Fall 2021

A Latent Class Approach to the Utilization Effects of the ACA

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by

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Submitted in partial fulfillment
of the requirements for the degree of
Master of Arts in Economics
Hunter College, City University of New York

2021

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Abstract

In late 2010, the dependent coverage provision of the Affordable Care Act raised the threshold below which young adults remain eligible for protection under the umbrella of their parents' health care up to the age of 26. This intervention has been examined to find the effect of insurance on various measures of health and of health services utilization. Rather than evaluating the effect of being newly insured on responses to any single health utilization measure, latent class analysis is used to delineate classes of health utilization behavior. Difference in difference analysis is then performed to determine the effect of the dependent coverage expansion on the proportion of the respondents sorting into each group. The expansion is found to have had a statistically significant effect on this measure.

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1 Introduction

1.1 Introduction

In late 2010, the Affordable Care Act raised the threshold under which young adults remain eligible for protection under the umbrella of their parents' health care up to the age of 26.This health insurance arrangement, known as dependent coverage, was previously available up to the age of 19, or the age of 23 in the event that the individual was in college. The exact protections varied by state, with factors like marriage status also playing a role. The dependent coverage expansion, however, applied to all offspring up to the age of 26, regardless of living situation or marriage status. The provision was passed in March of 2010, and was required in plans opening or renewed after September of that year. The next raft of renewals, and the first opportunity for legal force, was the open enrollment period beginning in January of the next year, with many insurance companies choosing to expand coverage earlier, of their own accord. (Deb & Norton, 2018; Pilkey et al., 2013) Evaluations of the effect of the policy on rates of insurance coverage revealed significant increases in the proportion of young adults covered by insurance.

There is precedent in attempts to identify a relationship between insurance status and healthcare utilization. This paper incorporates a number of previously used measures. Previous work on the volume of visits to the emergency room is robust, and includes both increased (as in Taubman et al. (2014)) and decreased (as in Hernandez-Boussard et al. (2014)) usage as a result of increased insurance access. Other measures used in this work whose relationship with insurance has been previously evaluated include visits to the doctor's office (as in Jhamb et al. (2015)), delay of medical visits or obtaining pharmaceuticals (as in Amuedo-Dorantes & Yaya (2016)). The presence of chronic conditions is also used, typically as an independent variable as in Deb et al. (2009), or, as in Amuedo-Dorantes & Yaya (2016), to delineate a subsample where effects may be more intense.

The use of difference-in-difference analysis to deal with questions of endogeneity is well represented in the literature as well. This technique is widespread in both the general health utilization literature and specifically in evaluating the impacts of the ACA, employed in Kolstad & Kowalski (2012b), Amuedo-Dorantes & Yaya (2016), Barbaresco et al. (2015) and myriad others. For the ACA, the standard difference in differences approach is as follows: the un-conditional expansion of dependent status to all those below the age of 26 allowed the use of the older group, who fell just outside of the expansion, to be used as a control for the younger, newly insured group. By measuring the change in both an affected and an unaffected, but otherwise identical, population, the effect of the policy is isolated; researchers are able to separate the response to cheaper healthcare access from demographic effects.

Health utilization in general is a multifarious property, with questions as to which health effects to measure, or how to nail down an effect perhaps only visible through aggregation. With regards to the relationships affecting the dependent coverage expansion, reforms may have sparse effects on many measures, or be weakened by the inclusion of those already covered by private insurance into the treatment group. Different cohorts may respond differently to the reforms. One group may utilize more preventative medicine, decreasing their reliance upon just in time care and stop-gap measures such as would be provided in an emergency room. Another group may find that healthcare has become affordable, where previously it was totally beyond reach. Yet another may experience a consistent need for quality of life interventions in the course of an incurable affliction. In the investigation of the effects of the ACA, emergency department use is perhaps the most widely studied, but parsing the literature does not produce the most consistent pattern, likely for the reasons described above. When evaluating any single measure, one may imagine opposite reactions among cohorts who are otherwise quite similar.

Mixture modeling allows for an increase in power over the traditional methodology; Latent class analysis allows us to delineate behavioral patterns, based on multi-measure interactions, which would otherwise have been missed. Rather than examining the movement in use of a single health product, we would examine bundles of products or patterns of usage. Using this methodology, this paper was able to identify two classes of health utilization, a group with a propensity towards relatively frequent hospital utilization, and one with relatively more. We were able to obtain plausible evidence of movement between these categories using standard difference in difference analysis.

The remainder of the paper is structured as follows: Section 1 summarizes previous work on the subject, section 2 describes the data used in this paper, section 3 the methodology, section 4 the results, and, finally, we conclude.

2 Literature Review

2.1 Impact of Insurance

As for what theory has to say about effects of insurance, predictions are ambiguous. Common sense would dictate that lowering the price of an item increase its use, but in situations where preventative medicine is out of reach, new access to preventative care may prevent longer hospital stays or more expensive care down the road. For medication, or visits to the doctor's office, usage may indeed go up, but that does not tell the full story if other interventions are being avoided. There has been a commonly held assumption that as the uninsured gain insurance, there would be a commensurate drop in Emergency Room usage as they used these comparatively expensive visits less and more traditional healthcare more—however, as discussed in Zhou et al. (2017), the uninsured use all types of healthcare less than their insured counterparts and they may very well increase consumption of all categories of health care, including ER usage, upon gaining insurance. In another scenario, an increase in Emergency Department visits may result from the health care system's failure to properly service expanding demand. (Smulowitz et al., 2011)

There is a plausible case for inefficient use of hospital resources among those without insurance, in addition to less utilization[1], however, the conclusion that these effects are the direct result of not having insurance is somewhat more difficult due to differences in demographics and income between the insured and uninsured or underinsured. In the 3 years before 2011, the insurance rate was 81 percent for those between 35 and 65, but only 65 percent for those between 23 and 30.[2] For the latter group, it must be taken into account that although younger people are more likely to be uninsured, they are also less likely to need medical care. Additionally, the effects of a possible perceived lack of need for health care would need to be disentangled from the financial effects of accessing healthcare without coverage. In fact, any study pursuing causal effects on or from health insurance would need

[1] On use; a 2010 survey of available evidence by Durand and Gentile found that actual evidence was inconclusive in either direction.

[2] Generated by the author with NHIS data

to take into account myriad alternative drivers of health behavior.

The impact of healthcare expansion on the use of medical services has been examined by a number of papers such as Amuedo-Dorantes & Yaya (2016); Barbaresco et al. (2015); Chua & Sommers (2014), among others. These attempts to cut through the endogeneity and delineate the relationship between insurance and hospital use have typically made use of sharp, involuntary delineations in insurance status. For example, Amuedo-Dorantes used the dependent coverage expansion within the Affordable Care Act to examine the impact of insurance coverage on the consumption of healthcare by young adults. The unconditional expansion of dependent status to all those below the age of 26 allowed the authors to use the older group, who fell just outside of the expansion, as a control for the younger, newly insured group. It allowed the authors to detect an increase in healthcare utilization associated with the change in status. Specifically, the paper found that the likelihood of foregoing prescription drugs was decreased by 31%, and of delaying needed care by 13%. Moreover, an even greater effect was found among those with chronic conditions, of 42% and 37%, respectively, for these measures.

2.2 Emergency Department Usage

The findings with respect to emergency department utilization have varied somewhat. Studies of the Massachusetts health reforms have generally found a negative or null relationship between insurance status and healthcare utilization. Instituted in 2006, the reforms entailed a health insurance mandate, a Medicaid expansion, expanded insurance marketplaces, and insurance subsidies. These reforms were seen by many as a model for the ACA. (Kolstad & Kowalski, 2012a) Miller (2012), who compared counties experiencing different levels of treatment due to differing pre-reform insurance rates found decreased visits as a result of the expansion. Kolstad & Kowalski (2012b), using a difference-in-difference specification in which other states served as control, isolated a bevy of effects on utilization, including shorter stays, fewer patients moving from ER to inpatient status, and a reduction in preventable admissions—measured through the presence of diagnoses deemed unlikely under adequate care. Chen et al. (2011) found no effect on ED use, even in particularly exposed safety net hospitals and Smulowitz et al. (2011) found a total increase in emergency usage but a decrease in low severity visits—defined as those with a low algorithmic probability of requiring ED care—while comparing ER usage in those already insured to usage by those newly insured under the reform. In the other direction, an investigation into the 2008 Oregon insurance lottery by Taubman et al. (2014) used the limited Medicaid expansion to estimate that a 40% increase in emergency department usage followed the change in status. Anderson et al. (2012), going a completely different way, uses the sudden drop in insurance coverage among those who have just aged out of their parents coverage to isolate a corresponding drop in emergency department usage.

The effects of the Affordable Care Act on emergency department use are a subject of much interest and investigation. In 2017, investigations by Nikpay et al. (2017), over 26 states, and Feinglass et al. (2017), in Illinois, found increases in ED usage. Both of these papers examine Medicaid expansions, and utilize the choices to expand Medicaid and increase Medicaid enrollment—respectively. Vernon et al. (2019) found a decline in visits in rural Georgia in 2019. Specifically in the case of the young adult expansion: Akosa Antwi et al. (2015), used a nationally representative sample of emergency department visits to find a miniscule but statistically significant decrease in usage. Hernandez-Boussard et al. (2014) found a decrease in visits while examining administrative records in three states. A 2018 survey by Breslau et al. (2018) of papers dealing with the Affordable Care Act found six discussing the effect of the dependent coverage expansion on emergency department use. The papers were evenly split, and the authors pointed out that those reporting no effect were population surveys, while those reporting a reduction used administrative data. One of these papers (Jhamb et al., 2015) used NHIS survey data, and found no effect on number of ER visits.

2.3 Other Outcomes

Out of the many outcomes that can be used to gauge healthcare utilization, use of emergency room facilities is likely the most examined. The volume of work on this outcome makes it possible to delineate the general thrust of the findings, and we have summarized the literature on emergency room use above. The other outcomes have a less robust representation in the literature, being treated in fewer papers and some only in alternate specifications of said papers. Illustrating the problem, Kolstad & Kowalski (2010) evaluates a measure not quite the same as the NHIS's delayed medical visit measure in the BRFSS's lack of access to care due to cost responses, finding a significant effect. The paper also attempts to examine increased take-up of preventative measures with a bevy of alternatives to our measures; including access to blood pressure medication, having had ones cholesterol checked, and having had a flu shot, of which only the last returned a significant result.

We can, however, say that all of our measures have been utilized previously. Statistically significant increases to the office visits measure have been detected by Deb & Norton (2018) as well as by Jhamb et al. (2015). Both the pharmaceuticals measure, and the measurement of delayed medical visits are used in Amuedo-Dorantes & Yaya (2016), which logged decreases in both behaviors as a result of the ACA. Barbaresco et al. (2015) uses a measure of care forgone because of cost, the same measure used in Kolstad & Kowalski (2010), but finds no significant effects from the ACA. Breslau et al. (2018), in a survey of the ACA literature, groups office visits together with similar measures of varying comparability, from an "outpatient or Primary care" measure, to the likelihood that one obtained a flu-shot, likely as a result of its scarcity. Amuedo-Dorantes & Yaya (2016) uses chronic conditions alongside the other measures, however, as is typical for this variable, it is used to find heterogeneous effects rather than as an outcome. In this case, for additional exploration; as a subsample among whom results were more dramatic. Our use of the chronic conditions measure is similar, as a characteristic of latent classes.

2.4 Mixture Modeling

Mixture modeling, a technique which allows the researcher to back nonlinear relationships out of groups of observed variables, is a versatile data analysis tool suited to both descriptive and causal analysis. The field of mixture modeling contains within it a number of subgroups. These include, among others, latent profile analysis, involving discrete latent variables and continuous observed ones, and latent class analysis, involving both discrete latent and continuous variables. Further, certain methods, like factor analysis, delineate hidden groups based on mean differences, while others, such as random effects models, delineate based on regression coefficients. All mixture models can also be referred to as structural equation models.(Oberski, 2016) Titles such as "Exploratory Factor Analysis", or "Principal Components Analysis", can refer to the intent with which the structural equation model has been put together, and the way in which variance is handled.

A single type of model can be used in very different ways. Gurka et al. (2014) used Confirmatory Factor Analysis to create a system for assigning metabolic syndrome severity scores sensitive to race, ethnicity, and gender. A randomized controlled trial by Zhu et al. (2021) uses Confirmatory Factor Analysis in a very different way, to determine the relationship between observed and latent variables, in this case questionnaire responses and underlying financial acumen. A randomized education intervention is performed. Pretreatment latent variables are then used, alongside the treatment variable, observed factors, and various covariates, in the estimation of a post treatment latent variable—allowing the authors to estimate treatment effects on an unmeasured variable that would have otherwise remained nebulous.

Health is a highly multidimensional property, and researchers benefit from being able to condense its many proxies into a single data item. Portrait et al. (1999) uses Grade of Membership analysis, described in Manton et al. (1992), in order to collapse 21 health indicators into six essential types. The paper then estimates the relationship between these types and mortality. In a vaguely similar study, Chung et al. (2011) create classes of drinking behavior from a questionnaire. However, going further, the authors track the movement of individuals from class to class over their lifespans, and create a second set of classifications based on movement through the first. Another paper, Deb et al. (2021), is quite close to our own specification, evaluating movement in a latent health variable by comparing states affected by the passage of a health care delivery law to a set of unaffected states. Again, the latent health variable is evolved from a collection of narrower health status measures.

3 Data

The National Health Interview Survey began in 1957, following the National Health Survey Act of the previous year. From the year 1960, the NHIS has been conducted by the National Center for Health Statistics. The survey is based initially upon households, but each person is interviewed or represented by a knowledgeable, adult proxy. A certain subset of adults surveyed are singled out for additional, more intensive questioning. This is one adult per family. The NHIS samples from every state within the United States, following a pattern that results in deliberate oversampling of certain population subgroups. Institutionalized individuals, such as those in jail or in the armed forces, are deliberately excluded. Weights may be used to allow national level estimates of person level variables, they are however, not used in our design. This should present no problem as the inclusion of weights typically decreases standard errors. This paper uses the IPUMS NHIS[3] data series, which harmonizes variables to allow comparison across years.

Our estimation uses available NHIS data on the target population and on a second, older, control group. The policy makes a treatment group, those aged 23 to 25, eligible to remain on their parent's health insurance. An older group, those aged 27 to 29, remain ineligible and serve as the control group. This age range has been established as comparable in the literature, having been used as a primary specification in Barbaresco et al. (2015) and a secondary specification in Amuedo-Dorantes & Yaya (2016), among others. Some other publications set those aged 19 to 23 as a control group, however, we follow those who point out the imperfect comparability of this age group due to college related health care coverage. In our estimations we use the years 2008 through to 2015. This allows three years of pre-intervention data, and five years of post-intervention data.

Between the two groups there are a couple of notable differences. The older group is more likely to have married, at 38% of older respondents compared to 22% of younger ones. Only 17% of the older sample is below the poverty line, compared with 21% of the younger sample. Older respondents are more likely to be household heads, and to have been informed they have a disease. All of these differences are included in either the original or an alternate, more comprehensive, set of controls. There is little difference in interpretation between the two. Although Blacks and Hispanics are overrepresented in the sample by design, they are equally distributed across age groups during regression. Blacks and Hispanics are overrepresented 15 vs 13% and 28 vs 18%, respectively. Both characteristics are controlled for in estimations.

As to the general trend in uninsurance, the younger group was experiencing an upward trend in the probability an individual was uninsured prior to the reform. Afterward, both

[3] Integrated Public Use Microdata Series (IPUMS) National Health Interview Survey (NHIS)

groups made gains in insurance status, with the insurance rate of the younger group increasing past that of their older counterparts by several percentage points. Prior to the reform, 27% of the older group was uninsured, versus 30% of the younger group. After the reform 25% of the older group was uninsured, versus 22% of the younger group.

In our estimations, we use the years 2008 through to 2015. This allows three years of pre-intervention data, and five years of post-intervention data. Due to the exclusion of birth date from the data, many publications before ours have excluded 26 year olds from their analyses. (Barbaresco et al., 2015) Knowing only that a person was 26 at time of response without knowing their date of birth, means that they could have been 25 for any proportion of the response period. Removing 26 year olds eliminates this ambiguity. In addition to this, we follow previous papers in designating our control group those aged 23 to 25. This specification has been used before, in the main specification of Barbaresco et al. (2015) as one example, and in an alternate specification of Amuedo-Dorantes & Yaya (2016) as another. Descriptive statistics, by treat and period, are contained in Table 7.1.

4 Methods

This paper investigates the effects of the Affordable Care Act Dependent Coverage Provision using a combination of latent factor analysis and regression techniques. Analysis starts with a series of measures previously established as related to healthcare utilization in the literature. Latent factor analysis is used to create behavioral categories based on responses. We then estimate the effect of the Dependent Coverage Provision on the probability an individual taken up in subsequent survey samples is sorted into one category over the other.

In the structural equation diagram, diagram 7.3, arrowheads show the relationships from independent variables to dependent ones. Rectangular icons indicate observed variables, and round ones variables that were not directly unobserved. Both residuals and an unobserved latent health variable are represented by round icons. This unobserved variable is labeled ”Health Care Utilization” and determines the outcomes on the left. It is calculated by a process similar to calculation of residuals, and through maximum likelihood estimation. The change in the probability of landing in a specific category, stemming from the treatment icon, is calculated while controlling for demographic and other characteristics, on the right.

Two types of variables are used as observable proxies for the latent health status variable in our estimation. Several are binary variables: one denoting that the respondent delayed seeking medical attention due to cost, one denoting that the respondent delayed obtaining pharmaceuticals due to cost[4], and a third indicating the presence of hypertension, diabetes, cancer, arthritis or an inability to perform daily tasks by oneself was used. Two ordinal variables were also used. The first denoting the number of times the respondent visited the emergency room, and the second visits to the doctor's office, both over the past 12 months. All of these variables serve as dependent variables in a set of equations with the latent health variable as the only regressor, and run simultaneously with the main estimation, which features the latent health variable as dependent variable in estimating the effect of the policy on health.

In estimating the regression, the following difference in difference specification is used as a base:

C=$\alpha + \beta_1 T_i P_t + \beta_2 Age_i + \beta_3 Year_t + \beta_4 X_{it} + \epsilon_{it}$

In it, β_1 refers to the coefficient of the interaction between the treated group and post implementation period, β_2 to the age trend, and β_3 to the time trend. The term β_4 refers to a series of individual characteristics, including: gender, race, Hispanic ethnicity, family size, highest grade achieved by respondent, and a measure of poverty. In our generic equation, C represents the unobserved utilization variable. As the model is similar to a logit model, we referred to Puhani (2012) and Karaca-Mandic et al. (2012) on the calculation of effects using derivatives, and of delta method standard errors. The regression is estimated with cluster-robust standard errors, with clustering based on age groups, in order to deal with serial correlation between responses of people of a given age over time. Estimation was performed in Stata 16, and standard errors are calculated using a finite sample correction utilizing G-1 degrees of freedom [5]. Of the demographic variables: gender, race, and Hispanic ethnicity are binary. The variables communicating family size and grade are ordinal, categorical, and top-coded: at 12 members and a master's degree, respectively. The poverty measure is a non-ordered categorical variable representing the ratio of reported income to poverty level.

[4]Both variables refer to a delay in the past 12 months

[5]Where G is the number of clusters.

5 Results

With respect to the major specifications, there are two. The first uses four proxies for health: one for emergency room visits, one denoting that the respondent delayed seeking medical attention due to cost, one denoting that the respondent delayed obtaining pharmaceuticals due to cost, and one for visits to the doctor's office. The second adds the, aforementioned, chronic conditions variable indicating the presence of one or more of the listed conditions. Both suggest that the policy reduced the likelihood of a treated individual sorting into a category of high healthcare use by around 4%. At 4.33% for the four proxy specification and 4.17% for the five proxy specification. Additional controls decreased the magnitude of the effect, but not by much, and significance was unaffected.

Table 7.4 shows the results of not only these two specifications, but a number of other versions as well. Both major specifications are also estimated with additional controls such as foreign born status, head of household status, and marriage status. Variations on the chronic conditions specification, estimating the effects of lag coefficients alongside both the main and expanded sets of controls, are displayed in column 2 and column 1 of Table 7.6, respectively. These returned significant effects in 2011, 2012 and 2014. The four proxy specification, represented in column 3, returned no significant lags.

A falsification test is executed using those aged 26 to 27 as a treatment group, and those aged 28 to 29 as control. In general, a falsification test evaluates the precepts of a model by evaluating alternate configurations for effects unlikely if the assumptions were valid. In this case, a significant effect on movement between use groups would have implied that some mechanism, other than the policy, was behind the inter-category movement observed in the main specification. These results are included in columns 1 and 2 of Table 7.5, for the four and five proxy specifications, respectively.

On determining the utilization category from responses: those who visited the ER more than once in the past 12 months are nearly certain to have sorted into the high-use group. This holds for both latent variable specifications. The predictive power of visiting the doctor, however, differs by a much wider margin. In the four proxy specification, 36% of those who visited the office more than once are high use cases, 60% of those with more than 6 visits, and

70% of those with more than 10. In the five proxy specification, 46% of those who visited the office more than once are high use cases, 72% of those with more than 6 visits, and 79% of those with more than 10.[6] Those with chronic conditions are about 10 percentage points more likely to fall into the low use group after reform, by simple tabulation, in either specification. A simple t-test confirms that the proportion of those with chronic conditions covered by insurance is larger after the reform by about three percentage points. Moreover, by simple tabulation, the difference in the proportion of those with chronic conditions sorted in to the low use category is around 10 percentage points between time periods.

It is notable that we were not able to obtain significant results in regressions featuring these proxy variables as standalone estimands. In Table 7.10, one is able to see that, although we are able to discern a significant effect of the dependent coverage expansion on coverage itself, we were not able to obtain significant effects on the likelihood that one visited the emergency room more than once, or that respondents delayed a medical visit, or obtaining pharmaceuticals, due to cost.[7] The specifications for these estimations are the same as for the main regressions, except that there are more demographic measures included as independent variables.

Latent class marginal means are shown in Table 7.2, where supra-column 1 shows the difference in response patterns between the two groups for the main specification. In Group 2, the low use intensity group, 2.6% of respondents report visiting their doctor's office 13 or more times in the past year, compared with 14.4% of those in group one. The edge in the proportion of group two reporting no visits is similarly large, 33.57%, versus 16.7%. The difference between those who have not utilized emergency room services is much larger, 90.6% of those in the low use group have not visited the emergency room in the last year, while just under 50% of the high use group have. In response to questions about whether one had delayed medical care due to cost, or receiving pharmaceuticals due to cost, approximately 30% of group 1 respondents returned that they had. This compares with the single digit proportions of positive responses given by group 2.

[6]These statistics are contained in tables 7.7 and 7.8 for the 3 and 4 proxy variable specifications, respectively.

[7]Amuedo-Dorantes was able to obtain significant effects for the latter two, using an unrestricted set of demographics variables

Evaluating the latent variables over a series of demographic variables returns notable differences between the two groups. Members of the low use group are half as likely to have a chronic condition, at 20.47% versus 40.09%; 6.62% are under .5 of the poverty ratio, compared to 15% of the high use group; Education levels are higher, with 38.16% possessing a bachelor's degree or higher, compared to 14.4% of the second group; 24.41% of the high use group are in excellent health, compared with 43.36% of the low use group. In summary, there are two latent classes: a high use group including individuals who are more likely to use health care in any capacity, and more likely to reach or exceed their care-access allotment, and a healthier, better educated, low use group who seldom come into contact with health services.

The specification including the presence of a chronic condition as an additional proxy variable returned qualitatively similar descriptive statistics and with the same clear delineation between high and low use, also shown in Table 7.2, in supra-column 2. The proportion of those in the high use category is predictably higher, with 46.4% reporting a chronic condition, as opposed to 14.8% of the low use bucket. There is a surprising change in the proportion of those identified as Hispanic in each bucket. The spread doubles from three percentage points to six; from a comparison between 20.4% and 23.3% to one between 24.35% and 18.35%.

Despite what seem to be promising results, the specifications perform inconsistently on tests for parallel trends. Table 7.9 shows a collection of estimations aimed at establishing the timing of the effect on the likelihood of being sorted into the low or high-use category. These estimations follow the pattern of previous specifications, but for the addition of coefficients signifying that a respondent was of treatment age in a specific pre-treatment period. In column 2, time-treatment interaction coefficients are uniformly insignificant and of a similar size. These results do not lend themselves to the interpretation that the reform had a significant effect on health service usage. In column 1 year-treatment interaction effects are significant only in 2012 and 2013. This scenario offers evidence that effects of the bill changed over time and a measure of support for the parallel trends assumption.

6 Conclusion

This paper tentatively finds a relationship between the dependent coverage expansion and changes in the healthcare usage patterns of young adults. This relationship was calculated to be a statistically significant movement of around 4% between latent usage patterns, from a more intensive usage pattern to a lower intensity pattern. This paper finds that the effect was not significant in all years following the policy change, only in two specific years.

This paper is able to comment on a relationship between high use in a single category of health care and high use across a wider array of measures. This paper is also able to affirm previous results showing that the effect of the reform was great among those with chronic conditions, doing both through a new, nonlinear pathway, by examining the effect the reform had on behavioral groupings developed using mixture modeling.

7 Tables and Figures

7.1 Descriptive Statistics

	Pre-Treat		Post-treat	
	Older mean	Younger mean	Older mean	Younger mean
Insured*	0.27	0.30	0.25	0.22
black*	0.16	0.17	0.14	0.14
hispanic ethnicity*	1.24	1.24	1.22	1.21
number of persons in family	2.65	2.42	2.56	2.34
citizen*	0.84	0.86	0.86	0.89
lusborn*	0.78	0.80	0.79	0.84
married*	0.38	0.23	0.35	0.20
head of house*	0.66	0.60	0.65	0.59
grade	14.18	14.03	14.33	14.20
Income measure	1.41	1.29	1.42	1.30
Poverty Measure	2.42	2.23	2.40	2.24
food stamps*	0.18	0.19	0.20	0.21
needs help*	0.01	0.02	0.01	0.01
arthritis*	0.05	0.03	0.05	0.03
asthma*	0.14	0.15	0.14	0.16
cholesterol*	0.02	0.01	0.03	0.01
cancer*	0.01	0.02	0.01	0.01
diabetic*	0.01	0.01	0.01	0.01
hypertension*	0.09	0.07	0.09	0.07
rarecondtn*	0.03	0.04	0.04	0.03
Observations	6360	4198	9702	6600

*Dichotomous Variable

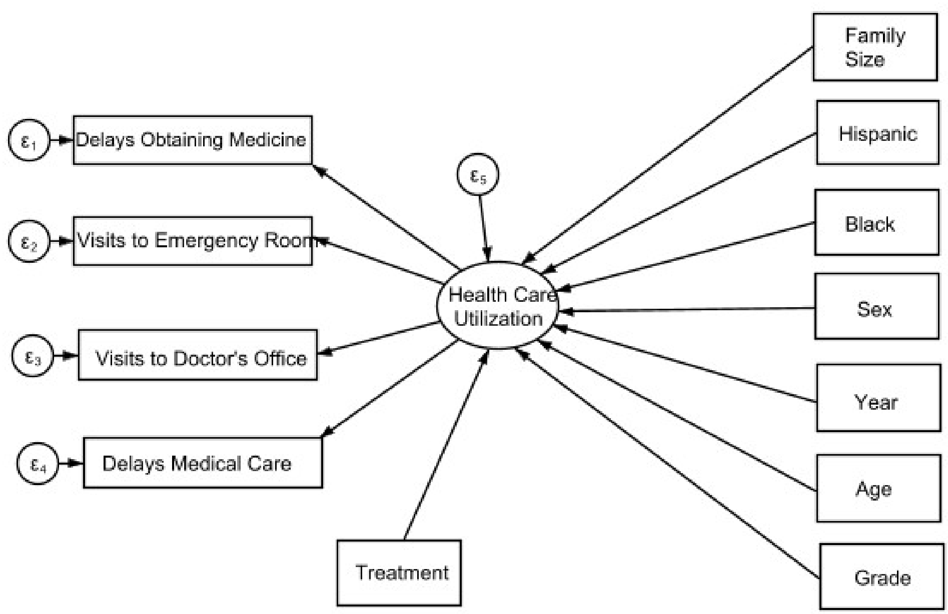
Descriptive Statistics

7.2 Class Means

	(1)		(2)	
	1	2	1	2
no office visits	0.167	0.336	0.134	0.359
1 office visit	0.117	0.238	0.111	0.246
2 to 3 office visits	0.229	0.245	0.241	0.240
4 to 5 office visits	0.136	0.0834	0.147	0.0755
6 to 7 office visits	0.0776	0.0306	0.0838	0.0255
8 to 9 office visits	0.0424	0.0186	0.0456	0.0159
10 to 12 office visits	0.0878	0.0222	0.0893	0.0186
13 or more office visits	0.144	0.0259	0.148	0.0187
delayed visit	0.315	0.0706	0.281	0.0771
delayed medicine	0.302	0.00997	0.256	0.0203
no ER visits	0.505	0.906	0.514	0.919
1 ER visit	0.231	0.0877	0.241	0.0765
2 to 3 ER visits	0.182	0.00642	0.170	0.00444
4 to 9 office visits	0.0816	5.49e-11	0.0746	6.13e-10
chronic condition			0.464	0.148
Observations	23931		23931	

Latent Class Means

7.3 Structural Equation Diagram



7.4 Main Estimation Results

	Four Proxy	Five Proxy	Four Proxy	Five Proxy
Diff. in Diff.	-0.0433***	-0.0399***	-0.0417***	-0.0393***
	(-4.22)	(-4.50)	(-4.56)	(-5.23)
Additional covar.	No	Yes	No	Yes
N	23931	23931	23931	23931

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The coefficients denote change in likelihood of sorting into high use category.

A list of covariates is omitted from the table.

7.5 Falsification tests

	Four Proxy	Five Proxy
Falsifications	-0.0161	-0.0203
	(-1.04)	(-1.37)
N	16595	16595

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

A list of covariates is omitted from the table.

7.6 Lag Estimation

	(1)	(2)	(3)
did2011	-0.0472*	-0.0522**	-0.00913
	(-2.51)	(-3.06)	(-0.49)
did2012	-0.0382*	-0.0426*	-0.0188
	(-2.46)	(-2.27)	(-0.90)
did2013	-0.0228	-0.0268	0.00267
	(-0.87)	(-1.19)	(0.12)
did2014	-0.0487*	-0.0460*	-0.0153
	(-2.42)	(-2.15)	(-0.64)
did2015	-0.0392	-0.0405	-0.0175
	(-1.21)	(-1.29)	(-0.68)
N	23931	23931	40206

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Estimation of Lags

7.7 Proportions of Specification 1

	(1) ER>1	(2) ER>2	(3) Visit>1	(4) Visit>6	(5) Visit>10
Percent High Users	.9896806	.9896806	.3699586	.5981866	.6897796
Observations	2035	2035	12323	4191	2495

Proportions of people who sorted into the high use group, by response type.

7.8 Proportions of Specification 2

	(1) ER>1	(2) ER>2	(3) Visit>1	(4) Visit>6	(5) Visit>10
Percent High Users	.9936118	.9936118	.4606021	.7158196	.7883768
Observations	2035	2035	12323	4191	2495

Proportions of people who sorted into the high use group, by response type.

7.9 Timing

	(1)	(2)
did2008	0.00273	
	(0.07)	
did2009	0.00765	
	(0.21)	
did2011	-0.0475*	
	(-2.37)	
did2012	-0.0502	
	(-1.64)	
did2013	-0.0387*	
	(-2.28)	
did2014	-0.0534	
	(-1.30)	
did2015	-0.0260	
	(-0.79)	
post-period		-0.0268
		(-1.21)
pre-period		0.0235
		(0.58)
N	23931	23931

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Tests for parallel trends

7.10 Standalone Regressions

	Prescription† Delayed	Delayed Care	Insured	Any ER Visits
Below 26	-0.0411***	-0.0469***	-0.0258**	0.0102
	(-5.95)	(-6.45)	(-2.77)	(1.13)
Post ACA	-0.0229**	-0.0242**		0.0270
	(-2.69)	(-2.63)		(1.53)
Interaction Effect	0.00930	0.00798		0.00280
	(1.16)	(0.93)		(0.26)
Interaction Effect			-0.0657***	
			(-6.37)	
N	39188	39188	39188	38780

t statistics in parentheses

A list of covariates is omitted from the table.

†Different post period

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

7.11 Demographic means in Specification 1

	HighUse mean	LowUse mean
Insured*	.3451548	.2263877
black*	.2317682	.1214505
hispanic ethnicity*	1.203963	1.232971
number of persons in family	2.809024	2.416736
citizen*	.9002664	.8464714
lusborn*	.8573094	.7858298
married*	.2753913	.3098466
head of household*	.6764902	.6148396
grade	13.58641	14.37863
food stamps*	.3864469	.1293724
needhelp*	.0301365	.0064156
arthritis*	.0880786	.0255509
asthma*	.2157842	.1225105
cholesterol*	.0210379	.0176481
cancer*	.028971	.0078103
diabetic*	.028305	.0073082
hypertension*	.1433566	.0614784
rarecondtn*	.0639361	.0275593
Observations	6006	17925

*Dichotomous Variable

Class Demographics for Specification 1

7.12 Demographic means in Specification 2

	HighUse2 mean	LowUse2 mean
Insured*	.2867015	.2433492
black*	.2222536	.1183492
hispanic ethnicity*	1.183472	1.243468
number of persons in family	2.762093	2.411223
citizen*	.9519109	.8212589
lusborn*	.9183472	.7555226
married*	.2788041	.3106295
head of household*	.6771964	.6105701
grade	13.75927	14.35689
food stamps*	.3584826	.1245843
needhelp*	.0344098	.0030879
arthritis*	.1050628	.0143705
asthma*	.2854322	.0871734
cholesterol*	.0244336	.0160221
cancer*	.0338457	.0043943
diabetic*	.0315893	.0045724
hypertension*	.1769849	.0420428
rarecondtion*	.0654351	.0245843
Observations	7091	16840

*Dichotomous Variable

Class Demographics for Specification 2

References

Akosa Antwi, Y., Moriya, A. S., Simon, K., & Sommers, B. D. (2015). Changes in emergency department use among young adults after the patient protection and affordable care act's dependent coverage provision. *Annals of Emergency Medicine*, *65*(6), 664–672.e2.

Amuedo-Dorantes, C., & Yaya, M. E. (2016). The impact of the aca's extension of coverage to dependents on young adults' access to care and prescription drugs: Aca and young adults' access to care and drugs. *Southern Economic Journal*, *83*(1), 25–44.

Anderson, M., Dobkin, C., & Gross, T. (2012). The effect of health insurance coverage on the use of medical services. *American Economic Journal: Economic Policy*, *4*(1), 1–27.

Barbaresco, S., Courtemanche, C. J., & Qi, Y. (2015). Impacts of the affordable care act dependent coverage provision on health-related outcomes of young adults. *Journal of Health Economics*, *40*, 54–68.

Breslau, J., Stein, B. D., Han, B., Shelton, S., & Yu, H. (2018). Impact of the affordable care act's dependent coverage expansion on the health care and health status of young adults: What do we know so far? *Medical Care Research and Review*, *75*(2), 131–152.

Chen, C., Scheffler, G., & Chandra, A. (2011). Massachusetts' health care reform and emergency department utilization. *New England Journal of Medicine*, *365*(12), e25.

Chua, K.-P., & Sommers, B. D. (2014). Changes in health and medical spending among young adults under health reform. *JAMA*, *311*(23), 2437.

Chung, H., Anthony, J. C., & Schafer, J. L. (2011). Latent class profile analysis: an application to stage sequential processes in early onset drinking behaviours: Early onset drinking behaviours. *Journal of the Royal Statistical Society: Series A (Statistics in Society)*, *174*(3), 689–712.

Deb, P., Gangaram, A., & Khajavi, H. N. (2021). The impact of the state innovation models initiative on population health. *Economics Human Biology*, *42*, 101013.

Deb, P., & Norton, E. C. (2018). Modeling health care expenditures and use. *Annual Review of Public Health*, *39*(1), 489–505.

Deb, P., Trivedi, P., & Zimmer, D. (2009). *Dynamic Cost-offsets of Prescription Drug Expenditures: Panel Data Analysis Using a Copula-based Hurdle Model*. No. 09/15 in Health, Econometrics and Data Group (HEDG) Working Papers.

Feinglass, J., Cooper, A., Rydland, K., Powell, E., McHugh, M., Kang, R., & Dresden, S. (2017). Emergency department use across 88 small areas after affordable care act implementation in illinois. *Western Journal of Emergency Medicine*, *18*(5), 811–820.

Gurka, M. J., Lilly, C. L., Oliver, M. N., & DeBoer, M. D. (2014). An examination of sex and racial/ethnic differences in the metabolic syndrome among adults: A confirmatory factor analysis and a resulting continuous severity score. *Metabolism - Clinical and Experimental*, *63*(2), 218–225.

Hernandez-Boussard, T., Burns, C. S., Wang, N. E., Baker, L. C., & Goldstein, B. A. (2014). The affordable care act reduces emergency department use by young adults: Evidence from three states. *Health Affairs*, *33*(9), 1648–1654.

Jhamb, J., Dave, D. M., & Colman, G. (2015). The patient protection and affordable care act and the utilization of health care services among young adults. *Medicine*.

Karaca-Mandic, P., Norton, E. C., & Dowd, B. (2012). Interaction terms in nonlinear models. *Health Services Research*, *47*(1pt1), 255–274.

Kolstad, J., & Kowalski, A. (2010). *The Impact of Health Care Reform On Hospital and Preventive Care: Evidence from Massachusetts*. w16012.

Kolstad, J., & Kowalski, A. (2012a). *Mandate-Based Health Reform and the Labor Market: Evidence from the Massachusetts Reform*. w17933.

Kolstad, J. T., & Kowalski, A. E. (2012b). The impact of health care reform on hospital and preventive care: Evidence from massachusetts. *Journal of Public Economics*, *96*(11-12), 909–929.

Manton, K. G., Woodbury, M. A., Stallard, E., & Corder, L. S. (1992). The use of grade-of-membership techniques to estimate regression relationships. *Sociological Methodology*, *22*, 321–381.

Miller, S. (2012). *The Effect of Insurance on Emergency Room Visits: An Analysis of the 2006 Massachusetts Health Reform*. ID 1711502.

Nikpay, S., Freedman, S., Levy, H., & Buchmueller, T. (2017). Effect of the affordable care act medicaid expansion on emergency department visits: Evidence from state-level emergency department databases. *Annals of Emergency Medicine*, *70*(2), 215–225.e6.

Oberski, D. (2016). *Mixture Models: Latent Profile and Latent Class Analysis*, (pp. 275–287). Human-Computer Interaction Series. Springer International Publishing.

Pilkey, D., Skopec, L., Gee, E., Amaya, K., Finegold, K., & Robinson, W. (2013). Dependent coverage expansion.

Portrait, F., Lindeboom, M., & Deeg, D. (1999). Health and mortality of the elderly: the grade of membership method, classification and determination. *Health Economics*, *8*(5), 441–458.

Puhani, P. A. (2012). The treatment effect, the cross difference, and the interaction term in nonlinear difference-in-differences models. *Economics Letters*, *115*(1), 85–87.

Smulowitz, P. B., Lipton, R., Wharam, J. F., Adelman, L., Weiner, S. G., Burke, L., Baugh, C. W., Schuur, J. D., Liu, S. W., McGrath, M. E., & et al. (2011). Emergency department utilization after the implementation of massachusetts health reform. *Annals of Emergency Medicine*, *58*(3), 225–234.e1.

Taubman, S. L., Allen, H. L., Wright, B. J., Baicker, K., & Finkelstein, A. N. (2014). Medicaid increases emergency-department use: Evidence from oregon's health insurance experiment. *Science*, *343*(6168), 263–268.

Vernon, M., Goggans, S., De Leo, G., & Heboyan, V. (2019). Costs and trends of emergency department utilization pre-aca and post-aca: Evidence from a rural georgia hospital. *Medical Care*, *57*(6), 407–409.

Zhou, R. A., Baicker, K., Taubman, S., & Finkelstein, A. N. (2017). The uninsured do not use the emergency department more they use other care less. *Health Affairs*, *36*(12), 2115–2122.

Zhu, A. Y. F., Yu, C. W. M., & Chou, K. L. (2021). Improving financial literacy in secondary school students: An randomized experiment. *Youth Society*, *53*(4), 539–562.