shares from the previous period. This has the effect of decreasing the magnitude of the coefficients and making some coefficients insignificant (% of PCPs of county maximum, Adults' Health rating, Adults' Health rating and poverty, number of regions). Further, now the standard deviation for HMO is significant at the 5% level, and the standard deviation for percent of PCPs of county maximum is significant at the 10% level. This signifies that the observed characteristics are not adequately explaining the heterogeneity and some of the heterogeneity is explained by unobserved demographics.

We also see that lagged log share is highly significant and possible. Recall that this value is the difference of the logged shares between the observed plan and the base plan in the previous period. Thus, any values of lagged log share less than zero occur when the base plan has a larger share than the observed plan, and the opposite is true for shares larger than zero. This shows that individuals prefer plans with larger market shares and dislike plans that have smaller market shares. The effect of the lagged share, however, may be biased upward since it is correlated with unobserved characteristics in the present. In this specification, lagged share is essentially serving as a control for time-invariant unobserved characteristics. As a result, this provides more confidence in the variables that remain constant despite the inclusion of the lagged share variable (percent of PCPs of county max and Hispanic, Adults' Health rating and rural, HMO).

In an effort to capture the network dissemination of information about perceived plan quality, Table 2.7 includes an interaction term between Adults' Health star rating and lagged shares. To reduce the number of parameters estimated, number of regions is excluded from the analysis.[20] Further, demographics for Adults' Health rating, lagged log shares and the interaction are removed in order to correctly identify the coefficient on the interaction term and keep the number of parameters to a minimum. When the interaction term with Adults' Health rating and lagged shares is included, the mean Adults' Health rating plot coefficient is no longer is statistically significant. The mean

[20]Number of regions is not significant at the mean or when interacted with demographics when used in place of HMO.

coefficient for lagged log shares is more than two times the value when no interaction term is included, as seen in Table 2.6. The mean interaction coefficient is negative and statistically significant.

The interpretation of these coefficients is complicated by the fact that the regressors are the difference of each value between plan j and the base plan. Thus, the interaction terms are the difference between the interaction of Adults' Health rating and lagged log shares for plan j and the interaction of Adults' Health rating and lagged log shares for the base plan in the market. To better explain the mean contributions to utility from the rating and lagged log shares, Figure 2.1 plots the contributions to utility for the sample. Specifically, I calculate the contributions to utility using the coefficient on the differenced lagged log share and the coefficient on the differenced interaction from Table 2.7 for each data point in the sample.[21]

Figure 2.1a plots the differenced Adults' Health rating for each plan-market versus this value. Since the rating is a discrete value from 2 to 4, the difference only takes the values of -2, -1, 0 or 1. Although there is a slight positive relationship between differenced Adults' Health rating and the contribution to utility, it is not a very strong one. Figure 2.1b plots the differenced lagged log shares values from the sample against the contribution to utility by the differenced Adults' Health rating and differenced lagged log share for each observation. Here, there is a clear positive relationship. Further, as the difference in lagged log share between plan j and the base plan becomes positive, so does the contribution to utility. This is the expected relationship, confirming that individuals prefer plans with larger market shares.

Lastly, the mean network size coefficient (percent of PCPs of county maximum) is now negative and statistically significant, indicating the counter-intuitive result that individuals prefer smaller networks. One explanation is that patients do not care about smaller networks, as long as it includes their doctor, or similarly, that smaller networks contain the best doctors. It is worth nothing however, that black Medicaid recipients prefer larger networks, as do Hispanic recipients (though this coefficient is not statisti-

[21] I exclude the coefficient on Adults' Health rating since it is not statistically significant.

cally significant). The coefficients on these demographics fully offsets the coefficient on the mean, showing that some subsets of the population do prefer larger networks.

2.7 Conclusion

In this paper, I explore what Medicaid recipients value when choosing a health insurance plan. Since 2014, most Medicaid recipients in Florida have been required to enroll in a Managed Medical Assistance plan. These plans are offered at no cost to the enrollee and offer the same core benefits, but different extended benefits and physician networks. Specifically, in this paper, using a modified BLP methodology, I estimate a demand model in a setting without prices, without an outside good and with a different number of plans in each market. Instead of a typical outside option of not buying a product, I identify one plan per county as the base plan, thereby adjusting all of the plan characteristics to be in reference to this base plan.

The estimation requires market shares, plan characteristics and demographics. For market shares, I use shares of joiners to each Medicaid plan in each county in Florida over seven months. These data were provided by the Agency of Health Care Administration. For plan characteristics I use a combination of physician network size, a dummy variable for whether the plan is an HMO, the number of regions in which the plan is offered, a rating for how well the plan keeps adults healthy, a one period lagged term of logged market shares and an interaction term between the Adults' Health rating and lagged market shares. These characteristics are from the plan websites, as well as the AHCA. For demographics, I use county-wide variables of percent black, Hispanic, living in a rural area and living below the poverty line. These values are from the HHS.

Due to limitations on the number of instruments used in estimation, not all combinations of plan characteristics and demographics can be identified. The results suggest that all of the plan characteristics are important, but not necessarily important to every demographic group. Black and Hispanic individuals seem to prefer a larger physician network, while HMOs and plans that are offered in more regions are preferred by all individuals, with no additional variation explained by demographics. Medicaid recipients also prefer plans with larger market shares. These results support the theory that people prefer to enroll in larger, well-known plans. Lastly, enrollees seem to prefer plans with higher Medicaid report card star ratings of keeping adults healthy. This characteristic is likely a proxy for plan reputation, which is supported by the fact that there is a negative coefficient on this characteristic for rural, where one is expected to have a smaller network of neighbors on Medicaid. In addition, this rating has a larger effect in highly impoverished areas where there is a larger network of people on Medicaid.

These results can be extended beyond the state of Florida, and beyond Medicaid. It is beneficial for the government to ensure that it is providing adequate coverage for all demographic groups, as Medicaid managed care gains popularity across the United States. These results can also be used by insurers to determine which characteristics are valued by members. Although this model excludes price as a characteristic, the results can be extended to the ACA health exchange, as they show that individuals choose plans based on the benefits that are offered and that the preferred benefits vary by demographic groups.

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2.A Tables

Table 2.1: Plan Characteristic Summary Statistics

Variable	Mean	Std. Dev.	Min	Max	Obs.
HMO	0.692	0.480	-	-	13
Number of Regions	3.923	2.871	1	9	13
Adults' Health (Star Rating)	2.923	0.760	2	4	13
% of PCPs of County Max	0.557	0.333	0	1	267
Lagged ln(share)	-1.658	0.804	-3.975	-0.337	1869

Source: Florida AHCA and MMA plan websites.

Table 2.2: Population Summary Statistics for Demographics

Variable	Mean	Std. Dev.	Min	Max
% black (2010)	0.145	0.095	0.028	0.56
% Hispanic (2010)	0.125	0.121	0.019	0.65
% in poverty (2012)	0.197	0.053	0.095	0.302
% in rural (2012)	0.375	0.323	0	1

Source: U.S. HHS Area Health Resource Files.

Table 2.3: Differenced Plan Characteristic Summary Statistics

Variable	Mean	Std. Dev.	Min	Max
% of PCPs of County Max	0.242	0.402	-0.818	1
HMO	-0.250	0.574	-1	1
# of Regions	-3.070	2.348	-8	0
Adults' Health (Star Rating)	0.290	0.706	-2	1
Lagged Ln(Share)	0.329	0.856	-2.294	2.428
Adults' Health $\times$ Lagged Share	0.575	2.549	-6.882	7.544
Observations	1400			
Counties	67			
Months	7			
Plans	13			

Source: Florida AHCA and MMA plan websites.

Table 2.4: Comparison of Results of Baseline Model

	OLS Logit Demand	BLP
% of PCPs of County Max	0.581 (0.063)	0.439 (0.110)
% of PCPs × Hispanic	1.510 (0.322)	4.070 (0.966)
HMO	0.243 (0.046)	0.414 (0.121)
Number of Regions	0.068 (0.009)	0.093 (0.026)
Adults' Health (Star Rating)	0.218 (0.097)	0.355 (0.147)
Adults' Health × Rural	-0.559 (0.107)	-1.697 (0.414)
Adults' Health × Poverty	1.069 (0.574)	2.473 (1.280)

Table 2.5: BLP Results: Baseline Model

	Means	Standard Deviations	Interactions with Demographic Variables			
Variable	β	σ	Black	Hispanic	Rural	Poverty
Constant	0.075 (0.116)	0.573 (0.443)	-	-	-	-
% of PCPs of County Max	0.439 (0.110)	0.362 (2.112)	-	4.070 (0.966)	-	-
HMO	0.414 (0.121)	0.082 (3.021)	-	-	-	-
Number of Regions	0.093 (0.026)	0.004 (1.442)	-	-	-	-
Adults' Health (Star Rating)	0.355 (0.147)	0.404 (0.647)	-	-	-1.697 (0.414)	2.473 (1.280)

Table 2.6: BLP Results including lagged log shares

Variable	Means β	Standard Deviations σ	Interactions with Demographic Variables Black	Hispanic	Rural	Poverty
Constant	0.085 (0.098)	1.015 (0.295)	-	-	-	-
% of PCPs of County Max	0.019 (0.082)	1.099 (0.585)	-	2.060 (0.707)	-	-
HMO	0.335 (0.098)	0.941 (0.286)	-	-	-	-
Number of Regions	0.026 (0.018)	0.004 (0.773)	-	-	-	-
Adults' Health (Star Rating)	0.359 (0.304)	0.035 (2.304)	-	-	-1.296 (0.392)	0.316 (2.111)
Lagged Log Shares	0.659 (0.072)	0.041 (2.099)	-	-	-	-

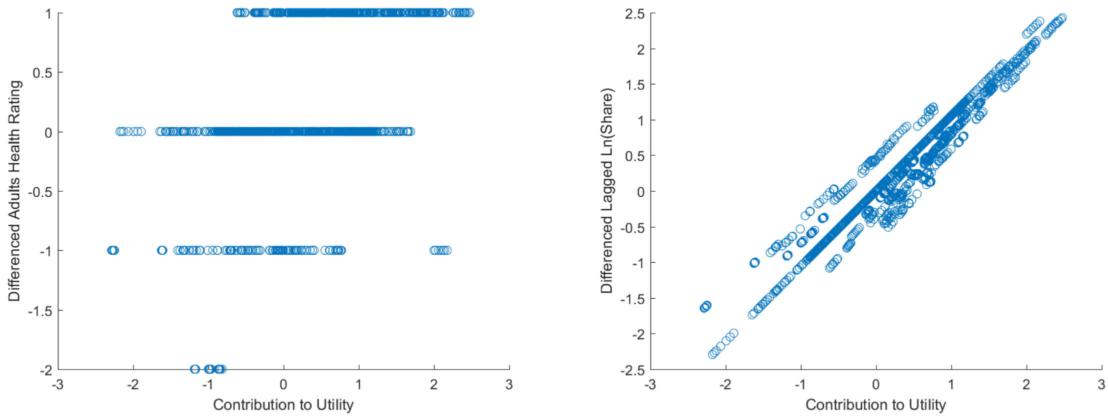
Table 2.7: BLP Results including interaction with adults' health rating and lagged shares

Variable	Means β	Standard Deviations σ	Interactions with Demographic Variables Black	Hispanic	Rural	Poverty
Constant	-0.122 (0.114)	1.094 (0.189)	-	-	-	-
% of PCPs of County Max	-0.423 (0.162)	0.038 (11.854)	5.633 (2.333)	1.043 (1.023)	-	-
HMO	-0.405 (0.474)	0.092 (4.887)	-	-	0.596 (0.685)	1.692 (3.516)
Adults' Health (Star Rating)	-0.141 (0.103)	0.062 (1.143)	-	-	-	-
Lagged Log Shares	1.551 (0.263)	0.757 (0.188)	-	-	-	-
Adults' Health × Lagged Shares	-0.201 (0.062)	0.001 (1.955)	-	-	-	-

2.B Figures

Figure 2.1: Contributions to Utility by Differenced Characteristics

(a) Adults' Health rating (b) Lagged Log Shares



Notes: These figures use the coefficients on the mean of differenced lagged log shares and mean of differenced Adults' Health × lagged log shares from Table 2.7 to calculate the contribution to utility by differenced Adults' Health and differenced lagged log share for each observation in the sample.

2.C Results using Alternative Instruments

This section compares the main results to those using additional instruments. I adapt an instrument introduced by Hausman et al. (1994) and Hausman (1996) of using prices from one city as instruments for other cities. The identifying assumption allows for city-specific valuations of the product to be correlated within a city over time, but independent across cities. Although this model does not have prices, plan characteristics can be used in place of prices, especially since they are closely related to costs. All of the characteristics are plan-specific and do not vary across counties, except for network size (percent of PCPs of county maximum). As such, network size, which is directly reflective of cost of finding and contracting with doctors, could be a good instrument. Due to the fact that each plan is offered in a different number of counties, I cannot generate a set of instruments from this that is similar to Hausman et al. (1994) and Hausman (1996).

I create two network instruments: (1) maximum county PCPs per member, (2) members per maximum county PCPs. The first instrument is calculated by taking the maximum number of PCPs of all plans in the county and dividing by the total enrollment (in thousands) in the county. The second instrument is the inverse of the first. These two instruments provide a county-specific measure of cost that does not vary within a county, but varies across counties. Since this method only results in one instrument, in order to identify the model, other instruments must be included. I add each instrument to the set of instruments used in the main results: the regressors, the average of the characteristics of other plans in the same market, and the interactions of the regressors.

Table 2.8: Results with Added Instrument: Maximum County PCPs per Member

	Means	Standard Deviations	Interactions with Demographic Variables			
Variable	β	σ	Black	Hispanic	Rural	Poverty
Constant	0.080 (0.119)	0.674 (0.664)	-	-	-	-
% of PCPs of County Max	0.431 (0.109)	0.181 (3.997)	-	4.284 (1.985)	-	-
HMO	0.402 (0.099)	0.042 (8.713)	-	-	-	-
Number of Regions	0.091 (0.039)	0.006 (2.202)	-	-	-	-
Adults' Health (Star Rating)	0.374 (0.190)	0.399 (0.548)	-	-	-1.711 (0.321)	2.490 (1.333)

Table 2.9: Results with Added Instrument: Members per Maximum County PCP

	Means	Standard Deviations	Interactions with Demographic Variables			
Variable	β	σ	Black	Hispanic	Rural	Poverty
Constant	0.086 (0.095)	0.664 (0.541)	-	-	-	-
% of PCPs of County Max	0.452 (0.091)	0.480 (1.638)	-	4.064 (1.190)	-	-
HMO	0.437 (0.121)	0.378 (0.919)	-	-	-	-
Number of Regions	0.092 (0.023)	0.003 (1.274)	-	-	-	-
Adults' Health (Star Rating)	0.351 (0.140)	0.183 (1.096)	-	-	-1.803 (0.452)	2.726 (1.179)

Tables 2.8 and 2.9 update the main results of Table 2.5 adding maximum county PCPs per member and members per maximum county PCP to the set of instruments, respec-

tively. In both specifications, the coefficients and the standard errors do not change dramatically. Further, the same coefficients continue to be statistically significant, indicating that the results are not highly sensitive to the instrument set.

Table 2.10: Results with Added Instrument: Maximum County PCPs per Member

Variable	Means β	Standard Deviations σ	Interactions with Demographic Variables Black	Hispanic	Rural	Poverty
Constant	0.101 (0.086)	1.016 (0.208)	-	-	-	-
% of PCPs of County Max	-0.020 (0.073)	0.703 (0.674)	-	2.416 (0.634)	-	-
HMO	0.358 (0.099)	0.939 (0.227)	-	-	-	-
Number of Regions	0.027 (0.016)	-0.001 (0.638)	-	-	-	-
Adults' Health (Star Rating)	0.309 (0.291)	-0.026 (2.218)	-	-	-1.384 (0.374)	0.209 (1.906)
Lagged Log Shares	0.649 (0.040)	0.019 (3.13)	-	-	-	-

Table 2.11: Results with Added Instrument: Members per Maximum County PCP

Variable	Means β	Standard Deviations σ	Interactions with Demographic Variables Black	Hispanic	Rural	Poverty
Constant	0.129 (0.076)	1.054 (0.384)	-	-	-	-
% of PCPs of County Max	-0.042 (0.077)	0.711 (0.738)	-	2.651 (0.803)	-	-
HMO	0.402 (0.086)	0.999 (0.308)	-	-	-	-
Number of Regions	0.031 (0.021)	0.006 (0.529)	-	-	-	-
Adults' Health (Star Rating)	0.431 (0.300)	0.027 (2.145)	-	-	-1.547 (0.374)	0.128 (2.010)
Lagged Log Shares	0.668 (0.096)	0.213 (0.506)	-	-	-	-

Similarly, Tables 2.10 and 2.11 update the main results of Table 2.6 adding maximum county PCPs per member and members per maximum county PCP to the set of instruments, respectively. The results are similar to those main results.

Table 2.12: Results with Added Instrument: Maximum County PCPs per Member

Variable	Means β	Standard Deviations σ	Interactions with Demographic Variables Black	Hispanic	Rural	Poverty
Constant	-0.149 (0.075)	0.991 (0.217)	-	-	-	-
% of PCPs of County Max	-0.325 (0.138)	0.038 (13.762)	4.233 (1.375)	1.382 (0.866)	-	-
HMO	-0.370 (0.436)	0.109 (3.292)	-	-	0.663 (0.857)	1.356 (4.422)
Adults' Health (Star Rating)	-0.138 (0.103)	0.051 (1.179)	-	-	-	-
Lagged Log Shares	1.479 (0.268)	0.670 (0.162)	-	-	-	-
Adults Health × Lagged Shares	-0.198 (0.076)	0.009 (1.256)	-	-	-	-

Table 2.13: Results with Added Instrument: Members per Maximum County PCP

Variable	Means β	Standard Deviations σ	Interactions with Demographic Variables Black	Hispanic	Rural	Poverty
Constant	-0.272 (0.083)	0.767 (0.173)	-	-	-	-
% of PCPs of County Max	-0.192 (0.178)	0.294 (1.898)	4.091 (1.744)	0.774 (0.762)	-	-
HMO	-0.532 (0.370)	0.188 (2.786)	-	-	0.796 (0.575)	2.995 (4.522)
Adults' Health (Star Rating)	-0.217 (0.106)	0.045 (1.160)	-	-	-	-
Lagged Log Shares	1.649 (0.268)	0.756 (0.161)	-	-	-	-
Adults Health × Lagged Shares	-0.236 (0.076)	0.010 (1.357)	-	-	-	-

Lastly, Tables 2.12 and 2.13 update the main results of Table 2.7 adding maximum county PCPs per member and members per maximum county PCP to the set of instruments, respectively. The results are similar to those main results, as well.

Chapter 3

Close Contests and Future Voter Turnout

3.1 Introduction

In the United States, recent presidential election years have experienced low voter turnout: 65% of eligible individuals voted in the 2016 election and that number was only slightly higher at 67% in 2012.[1] At an international level, the turnout in the United States is low compared to most developed nations, as seen in Figure 3.1. Researchers have long studied the reasons for voting and abstaining. Many studies suggest that a series of contemporaneous activities, such as advertising (Ashworth and Clinton, 2007; Coate and Conlin, 2004; Goldstein and Freedman, 2002; Gordon and Hartmann, 2013; Krasno and Green, 2008), close contests (Shachar and Nalebuff, 1999; Stromberg, 2008), campaign spending (Gerber, 1998; Levitt, 1994), economic conditions (Brunner et al., 2011; Burden and Wichowsky, 2014), and specific candidate characteristics (Jones, 2017; Washington, 2006) may influence voter behavior. A growing literature seeks to understand how past occurrences from previous electoral cycles affect persistence in electoral participation, examining whether election outcomes today can affect a person's likelihood of voting in subsequent elections (Coppock and Green, 2016). In this paper, we take a new perspective on this question by exploring how close state contests in Presidential elections can affect future voter turnout. In particular, we study if these close contests differentially affect those who supported losers, winners, or those who did not vote in the previous presidential election.

Instead of looking at the overall closeness of the election as a predictor of future voting behavior, we exploit a unique future of the U.S. Presidential Election system: the electoral college system. Since candidates must win enough state contests to secure an electoral victory, they campaign and focus their effort in close contests where the predicted margin of victory between the two parties is relatively small. While this campaign activity may impact the likelihood that individuals vote in the contemporaneous election, it is also possible that ex-post closeness may have an effect on individual behavior in subsequent elections. These behaviors may differ based on who the individual supported in the ex

[1] Statistic from International Idea Institute for Democracy and Electoral Assistance `https://www.idea.int/data-tools/question-countries-view/522/295/ctr`.

post close state contest and whether or not that individual showed up to vote. Ignoring states that are close in the subsequent election, we explore the extent to which realized close state contests in presidential elections affect future presidential voting behavior.

There are two mechanisms through which a particularly close election may influence future voting behavior that depend on previous voter behavior. First, if individuals exhibit loss aversion (Kahneman and Thaler, 1991; Tversky and Kahneman, 1991), the utility loss from supporting losers may be greater than the utility gain from supporting winners, deterring future political participation for those who supported losing candidates. This effect may be amplified in close elections, where the predicted outcome is closer to random. In these close contests, individuals may have more emotional reactions than to those that are won by wide margins.[2] If loss aversion does not exist in close contests, individuals who supported winners in close elections may decide to continue participating in future elections at equal or higher rates, as their participation resulted in their preferred outcome. Second, people may choose not to vote because of beliefs of zero probabilities of affecting elections outcomes. After a close election, people may update their beliefs that they can affect the outcome of the election, which increases the likelihood of voting in future elections. This would result in previous nonvoters heading to the polls the next election cycle.

We use individual-level voting behavior data from the American National Election Survey (ANES), from 1952-2012, to study how future voting behavior in presidential elections is affected by past election outcomes. In particular, we study how a "close" election today affects the likelihood of voting in the next election, splitting the results for those who voted for the victor, those who voted for the non-victor, and those who did not vote. We define the closeness of elections using the outcomes from each state's electoral contest. We further examine how these effects differ across demographics. Age, gender and income may affect the incentives to vote. Since close elections in one year may result in similarly close elections in the following election cycle, we are careful to exclude all individuals who contemporaneously live in states with close electoral contests.

[2]This is similar to a finding in Card and Dahl (2011), though they look at immediate actions, acts of domestic violence, and close upsets in football games based on expected win margins.

Thus, we are able to identify the impact of ex-post close elections on turnout in the next election. In all models, we include state and time fixed effects to ensure that our comparisons are within a state, as states have distinct electoral environments, and to control for any differences across national election environments that may affect both previous and subsequent turnout.

Our findings suggest that those who report not voting in the previous election are more affected by realized close state electoral contests. Those who did not vote in close contests (but were eligible to vote) were 3.5 percentage points more likely to vote than those who did not vote in states where the contest for electoral votes was not close.[3] The magnitude of this effect on previous non-voters is largest for the youngest (22-29) and the oldest (aged 65 or older) cohorts. For these groups, the results suggest that those who skipped participating in an election were more likely to participate in the subsequent election when the previous contest was close, perhaps suggesting a level of guilt. The results for the young population are in line with the effects found in Meredith (2009), where individuals just eligible to participate in national elections were 7 percentage points more likely to participate in subsequent elections. The estimates were close to zero in magnitude for the middle (age 30-64) cohort. While there is no average effect on subsequent voting for those who chose non-victors, females who voted for a loser in states with slim margins of victory were 3 percentage points less likely to participate in the subsequent election than those who chose a victor in the previous close contest. This effect is even larger (11 percentage points) for low-income eligible voters.[4] These results are robust to a variety of measures of closeness.

Our study primarily contributes to two strands of existing literature. First, we add to previous work explaining factors that may affect persistent voting behaviors. A recent review of the literature by Coppock and Green (2016) shows that shocks to voting have long-run effects on voting habit formation. Previous research could be compartmentalized into three categories: experimental GOTV effects (Gerber et al., 2003; Green and Gerber,

[3]In this specification, we define a close election as one where the margin was within 5 percentage points. The paper uses alternate definitions of closeness for robustness.

[4]In our data, low-income is defined by those earning within the 16 percentile of the income distribution.

2002; Michelson et al., 2003), regression discontinuities based on whether or not a national election occurred in the year the individual became eligible to vote (Meredith, 2009), and quasi-experimental settings shocking voter behavior (Atkinson and Fowler, 2014; Denny and Doyle, 2009; Franklin and Hobolt, 2011; Green and Shachar, 2000). Nearly all of these studies support the fact that shocks to voting have persistent effects. An additional literature uses a more theoretic approach to understanding persistent turnout. Shachar (2003) develops a model where one's current utility depends on previous voting decisions. He estimates the model using data from the 1972 and 1976 US presidential elections and finds that this type of habit formation model fits the data better than a simple party preference model. Shachar (2003) also shows that persistent voting for the same party over time decreases with voter age. We also consider a different type of shock to habit in this paper, by specifically examining how initial vote decisions during particularly close contests differentially affect behavior depending on vote choice in the previous election.

The effect of previous elections on subsequent turnout has been investigated via the spillover effects of gubernatorial races on presidential elections. Erikson et al. (2015) use a regression discontinuity design to show that governors who won by close margins negatively affected vote shares for the subsequent presidential candidate of the same party's election. They attribute this to a balancing of idealogy. We instead focus on competitiveness of the same election, but variation in state's relative influence in the potential election via close Electoral College contests within a state in one year and not the subsequent year.

Second, we contribute to a literature on the predicted closeness of elections. This strand of literature generally finds that elections that are expected to be close increase participation, often through politician effort. Shachar and Nalebuff (1999) develop and structurally estimate a model that assumes US presidential candidates expend effort based on the predicted closeness of an election. Their results suggest that a 1 percent increase in the predicted closeness of a race increases turnout by 0.3 percent. Stromberg (2008) similarly shows that a model where candidates attempt to maximize the probability of winning the presidential election given the complex electoral college system (electoral college votes and predicted closeness of each race) generates similar predictions to actual candidate campaign strategies. Lipsitz (2009) finds that battleground status early in a campaign leads to slightly increased voter turnout; however, their results do not include state fixed effects to account for differences across states in voter turnout. Thus, there could be omitted variable bias remaining due to state unobservable characteristics giving states higher propensities to be battleground states as well as have higher turnouts.[5] Some research has tried to explain this small battleground effect via voting norms (Doherty et al., 2017).

In contrast with the existing literature that finds a link, albeit small, between predicted closeness and turnout, Gerber et al. (2017) find that voters perceive races to be closer than polls would suggest, and that perceived closeness has a minimal, if any, effect on voter turnout. We contribute to this literature by looking at closeness in a different way. Understanding that voters often perceive a contest to be closer than polls would suggest (Gerber et al., 2017), when a contest is realized to be close after the election concludes, do voters change their participation behavior in the following election? A realized close election may affect voter behavior if polls are noisy and voters perceive them to be unreliable measures of how close the race is. These completed elections with slim margins of victory may also particularly resonate with individuals in ways that are specifically tied to their own decisions.

3.2 Data

Our empirical strategy relies on two sources of data: individual level voter data and the closeness of state electoral college contests in presidential elections over time. We detail the data collection of each below.

We use data from the American National Election Studies (ANES) from 1952-2012 to understand individual voting behavior, exploiting an underused question regarding who

[5]With a similar question, Enos and Fowler (2016) examine the "battleground effect" by looking at media markets that span battleground and non-battleground states to determine the relative impact of non-media campaigning. However, this operates under the assumption that close elections do not affect voter turnout, as the battleground state and its non-battleground bordering state differ in perceived and ex post closeness.

the individual voted for in the previous presidential election. We analyze election voting behavior in subsequent presidential elections to see if closeness of the previous election impacts voting behavior four years later. For the presidential election analysis, we use data for each presidential election from 1952-2012.[6] Most states have 15 presidential elections in our data, except for Alaska and Hawaii which did not become states until 1959, and DC whose residents did not receive the right to vote until 1961 under the twenty-third amendment.

We separately collect data on the closeness of each state election for electoral votes from 1948-2008 to determine if the margin of victory is small enough to have a race where the winner is ex ante uncertain. Data on state margin of victories and electoral votes are from the American Presidency Project (APP).[7] The margins of victory (margin) are state-specific for each election and defined as the difference between the percent of the state popular vote garnered by the winner of the state electoral college votes and the percent of the state popular votes received by the runner-up.

There are several elections that complicate the calculation of the margin. From 1944 to 1964, unpledged electors were listed as a candidate on ballot in the South. An unpledged elector is an individual who is nominated as an elector but not tied to a specific candidate. The presence of unpledged electors on ballots in southern states arose due to differences in the Democratic party over segregation and civil rights.[8] Due to the difference in political platform and the fact that the votes for these unpledged electors did not go to the nominated Democratic candidates, we treat unpledged electors as a third party.

Occasionally all of the state electoral votes are not awarded to one candidate. In these instances, we consider the state with the majority of the electoral votes to be the victor.[9] This number is positive for voters of the victor of the state electoral college votes

[6] 1984 is excluded from our analysis since individuals were not asked about previous voting behavior.

[7] The APP is hosted at the University of California, Santa Barbara and is a collaboration between John T. Woolley (UCSB) and Gerhard Peters (Citrus College). http://www.presidency.ucsb.edu

[8] For more on Southern Democrats during this period, see Kuziemko and Washington (2018).

[9] Specifically, each instance of this follows: In 1948, Strom Thurmond, a Dixiecrat, won one electoral vote in Tennessee, while Harry Truman, a Democrat, won the other eleven electoral votes. We consider this state to be won by Democrats. In 1960, in Alabama, five electoral votes were awarded to the Democratic candidate, John F. Candidate, while six were awarded to unpledged electors. We consider a third party to have won this election, with the Democratic party as the runner up. The same year, in Oklahoma, seven electoral votes were awarded to the Republican candidate, Richard Nixon, while one was

and negative for voters of the non-victor. For example, in Pennsylvania in 2012, Barack Obama won 51.97% of the votes, while Mitt Romney won 46.59% of the votes. The margin of victory for this state and year is 5.39%. Those who voted for Obama in Pennsylvania in 2016 would have a margin of 5.39% and those who voted for Romney would have a margin of -5.39%. These margins would be used to determine voting behavior in the following midterm election in 2014, and presidential election in 2016. The ANES data do not do not reveal for whom an individual voted if she did not vote for the Democrat or Republican, just that she voted for "other." For this reason, we exclude from our analysis those who voted for "other" in the previous election. Third party candidates are still essential to our analysis, as they are present in the margin calculations if a third party candidate wins the state electoral votes or is the runner-up.

We focus on two main measures of closeness of elections in our analysis: margins less than 5% and continuous margins. Continuous margins are the absolute value of the margin of victory. In lieu of a negative sign on the margin when voting for the non-victor, an interaction term between margin and an voting for a non-victor accounts for voting for a non-victor in a close election. We use two additional measures of closeness for robustness: margins of less than 1% and margins of less than 10%. Appendix Tables 3.8 and 3.9 show the specific number of close elections and the number of consecutive close election by state for each measure of closeness we define, respectively. As seen in these tables, the same states are not competitive every year, and few states are competitive consecutively across years. Indeed, the probability of a subsequent close election in a given state conditional on having a close election the previous presidential cycle is 0.23, which is not very different than the probability of having a close election given that the

awarded to unpledged electors. We consider the victor of this state to be Nixon. In 1968, North Carolina split its electoral votes: with 12 going to Richard Nixon, the Republican candidate, and one going to the Independent candidate, George Wallace. We consider this election a win for Nixon. Similarly, in 1972, 11 of Virginia's electoral votes were awarded to Nixon, while one was awarded to John Hospers, a Libertarian. We consider this a Republican victory. In 1976, in Washington, eight electoral votes went to Gerald Ford, the Republican candidate, while one elector voted for Ronald Reagan. We identify this as a Republican victory. In 1988, in West Virginia, Michael Dukakis, the Democratic candidate, won five electoral votes, with the sixth elector voting for Lloyd Bentsen who was the Democratic vice presidential nominee. We consider this state to be won by Democrats. In 2004, Minnesota awarded 9 electoral votes to John Kerry, the Democratic candidate, with one faithless elector voting for John Edwards, the Democratic vice presidential nominee. We consider this a Democratic victory.

state was not close the previous cycle (0.18).

Table 3.1 reports the probability of voting for president given that an individual voted for a victor, voted for a non-victor or did not vote in the previous presidential election. We report these conditional probabilities for all elections, and separately for those in states with close (or not close) elections in the previous presidential election.

It is possible that states that were close last election cycle are more likely to be close in the current election cycle. If so, our results may capture the effect of contemporaneous closeness on voter participation. We report the frequency of repeat close elections in Appendix Table 3.9 and see little consecutive overlap within state. We further note that the probability of a close election given the last presidential election was close is 0.23. However, our results could still show that individuals are rationally choosing to participate for the first time in close elections since they may be more likely to influence the state electoral decision. To avoid this, we exclude all states that have close elections in the year individuals are surveyed (based on our 5% margin definition) and reproduce Table 3.1 with all states that are not close in the current year. Table 3.1 further reports the probability of voting for president given that an individual voted for a victor, a non-victor or did not vote in the previous presidential election for this sample.

Table 3.2 aims to descriptively explain persistence in individual voting behavior, though we include state and year fixed effects in each regression to account for cross state and over time differences in preferences. Column (1) reports that those who voted in previous presidential elections are roughly 50 percentage points more likely to vote again the subsequent presidential election. This is a large amount given that the average voter turnout is 68 percent for presidential elections. This suggests that previous participation is a strong predictor of subsequent electoral participation. Column (2) shows that controlling for self-reported interested in politics only slightly decreases the magnitude of the coefficient on previous presidential voting, suggesting that habit formation of voter turnout is not simply based on an individual's utility generated from politics. Column (3) includes individual demographics to better explain turnout and how demographics interact with previous voter participation to predict contemporaneous turnout.

White individuals who voted in the previous election are more likely to participate in the subsequent election than non-white individuals who voted previously. Further, young individuals (those under 35) who voted in a previous election were less likely to participate in a subsequent election than older individuals who voted last election. While low income voters who did not participate last cycle are less likely to participate again than middle income individuals who did not vote, there is no difference in low and middle income individuals who voted last election cycle. Surprisingly, those in the highest part of the income distribution who voted last election are less likely to vote again than middle income individuals who previously participated.

3.3 Methodology

The closeness of the presidential election in a given state can inform an individual's future voting behavior through several potential mechanisms. First, the closeness of the state electoral contest can ex-post inform an individual on the probability of influencing the outcome of the state election. Individuals who did or did not participate in a close election may be more likely to participate in subsequent elections if they think they are more likely to be pivotal in the future. The second potential mechanism is behavioral in nature. If an individual did not vote in an election that ended up being close, that person may feel remorse and be more likely to participate in the subsequent presidential election. Similarly, individuals who voted for a non-victor in a close election may be less likely to vote again if they feel as if their votes were not influential and those who voted for a victor in a close election may be more likely to vote again if they feel as if their votes were pivotal.

We exploit variation in the closeness of state electoral votes in the previous presidential election across individuals and individuals' past voting behavior to explain their likelihood of participating in the subsequent presidential election. Our identification strategy relies on quasi-random within state variation in the closeness of the previous election. Specifically, we estimate Equation 3.1, where Y_{ist} equals one if individual i in state s in year t voted in the current election election cycle, No Vote equals one if the individual did not vote in the previous presidential election and zero otherwise, and Voted Non-Victor equals one if the individual voted for a loser of the state's electoral votes in the last election and zero otherwise. Close entails one of the four measures of closeness explained above, where our preferred specification is a dummy variable equal to one if the state electoral college contest was within five percentage points and zero otherwise. Our main coefficients of interest are α_4 and α_5, which capture the interaction between closeness and previous voter behavior.

$$\begin{aligned} Y_{ist} = {} & \alpha_0 + \alpha_1 \text{ No Vote}_{ist} + \alpha_2 \text{ Voted Non-Victor}_{ist} \\ & + \alpha_3 \text{ Close}_{st} + \alpha_4 \text{ No Vote} \times \text{ Close}_{ist} \\ & + \alpha_5 \text{ Voted Non-Victor} \times \text{ Close}_{ist} + \delta_s + \gamma_t + \varepsilon_{ist} \end{aligned} \tag{3.1}$$

In Equation 3.1, we further include state fixed effects (δ_s) to account for differences across states in persistent political participation and the state electoral environment and year fixed effects (γ_t) to control for changes in participation and the evolution of electoral contests over time. These fixed effects allow our identification strategy to make cross state comparisons in changes in within state closeness over time. This, for example, accounts for the different political preferences in Arkansas and Colorado and the fact that participation in politics was different in 1974 than 2008. We are careful to cluster our standard errors at the state level throughout and provide standard errors adjusted for heteroskedasticity.[10] In order to avoid capturing any effects of recurrent close elections, we focus our analysis only on those that are not close in the current year, dropping those states that have close current electoral elections. Here we define not close elections as those with margins greater than 5%.

[10]We do not use the ANES weights in our analysis due to inconsistencies in the weights across years. For the midterm election analysis, for the five years of data, weights are only reported for 1958 and in this year, are only reported as values 1 or 2. In the rest of the years, weights are not reported in the codebooks, and the aggregate data reports a 1 for each individual. For the presidential election analysis, seven years (1952, 1956, 1964, 1968, 1972, 1980 and 1988) are missing weights, while years 1960 and 1976 have anomalous weights.

3.4 Results

We seek to document the effect of close previous elections on the persistence in voter turnout for the sample of elections that are not close in the current year. Table 3.3 shows the effects by measure of closeness of previous election. First, we find that those who did not vote in the previous election were more likely to participate in the subsequent presidential election if the previous state electoral contest was close across all measures. The magnitude suggests that when compared to those voting for victors in close states in the previous presidential election, those who did not vote were 5 to 6 percentage points more likely to participate in the following presidential election, which is roughly 8% of the mean. This effect is statistically different from zero for all measures of closeness for the previous election. This suggests that non-voters are affected by previous state electoral contests and the perception of influencing an election, suggesting that there is some guilt or remorse from not voting in previous close contests. There is no difference in the persistence across those who voted for victors and non-victors in the previous election. The effects are similar if we use the continuous measure of vote margin, where smaller margins increase participation for previous non-voters.

The effect of the previous election year's closeness on current participation for non-voters in Table 3.3 could be caused by young people voting for the first time after not being eligible in the previous election year. Table 3.4 drops individuals ages 18-21 from the specification, since they were previously ineligible to vote. The results show that focusing only on those who were eligible to vote slightly reduces the effect of the previous election year's closeness on current participation for nonvoters. This effect is still statistically different from zero for all measures except for the 1% measure of closeness, though that specification has less power and its magnitude is not different in magnitude than the other magnitudes in the specifications of closeness.

We now explore heterogeneity in our main effect from Table 3.4 by gender, age, and income to determine which segments of the population are most affected by close elections.[11] For these results, we focus on our 5% measure of closeness and our continuous

[11] We find no statistically different effects across race.

measures, though our results are robust to the other measures and these results are reported in the Appendix. Table 3.5 separates the results by gender, where we see that females are more affected by close margins than males. In addition, females who supported losing candidates were less likely to vote in a subsequent presidential election than those who supported winners in similarly close races. While this effect may suggest that females supporting non-victors in close elections are less likely to vote next election cycle, this result is only marginally significant at the 10 percent level and not statistically different from the average effect in Table 3.4.[12] This evidence could loosely support research suggesting that females exhibit loss aversion more than men (Eckel and Grossman, 2002). The fact that females and males respond differently to ex-post close elections is similar to their differences in responses to advertising strategies found in Galasso and Nannicini (2013).

Table 3.6 shows the effects by age groups, where we find that some of the effect is coming from the young voters. Young individuals who did not vote in the previous election were more likely to participate in the subsequent presidential election if the previous state electoral contest was close across all measures, except using the 1% margin level (see Appendix Table 3.12). These results are excluding those 18-21 who are voting for the first time, as they were not eligible to vote in the previous election. This result suggests that closeness matters in engaging young voters for the first time and can potentially make voting a habit. This population has the lowest average rate of voter turnout (56%) with the effect roughly 14 percent of the mean at the 5% margin level. While some may argue that young people are the most likely to move, Brown et al. (2013) report that 82% of 18 year olds reside in the same state at age 29. In Column (5), we see that those over 65 are more likely to participate in the subsequent presidential election if the previous state electoral contest was close, though this result is not robust across measures of closeness.

While the overall effect on previous non-voters is not statistically different from the average effect when we split our sample based on income, we find evidence across measures that low-income individuals who voted for losing candidates last election season in close

[12] The results for the other measures of closeness and including individuals age 18-21 are included in Appendix Tables 3.10 and 3.11, respectively.

contests are less likely to participate in subsequent presidential elections than those who supported winners (Table 3.7). These effects on low-income individuals–those below the 16th percentile of income–are important in magnitude and statistical significance. Low-income individuals have lower average rates of voter turnout, where roughly 54 percent of low income individuals surveyed voted in the given presidential contest. Thus, the effects reported represent an 11.6 percentage point decrease in subsequent turnout, or approximately one-fifth of mean turnout. Learning to target low-income individuals who previously voted for losing candidates can have important implications for participation among this group and inform campaigns on who to appropriately target in subsequent elections. This effect is not statistically significant at the 1% or 10% margin but the sign is consistent (see Appendix Table 3.13). Further, for non-low income individuals, those who did not vote in a close election are more likely to vote if the previous election was close. This is not true of low income individuals. The fact that low-income individuals are susceptible to shocks in turnout is comparable to literature finding that low-income and less educated individuals are more greatly affected by stricter voter id laws (Alvarez et al., 2007). However, as Hodler et al. (2015) find, decreasing the cost of voting may increase participation among groups who are less educated and politically aware, which could actually decrease lower expenditures on welfare.[13]

3.5 Discussion

While our results suggest that previous closeness is an important determinant for the persistence in voting, there are several caveats to mention with this research. First, given the nature of the data, measurement error can occur such that participants are likely to report voting in previous elections when they did not. Shachar and Eckstein (2007) show that in the Israeli context, 23 percent of voters misresport their previous electoral behavior. For this to be a threat to our identification strategy, reporting will need to vary by close and not close state electoral contests. Research suggesting potential bandwagon

[13]Garmann (2016) uses a natural experiment in Germany to show that making local elections concurrent increases turnout, though he cautions that this could again increase participation among the least informed voters.

effects in vote choice imply that this would shift more voters to state that they supported the winner (Morton et al., 2015). Shachar and Eckstein (2007) further find that voters are more likely to report past voting to make it more consistent with current choices.[14] If that is the case, this would still need to vary by close and not close elections for it to bias the results. Assuming that this misreporting is more likely to happen in close elections, this would suggest that if people were more likely to report supporting the winner in the previous election, they may also be more likely to state that they voted again in the present election. This would make the effect of not voting in close contests relatively conservative. In addition, since the bulk of our findings are for those who reported not voting in the previous election and average effects for those who did and did not support the winning candidate do not differ, we think our estimates likely understate the true effect.

Another potential concern may be that we measure closeness at the conclusion of the race. Using an ex-post measure of closeness allows us to use additional years of data for which reliable polling information is not available. Research has found that both election markets and polls are good predictors of election outcomes, with their predictive power rising as the election nears (Berg et al., 2008; Wolfers and Zitzewitz, 2004). Although predictive closeness is a strong measure of ex-post closeness, it is possible that a poll incorrectly predicts closeness or a state is competitive for a short period in a contemporaneous election; to the extent that contemporaneous predicted closeness affects mobilization (Shachar, 2003), this could increase voter turnout in that state.[15] Since we exclude states with contemporaneous ex-post close elections, this would only bias our results if this inaccurate polling occurs in states that were close at some point in the previous presidential election. We argue that our least restrictive competitiveness measure–races within 10 percentage points–allows us to rule out that a state was at one point close in the current election, did not end up within a 10 point margin, and saw an

[14]Shachar (2003) reports that two out of three individuals vote for the same party in subsequent elections.

[15]In a study of Swiss referenda, Bursztyn et al. (2017) find that closer elections only increase turnout where polls exist. In the US context, it is plausible that competitive states are more likely to have their own polls.

increase in turnout due to the closeness at one point in the campaign.

An additional constraint is the lack of reliable survey weights in the data over time to correct for the bias in who decides to complete the survey. If more people in the sample are more likely to turnout and complete the survey, our results may not be generalizable to other populations. Figure 3.2 plots the voting rates in each presidential election, for the ANES data and using national voting statistics. Although the two series do not match exactly, the trends are similar. We do see that ANES respondents have higher voting rates than in the voting statistics. If we drop each year one at a time in a leave-one-out approach, none of our results are statistically different from the average effect.[16] To look at this more carefully, we next look at the percent of people in each state who vote in each presidential election. Figure 3.3 compares the percent of people in each state who voted, in the ANES data and in voting statistics and then correlates that to the competitiveness in that state's prior election. Each observation is the difference (Actual-ABES) in a given state and year, where the x-axis shows the margin of victory. Since the difference provides a negative estimate in most cases, the ANES data provides an overstatement of voter turnout. However, fitting a line between the difference and competitiveness results in a flat slope, suggesting the two are uncorrelated. We repeat this by year in Figure 3.4, where the relatively flat slope holds up in most years, with the exception of 1992 and 2008. In addition, we formally test that the difference in turnout measures is not dependent on closeness in Table 3.15. Here, we include state and year fixed effects, as we do in our primary specifications. In all cases, the effect of closeness on the difference in measures is not statistically different from zero at the ten percent level. The magnitudes are also relatively close to zero, reflecting between a 1 percentage point difference in measures based on the 5% closeness measure.

Finally, while we find interesting subgroups through which we expect the effects of closeness to operate (close states, females, the young, and low-income individuals), we cannot pin down the precise mechanisms through which previous close elections affect previous non-voters. For example, it could be that since presidential campaigns operate

[16] These results are available upon requestn.

more heavily in contested states, these activities remain memorable for individuals even if they did not vote. Given research on the limited duration of the effects of advertising (Gerber et al., 2011; Hill et al., 2013), it is unlikely that these effects could persist over four years.[17]

3.6 Conclusion

In this paper, we explore how close state electoral contests can affect future voter turnout. In particular, we study if these close contests differentially affect those who supported losers, winners, or those who did not vote in the previous electoral contest. Using individual-level voting behavior data, we study how future voting behavior in presidential elections is affected by past election outcomes. Our findings suggest that those who report not voting in the previous election are most affected by realized close state electoral contests. Those who did not vote in close contests (but were eligible to vote) were 3.5 percentage points more likely to vote than those who did not vote in states where the contest for electoral votes was not close. The magnitude of this effect on previous non-voters is largest for the youngest (22-29) and the oldest (aged 65 or older) eligible voters. While there is no average effect on subsequent voting for those who chose a non-victor, females who voted for the loser of a contest in states with slim margins of victory were 3 percentage points less likely to participate in the subsequent election. This effect is even larger (11 percentage points) for low-income ($<$ 16 percentile) eligible voters.

Our results have implications for a broader literature studying how persistent voter behavior responds to external forces. While others have examined the effects of close contemporaneous contests on voter behavior, few studies investigate voter behavior for contests that are not close. While these results might not be directly relevant for a presidential election, where candidates only campaign in states that are contemporaneously close, the findings are important for down-ballot candidates. If inactive voters are more likely to show up to the polls in presidential years following a previous close presidential contest, candidates for local office should internalize that behavior in their campaign

[17] Hill et al. (2013) find that the rate of decay is at most six weeks for presidential elections.

strategies. Candidates for Congress, governor, or local office should further consider that certain individuals–women and low-income voters who chose the losing candidate in a previous close state presidential election–may be less likely to show up, even though they did in the past. Mobilizing these groups may require more effort on the part of campaigns due to potential loss aversion. Local candidates should re-consider their campaign strategies based on this information.

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3.7 Tables

Table 3.1: Probability of Voting for President

	all elections	close previous elections	not close previous elections
All elections			
Voted for Winner in Previous Election	0.8233 (0.0035)	0.8180 (0.0071)	0.8250 (0.0040)
Voted for Non-Victor in Previous Election	0.8249 (0.0039)	0.8095 (0.0076)	0.8311 (0.0046)
Did not Vote in Previous Election	0.3305 (0.0049)	0.3546 (0.0101)	0.3225 (0.0057)
Number of Observations	30,506	7,883	22,623
Non-close elections			
Voted for Winner in Previous Election	0.8252 (0.0040)	0.8046 (0.0087)	0.8315 (0.0045)
Voted for Non-Victor in Previous Election	0.8202 (0.0045)	0.7987 (0.0091)	0.8282 (0.0052)
Did not Vote in Previous Election	0.3348 (0.0057)	0.3683 (0.0116)	0.3235 (0.0065)
Number of Observations	23,085	5,785	17,300

Notes: Standard errors in parentheses. Close elections are defined as those with a margin of victory less than 5%. The means in columns (2) and (3) are statistically different at the 5% significance level, except for those who voted for a winner in the previous election in the sample of all elections.

Table 3.2: Probability of voting in next election

	(1)	(2)	(3)
voted in previous pres. election	0.482***	0.442***	0.509***
	(0.00851)	(0.00845)	(0.0115)
some interest in politics		0.157***	
		(0.00962)	
very interested in politics		0.218***	
		(0.00944)	
female			-0.00688
			(0.0118)
white			0.00752
			(0.0122)
young			0.116***
			(0.00985)
low income			-0.0828***
			(0.0107)
high income			0.116***
			(0.0428)
voted × female			-0.00722
			(0.0110)
voted × white			0.0259*
			(0.0137)
voted × young			-0.196***
			(0.0122)
voted × low income			0.0134
			(0.0124)
voted × high income			-0.0933**
			(0.0413)
Mean DV	0.678	0.677	0.678
Number of Years	15	15	15
Number of States	51	51	51
Observations	30506	29323	30506

Notes: Standard errors reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All columns include year and state fixed effects and have standard errors that are clustered at the state level.

Table 3.3: Probability of voting for president in next election: for not close elections

	$< 1\%$	$< 5\%$	$< 10\%$	continuous
didn't vote in pres. election	-0.476***	-0.490***	-0.500***	-0.447***
	(0.00990)	(0.0104)	(0.0110)	(0.0143)
voted for non-victor	0.00580	0.00909	0.0102	-0.00676
	(0.00589)	(0.00751)	(0.00844)	(0.00903)
close margin	-0.00294	-0.0208*	-0.0117	
	(0.0199)	(0.0121)	(0.00839)	
didn't vote × close	0.0490**	0.0644***	0.0608***	
	(0.0229)	(0.0122)	(0.0132)	
voted for non-victor × close	-0.00000917	-0.00933	-0.00678	
	(0.0291)	(0.0156)	(0.0130)	
margin of victory				-0.0395
				(0.0464)
didn't vote × margin				-0.183***
				(0.0661)
voted for non-victor × margin				0.0989
				(0.0651)
Mean DV	0.677	0.677	0.677	0.677
Number of Years	15	15	15	15
Number of States	51	51	51	51
Observations	23085	23085	23085	23085

Notes: Standard errors reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. 'Close margin' and 'close' is defined as margin of victory less than 5%. Victors are winners of the electoral votes within a state. All columns include year and state fixed effects and have standard errors that are clustered at the state level.

Table 3.4: Probability of voting for president in next election: for not close elections for age 22+

	$< 1\%$	$< 5\%$	$< 10\%$	continuous
didn't vote in pres. election	-0.496***	-0.508***	-0.514***	-0.471***
	(0.00878)	(0.00922)	(0.0104)	(0.0137)
voted for non-victor	0.00584	0.00918	0.00983	-0.00701
	(0.00587)	(0.00742)	(0.00814)	(0.00923)
close margin	-0.00290	-0.0215*	-0.0145	
	(0.0194)	(0.0128)	(0.00894)	
didn't vote × close	0.0437	0.0562***	0.0476***	
	(0.0279)	(0.0142)	(0.0154)	
voted for non-victor × close	-0.00312	-0.0107	-0.00667	
	(0.0278)	(0.0161)	(0.0131)	
margin of victory				-0.0307
				(0.0450)
didn't vote × margin				-0.153**
				(0.0624)
voted for non-victor × margin				0.0990
				(0.0648)
Mean DV	0.688	0.688	0.688	0.688
Number of Years	15	15	15	15
Number of States	51	51	51	51
Observations	21928	21928	21928	21928

Notes: Standard errors reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. 'Close margin' and 'close' is defined as margin of victory less than 5%. Victors are winners of the electoral votes within a state. All columns include year and state fixed effects and have standard errors that are clustered at the state level.

Table 3.5: Probability of voting for president in next election: for not close elections by gender for age 22+

	female		male	
	(1)	(2)	(3)	(4)
didn't vote in pres. election	-0.512***	-0.469***	-0.497***	-0.476***
	(0.0105)	(0.0164)	(0.0119)	(0.0177)
voted for non-victor	0.0110	-0.0119	0.00868	-0.00175
	(0.00938)	(0.0144)	(0.0116)	(0.0151)
close margin	-0.0361**		-0.000796	
	(0.0139)		(0.0195)	
didn't vote × close	0.0502**		0.0617***	
	(0.0208)		(0.0194)	
voted for non-victor × close	-0.0291*		0.00636	
	(0.0171)		(0.0241)	
margin of victory		0.00381		-0.0763
		(0.0623)		(0.0645)
didn't vote × margin		-0.208***		-0.0431
		(0.0740)		(0.0971)
voted for non-victor × margin		0.110		0.0873
		(0.0920)		(0.0938)
Mean DV	0.668	0.668	0.711	0.711
Number of Years	15	15	15	15
Number of States	51	51	51	51
Observations	11991	11991	9937	9937

Notes: Standard errors reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. 'Close margin' and 'close' in columns (1) and (3) is defined as margin of victory less than 5%. Victors are winners of the electoral votes within a state. All columns include year and state fixed effects and have standard errors that are clustered at the state level.

Table 3.6: Probability of voting for president in next election: for not close elections by age

	22-29		30-64		65+	
	(1)	(2)	(3)	(4)	(5)	(6)
didn't vote in pres. election	-0.381***	-0.308***	-0.531***	-0.518***	-0.595***	-0.561***
	(0.0279)	(0.0286)	(0.0103)	(0.0140)	(0.0156)	(0.0343)
voted for non-victor	0.0230	0.0219	-0.0000395	-0.0146	0.0312**	0.0114
	(0.0224)	(0.0308)	(0.00895)	(0.0129)	(0.0155)	(0.0224)
close margin	-0.0239		-0.0200		-0.0188	
	(0.0415)		(0.0173)		(0.0343)	
didn't vote × close	0.0815*		0.0175		0.0943**	
	(0.0445)		(0.0258)		(0.0369)	
voted for non-victor × close	-0.00945		-0.00390		-0.0301	
	(0.0468)		(0.0224)		(0.0300)	
margin of victory		0.0483		-0.0741		0.100
		(0.150)		(0.0457)		(0.0963)
didn't vote × margin		-0.360**		-0.0516		-0.0836
		(0.142)		(0.0648)		(0.179)
voted for non-victor × margin		0.00469		0.0992		0.0928
		(0.148)		(0.0887)		(0.112)
Mean DV	0.559	0.559	0.709	0.709	0.723	0.723
Number of Years	15	15	15	15	15	15
Number of States	50	50	51	51	50	50
Observations	3486	3486	14512	14512	3930	3930

Notes: Standard errors reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. 'Close margin' and 'close' in columns (1) and (3) is defined as margin of victory less than 5%. Victors are winners of the electoral votes within a state. All columns include year and state fixed effects and have standard errors that are clustered at the state level.

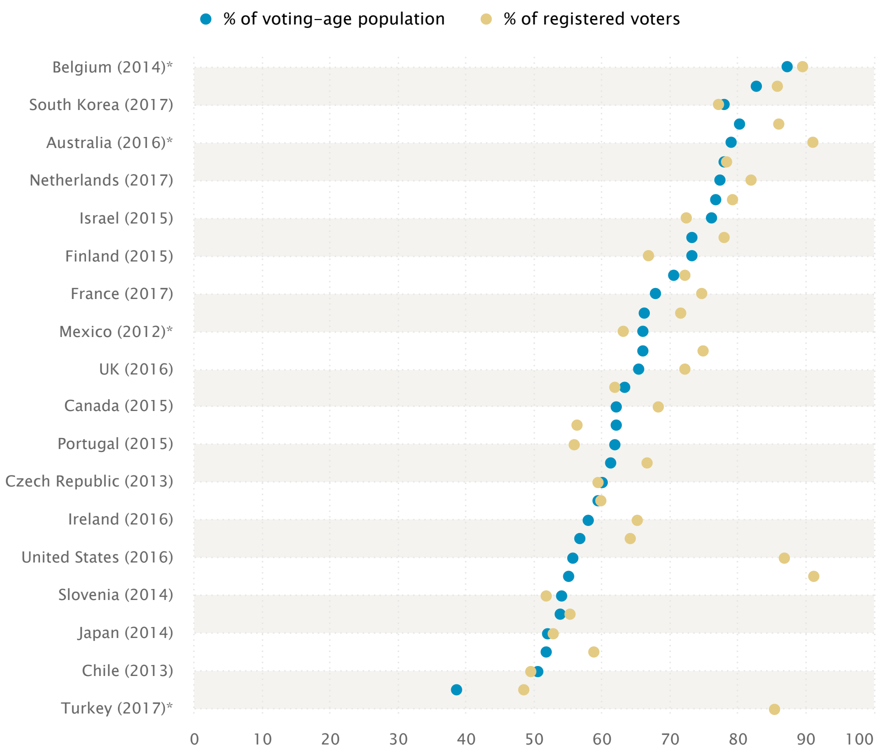
Table 3.7: Probability of voting for president in next election: for not close elections by income for age 22+

	low income		not low income	
	(1)	(2)	(3)	(4)
didn't vote in pres. election	-0.509***	-0.487***	-0.486***	-0.454***
	(0.0184)	(0.0270)	(0.0107)	(0.0157)
voted for non-victor	0.0509**	-0.0287	0.00482	0.000239
	(0.0194)	(0.0243)	(0.00849)	(0.0103)
close margin	0.0322		-0.0284*	
	(0.0334)		(0.0142)	
didn't vote × close	0.00816		0.0458**	
	(0.0396)		(0.0179)	
voted for non-victor × close	-0.116***		0.000360	
	(0.0298)		(0.0199)	
margin of victory		-0.0786		-0.00806
		(0.121)		(0.0503)
didn't vote × margin		-0.137		-0.147*
		(0.111)		(0.0766)
voted for non-victor × margin		0.380***		0.0322
		(0.132)		(0.0701)
Mean DV	0.539	0.539	0.725	0.725
Number of Years	15	15	15	15
Number of States	50	50	51	51
Observations	3554	3554	17191	17191

Notes: Standard errors reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. 'Close margin' and 'close' in columns (1) and (3) is defined as margin of victory less than 5%. Victors are winners of the electoral votes within a state. All columns include year and state fixed effects and have standard errors that are clustered at the state level. Low income is defined as those with incomes from 0 to 16 percentile, as reported by ANES.

3.8 Figures

Figure 3.1: Voter turnout in recent national elections



Source: Pew Research Center (2017) `http://www.pewresearch.org/fact-tank/2017/05/15/u-s-voter-turnout-trails-most-developed-countries/`

Figure 3.2: Percent that vote in presidential elections

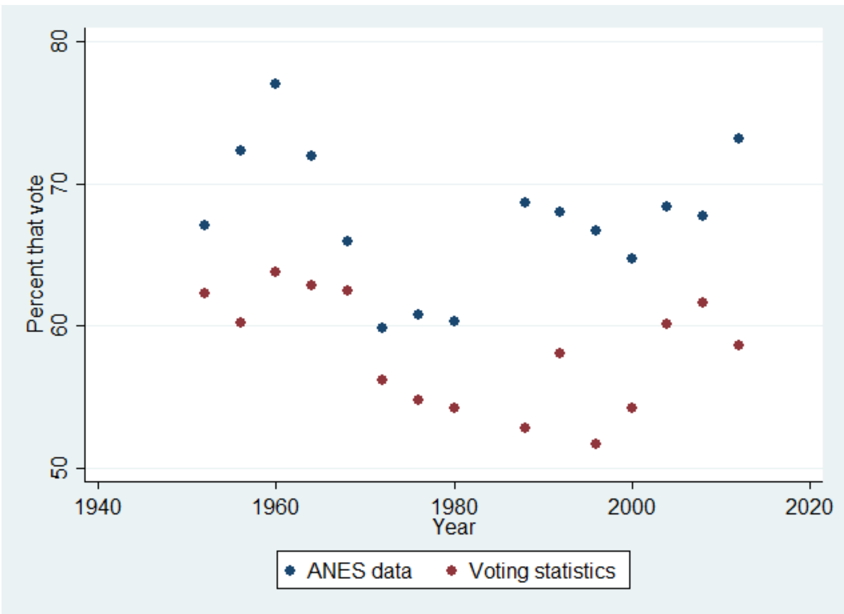


Figure 3.3: State voting in ANES and CPS and Competitiveness

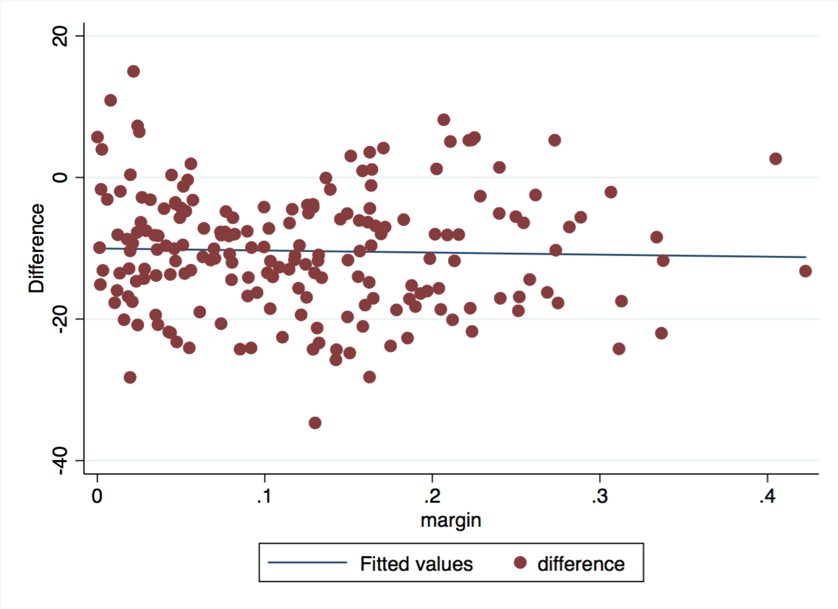
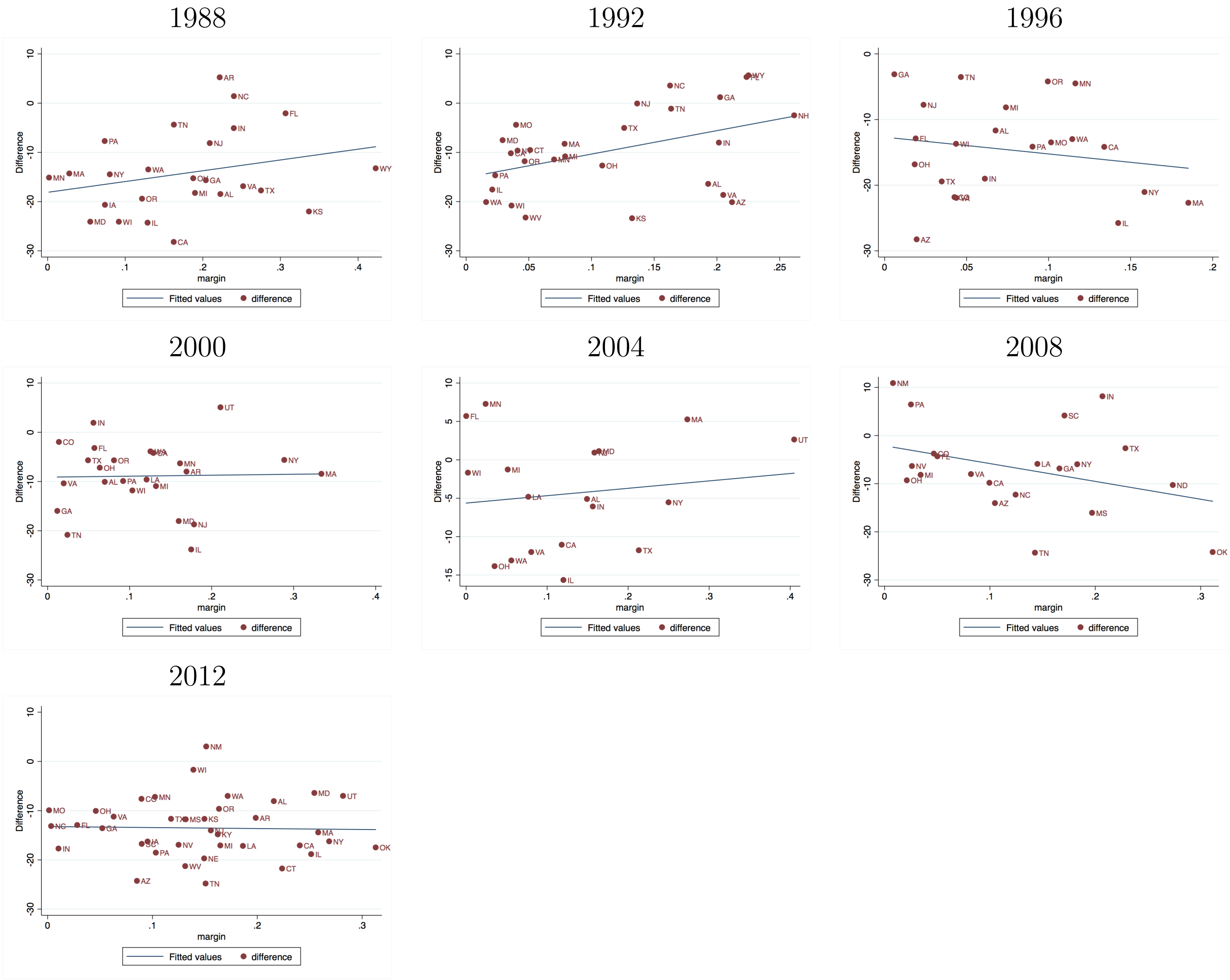


Figure 3.4: State voting in ANES and CPS and Competitiveness by year



3.A Appendix

Table 3.8: Number of Close Presidential Elections

State	Number of Elections	Close margin		
		< 1%	< 5%	< 10%
AK	13	0	2	3
AL	16	0	1	3
AR	16	1	1	6
AZ	16	1	3	6
CA	16	2	5	6
CO	16	0	3	9
CT	16	0	1	7
DC	12	0	0	0
DE	16	0	5	8
FL	16	1	5	9
GA	16	1	2	4
HI	13	1	3	5
IA	16	2	4	7
ID	16	0	2	3
IL	16	2	5	7
IN	16	1	2	5
KS	16	0	0	4
KY	16	2	4	8
LA	16	0	1	5
MA	16	1	2	5
MD	16	0	4	7
ME	16	1	2	5
MI	16	0	3	9
MN	16	1	5	8
MO	16	3	8	11
MS	16	0	3	5
MT	16	0	4	8
NC	16	2	6	8
ND	16	0	0	4
NE	16	0	0	2
NH	16	0	3	8
NJ	16	1	5	6
NM	16	3	5	7
NV	16	0	7	8
NY	16	1	4	7
OH	16	2	7	9
OK	16	0	1	4
OR	16	2	5	10
PA	16	0	7	12
RI	16	0	2	3
SC	16	0	3	7
SD	16	0	4	7
TN	16	3	7	8
TX	16	0	5	6
UT	16	0	0	3
VA	16	0	3	9
VT	16	0	1	4
WA	16	0	4	9
WI	16	2	9	11
WV	16	0	3	7
WY	16	0	1	2

1984 is included in the table, but ANES did not ask about previous election voting history in that year.

Table 3.9: Number of Consecutive Close Presidential Elections

State	Number of Consecutive Elections	Close margin < 1%	< 5%	< 10%
AK	12	0	0	0
AL	15	0	0	1
AR	15	0	0	2
AZ	15	0	1	2
CA	15	0	0	0
CO	15	0	1	5
CT	15	0	0	2
DC	11	0	0	0
DE	15	0	1	2
FL	15	0	1	6
GA	15	0	1	1
HI	12	0	1	1
IA	15	1	1	2
ID	15	0	0	1
IL	15	0	0	2
IN	15	0	0	1
KS	15	0	0	0
KY	15	0	1	4
LA	15	0	0	1
MA	15	0	1	2
MD	15	0	0	3
ME	15	0	1	2
MI	15	0	0	3
MN	15	0	2	4
MO	15	1	2	6
MS	15	0	1	2
MT	15	0	1	2
NC	15	0	2	3
ND	15	0	0	0
NE	15	0	0	0
NH	15	0	1	4
NJ	15	0	0	0
NM	15	1	1	4
NV	15	0	3	3
NY	15	0	1	3
OH	15	0	2	4
OK	15	0	0	1
OR	15	0	1	5
PA	15	0	1	8
RI	15	0	0	0
SC	15	0	0	1
SD	15	0	1	3
TN	15	1	3	4
TX	15	0	1	1
UT	15	0	0	1
VA	15	0	1	5
VT	15	0	0	0
WA	15	0	0	4
WI	15	1	3	7
WV	15	0	0	2
WY	15	0	0	0

1984 is included in the table, but ANES did not ask about previous election voting history in that year.

Table 3.10: Probability of voting for president in next election: for not close elections by gender for age 22+

	female		male	
	$< 1\%$	$< 10\%$	$< 1\%$	$< 10\%$
didn't vote in pres. election	-0.501***	-0.521***	-0.485***	-0.499***
	(0.0101)	(0.0125)	(0.0113)	(0.0136)
voted for non-victor	0.00335	0.00687	0.00865	0.0127
	(0.00821)	(0.0119)	(0.00961)	(0.0125)
close margin	0.00650		-0.0129	
	(0.0278)		(0.0265)	
didn't vote × close	0.0325		0.0595	
	(0.0360)		(0.0358)	
voted for non-victor × close	-0.0299		0.0222	
	(0.0354)		(0.0317)	
close margin		-0.0176		-0.0102
		(0.0122)		(0.0113)
didn't vote × close		0.0492**		0.0406**
		(0.0209)		(0.0195)
voted for non-victor × close		-0.00796		-0.00469
		(0.0198)		(0.0171)
Mean DV	0.668	0.668	0.711	0.711
Number of Years	15	15	15	15
Number of States	51	51	51	51
Observations	11991	11991	9937	9937

Notes: Standard errors reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Victors are winners of the electoral votes within a state. All columns include year and state fixed effects and have standard errors that are clustered at the state level.

Table 3.11: Probability of voting for president in next election: for not close elections by gender

	female		male	
	(1)	(2)	(3)	(4)
didn't vote in pres. election	-0.494***	-0.443***	-0.479***	-0.452***
	(0.0120)	(0.0177)	(0.0127)	(0.0173)
voted for non-victor	0.0118	-0.0105	0.00785	-0.00286
	(0.00970)	(0.0140)	(0.0114)	(0.0150)
close margin	-0.0356**		-0.000161	
	(0.0138)		(0.0185)	
didn't vote × close	0.0675***		0.0584***	
	(0.0188)		(0.0207)	
voted for non-victor × close	-0.0273		0.00687	
	(0.0172)		(0.0235)	
margin of victory		-0.00786		-0.0815
		(0.0626)		(0.0647)
didn't vote × margin		-0.235***		-0.0839
		(0.0759)		(0.105)
voted for non-victor × margin		0.108		0.0911
		(0.0911)		(0.0947)
Mean DV	0.658	0.658	0.699	0.699
Number of Years	15	15	15	15
Number of States	51	51	51	51
Observations	12632	12632	10453	10453

Notes: Standard errors reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Victors are winners of the electoral votes within a state. All columns include year and state fixed effects and have standard errors that are clustered at the state level.

Table 3.12: Probability of voting for president in next election: for not close elections by age

	22-29		30-64		65+	
	$< 1\%$	$< 10\%$	$< 1\%$	$< 10\%$	$< 1\%$	$< 10\%$
didn't vote in pres. election	-0.365***	-0.406***	-0.526***	-0.528***	-0.576***	-0.616***
	(0.0244)	(0.0279)	(0.00971)	(0.0112)	(0.0159)	(0.0199)
voted for non-victor	0.0171	0.000924	-0.00147	0.00599	0.0245*	0.0234
	(0.0235)	(0.0265)	(0.00800)	(0.0103)	(0.0133)	(0.0161)
close margin	-0.00159	-0.0628*	0.00472	0.000453	-0.0395	-0.0323
	(0.0585)	(0.0333)	(0.0203)	(0.0116)	(0.0739)	(0.0226)
didn't vote × close	0.0859	0.108***	-0.00368	0.00352	0.0448	0.101***
	(0.0682)	(0.0362)	(0.0446)	(0.0178)	(0.108)	(0.0287)
voted for non-victor × close	0.0130	0.0483	-0.000165	-0.0157	-0.0227	0.00256
	(0.0907)	(0.0352)	(0.0263)	(0.0172)	(0.0701)	(0.0254)
Mean DV	0.559	0.559	0.709	0.709	0.723	0.723
Number of Years	15	15	15	15	15	15
Number of States	50	50	51	51	50	50
Observations	3486	3486	14512	14512	3930	3930

Notes: Standard errors reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All columns include year and state fixed effects and have standard errors that are clustered at the state level.s

Table 3.13: Probability of voting for president in next election: for not close elections by income for age 22+

	low income		not low income	
	$< 1\%$	$< 10\%$	$< 1\%$	$< 10\%$
didn't vote in pres. election	-0.506***	-0.526***	-0.477***	-0.490***
	(0.0163)	(0.0197)	(0.0103)	(0.0128)
voted for non-victor	0.0262	0.0427*	0.00373	0.00533
	(0.0183)	(0.0217)	(0.00681)	(0.00904)
close margin	0.0216	0.00481	-0.00826	-0.0164*
	(0.0609)	(0.0290)	(0.0225)	(0.00966)
didn't vote × close	-0.0550	0.0449	0.0544	0.0362*
	(0.0776)	(0.0390)	(0.0392)	(0.0203)
voted for non-victor × close	-0.0626	-0.0445	0.00725	-0.000564
	(0.0723)	(0.0331)	(0.0315)	(0.0142)
Mean DV	0.539	0.539	0.725	0.725
Number of Years	15	15	15	15
Number of States	50	50	51	51
Observations	3554	3554	17191	17191

Notes: Standard errors reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. 'Close margin' and 'close' in columns (1) and (3) is defined as margin of victory less than 5%. Victors are winners of the electoral votes within a state. All columns include year and state fixed effects and have standard errors that are clustered at the state level. Low income is defined as those with incomes from 0 to 16 percentile, as reported by ANES.

Table 3.14: Probability of voting for president in next election: for not close elections by income

	low income		not low income	
	(1)	(2)	(3)	(4)
didn't vote in pres. election	-0.490***	-0.453***	-0.470***	-0.436***
	(0.0202)	(0.0303)	(0.0114)	(0.0158)
voted for non-victor	0.0496**	-0.0293	0.00438	-0.000311
	(0.0192)	(0.0251)	(0.00837)	(0.00987)
close margin	0.0270		-0.0263**	
	(0.0347)		(0.0129)	
didn't vote × close	0.0363		0.0452***	
	(0.0409)		(0.0162)	
voted for non-victor × close	-0.112***		0.000633	
	(0.0287)		(0.0192)	
margin of victory		-0.0807		-0.0200
		(0.126)		(0.0489)
didn't vote × margin		-0.195		-0.156**
		(0.125)		(0.0727)
voted for non-victor × margin		0.384***		0.0335
		(0.132)		(0.0690)
Mean DV	0.529	0.529	0.716	0.716
Number of Years	15	15	15	15
Number of States	50	50	51	51
Observations	3857	3857	17909	17909

Notes: Standard errors reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. 'Close margin' and 'close' in columns (1) and (3) is defined as margin of victory less than 5%. Victors are winners of the electoral votes within a state. All columns include year and state fixed effects and have standard errors that are clustered at the state level. Low income is defined as those with incomes from 0 to 16 percentile, as reported by ANES.

Table 3.15: ANES Turnout Data and Actual Turnout Data do not Differ Based on Closeness

Dependent Variable = Actual State Voter Turnout - ANES State Voter Turnout				
	(1)	(2)	(3)	(4)
Close Margin (1%)	4.140			
	(2.553)			
Close Margin (5%)		1.072		
		(0.975)		
Close Margin (10%)			0.717	
			(1.172)	
Margin				-1.795
				(6.789)
N	195	195	195	195

Notes: Standard errors clustered at the state level reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. 'Close Margin' is a dummy variable in all cases equal to one if the previous state electoral contest was within the given margin of error and zero otherwise. Margin is continuous. The dependent variable is the difference between the actual state voter turnout from the CPS and ANES state voter turnout for the given state and year pair.