Health Insurance and Young Adults' Avoidable Hospitalizations: Evidence from the Affordable Care Act Dependent Coverage Mandate

Yanling Qi*

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Abstract:

In 2010, the Patient Protection and Affordable Care Act was signed into law with the goal of achieving nearly universal health insurance coverage. One of the first provisions to take effect targeted young adults, whose eligibility for dependent coverage under their parents' private insurance plans was extended until the age of 26. In this paper, I derive a conceptual model of avoidable hospitalizations to decompose impacts from ACA dependent coverage into an access effect, efficiency effect, and ex ante moral hazard effect. Additionally, I use years 2002-2011 of the HCUP National Inpatient Sample (NIS) – a 20% sample of the universe of inpatient hospital discharges across the United States – to examine the impact of this policy change on avoidable hospitalizations for young adults. I use a difference-in-differences approach to estimate the impact on treated young adults aged 23-25 as compared to a slightly older age group (ages 27-29) that was not subject to the reform. My primary results show that this mandate increases avoidable hospitalizations, especially for those associated with chronic health conditions. This suggests that the access effect and the moral hazard effect dominate the efficiency effect from my conceptual model. In other words, the lower out-of-pocket prices of avoidable hospitalizations and the reduced costs of risky health behaviors outweigh any improvements in the quality of primary care. The effects are stronger for females, whites, and those living in the third income zip code quartiles. Further, I identify some suggestive evidence that the increase for avoidable hospitalization is much larger than that for unavoidable hospitalization, indicating a positive effect on increasing avoidable hospitalizations, after considering both the access effect and efficiency effect.

JEL Codes: I13, I18
Keywords: Affordable Care Act, health care reform, young adults, dependent coverage mandate, health insurance, quality of primary care, avoidable hospitalizations

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*Department of Health Care Administration, College of Health & Human Services, California State University, Long Beach, CA90840. Email: Yanling.Qi@csulb.edu. Phone: (562) 985-4009.

I. Introduction

On March 23, 2010, President Obama signed the Patient Protection and Affordable Care Act (ACA) into law.[1] One of the first implemented provisions of the ACA was targeted at young adults, who often face the risk of losing their health insurance coverage as early as age 19. Prior to the ACA, insurance companies typically removed enrolled children from their parents' plans at age 19 for non-students and 23 for full-time students (Anderson et al., 2012 and 2014).[2] Under the new law, starting in September 2010, young adults are allowed to stay on their parents' plan until they turn 26 years old, with the same benefits.[3] By allowing young adults to maintain coverage under their parents' health plan, the law makes it easier and more affordable for them to get health care.

Historically, the rate of insurance coverage for young Americans decreased at age 19, as these young adults may have lost their health insurance due to being ineligible to maintain coverage under their parents' plan or because of their employment status (unemployed, part-time employment, entry-level employment or small business employment without employer-sponsored coverage). For these reasons, young adults typically have the lowest rate of insurance coverage in comparison with other age groups. To be more specific, the rate of insurance coverage for young adults in the age group of 19-25 was only 68.6 percent in 2009, while the national rate was 83.9 percent (DeNavas-Walt et al., 2010).

Contrary to the idea that young people do not "need" health insurance, one out of six young adults experiences a chronic illness like cancer, asthma or appendicitis (National Center for Health

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[1] For more information one can visit the following websites:
http://www.whitehouse.gov/healthreform/healthcare-overview
http://www.hhs.gov/healthcare/rights/law/index.html

[2] There was a great deal of prior state-to-state variation in dependent coverage rules, including differences in age limits and marital status requirements.

[3] For more on this policy see: http://www.hhs.gov/healthcare/rights/youngadults/index.html; http://www.cms.gov/CCIIO/Resources/Files/adult_child_fact_sheet.html.

Statistics, 2009). Also, young adults often partake in behaviors such as overeating, sedentary lifestyles, smoking, excessive drinking, and unprotected sex that pose long-term risks. Additionally, compared to insured young adults, uninsured peers are two-to-four times more likely to delay healthcare due to costs (Cantor, 2010). Moreover, young adults are at risk for their health as well as their finances: nearly half of uninsured young adults report problems associated with paying medical bills (Collins, 2012). Lacking health insurance as a young adult tends to cause health and economic problems in later adulthood (Merluzzi, 1999; Callahan, 2005; Nicholson, 2009).

A recent literature has developed showing that the ACA expansion of dependent coverage increased the rate of insurance coverage among the targeted group of young adults (Cantor et al., 2012; Sommers and Kronick, 2012; Sommers et al., 2013; Akosa Antwi et al., 2013 and 2015; Barbaresco et al., 2015; Chua and Sommers, 2014). However, there is little, if any, evidence on the effect of this aspect of the ACA on the quality of care received by young adults. The purpose of this paper is to evaluate the impact of the ACA expansion of dependent coverage on primary care quality by examining changes over time in the probability of having an avoidable hospitalization among the targeted group of young adults as compared to young adults just outside this age range.

As in the Kolstad and Kowalski (2012) (hereafter as KK) study of the Massachusetts health care reform, I analyze the universe of hospital discharges from a nationally-representative sample of roughly 20 percent of all hospitals in the United States that is compiled by the Agency for Healthcare Research and Quality (AHRQ) Healthcare Cost and Utilization Project (HCUP). This sample is known as the National Inpatient Sample (NIS). In addition, I also follow KK and use the AHRQ-provided methodology for identifying avoidable hospitalizations in the data. While conventional wisdom suggests that an increase in insurance coverage would result in more preventive care in an outpatient setting and thus fewer avoidable hospitalizations, I develop a conceptual model in which the impact of the expansion of dependent coverage on the probability of having an avoidable hospitalization is ambiguous and use that to motivate my empirical work. In contrast to KK's findings for the Massachusetts reform, my primary results suggest that the ACA expansion of dependent coverage for young adults aged 23-25 leads to an *increase* in overall avoidable hospitalizations, which is driven by a large increase in *chronic* avoidable hospitalizations. The effects are stronger for female, whites, and the middle income quartiles of patient's zip code.

Some would interpret this result as implying the ACA led a reduction in primary care quality. It may instead suggest a tradeoff between two forces likely to increase avoidable hospitalization rates, the moral hazard aspect of expanding insurance coverage as well as improved access to hospitals, and the efficiency effect associated with increasing access to primary care relative to hospital and emergency room care, which should reduce avoidable hospitalization rates. The size of this tradeoff is likely different for the young adults targeted by this reform as compared to older adults, children, or the elderly.

The rest of this paper is organized as follows: Section II provides an overview of the relevant literature, section III describes the conceptual relationship between the ACA expansion of dependent insurance coverage for young adults and the number of avoidable hospitalizations, section IV describes my methodology, and section V describes the data. Section VI presents my results and section VII provides a discussion of these results. Conclusions are given in section VIII.

II. Literature Review

In this section I review the literature on previous state policy as well as the ACA mandate with respect to dependent coverage and related types of coverage expansions. I focus on the literature dealing with the impacts of expansions of coverage on general health care utilization, risky behaviors, and health outcomes, as well as avoidable hospitalizations.

A. Dependent Coverage Policies and Insurance Coverage

Prior to the ACA, about two thirds of states implemented state-level policies allowing for some type of dependent coverage expansion. However, researchers found small or even no net impact of these policies on the number of uninsured young people (Levine et al., 2011; Monheit et al., 2011; Blum et al., 2012). This was due in part to the scope of these reforms being limited by the state definitions of a dependent, which could include restrictions related to student status, marital status, co-residence with parents and tax dependent status. Additionally, all state laws excluded self-funded benefit programs, which meant that they did not apply to around half of employer-provided plans. In addition, increases in dependent coverage could have been offset by reductions in other types of coverage.

In contrast, the ACA dependent coverage expansion aimed to improve net coverage among young adults by relaxing the eligibility requirements and extending the same requirements to employers who have self-insured plans. Recent studies have shown that the ACA dependent coverage expansion has significantly increased health insurance coverage levels for young adults across all racial groups and for both the employed and the unemployed (Cantor et al., 2012; Sommers and Kronick, 2012). Other research focused on health care utilization also shows significant increases in health insurance coverage (Sommers et al., 2013; Akosa Antwi et al., 2013 and 2015; Barbaresco et al., 2015; Chua and Sommers, 2014). This increase in coverage provides protection to young adults at risk of losing insurance in the absence of the law, especially for men, unmarried adults, non-students, and those with poor health (Cantor et al., 2012). Thus the ACA dependent coverage reform has successfully increased health insurance coverage, which decreases the price of medical care faced by young adults.

B. The Impact of the ACA Dependent Coverage Expansion on Utilization, Health Outcomes, and Risky Behaviors

One would predict that increases in coverage would lead to overall increases in medical care access and consumption as a result of reduced medical care prices. Sommers et al. (2013) show that the ACA dependent coverage expansion reduces delays in getting care and care foregone due to costs. Akosa Antwi et al. (2015) find that the number of overall (non-birth) hospital visits as well as inpatient visits associated with a mental health diagnosis increase as a result of the ACA dependent coverage expansion.[4] The authors do not find evidence of a noticeable impact on hospital length of stay or number of procedures. Barbaresco et al. (2015) find an increase in the probability of having a personal doctor and a decrease in medical care foregone because of costs as a result of the ACA dependent coverage expansion. However, they find mixed results with respect to preventive care utilization, including a statistically significant reduction in flu shots but no clear effects on pap tests for women or well-patient checkups. Chua and Sommers (2014) do not find any impact of the ACA dependent coverage expansion on inpatient or outpatient utilization.

There is less work considering the impact of dependent coverage expansions on health outcomes or risky behaviors. In terms of health outcomes, Chua and Sommers (2014) show significant increases in excellent self-reported mental and physical health as a result of the ACA dependent coverage expansion. Barbaresco et al. (2015) find a statistically significant increase in

[4] Rather than focusing on gains in coverage, Anderson et al. (2012 and 2014) examine the consequences of young adults "aging off" (age 19 and age 23 for students) of their parents' insurance plans and find a 61 percent reduction in inpatient hospital admissions.

self-reported excellent health, but no significant changes in mental health, physical health, or functional limitations. With respect to risky behaviors, Barbaresco et al. (2015) find mixed results, with increases in overall and binge drinking, along with decreases in BMI (body mass index) and obesity. None of these behavioral results are statistically significant.

C. Other Types of Coverage Expansions and Avoidable Hospitalizations

Billings and Teicholz (1990) first developed the concept of using avoidable (or ambulatory care sensitive (ACS)) hospitalizations as an indirect indicator of problems associated with primary care quality and access to care. The idea here is that certain hospitalizations could be avoided if the patient has access to high quality primary care. Thus, this approach allows researchers to use hospital discharge data, which is readily available, to assess ambulatory care quality.

Dafny and Gruber (2005) use such an approach to investigate the impact of the Medicaid expansions of the 1980s and 1990s on low income children made newly eligible for public coverage using data from the National Hospital Discharge Survey. They find that total hospitalizations increase significantly as a result of these coverage expansions. A decomposition of all hospital stays into those that are avoidable versus those that are unavoidable suggests that the increase for unavoidable hospitalizations is much larger than that for avoidable hospitalizations. In addition, the increase in avoidable hospitalizations they estimate is not statistically significant. They take this as evidence that there is an "efficiency" effect associated with expanding coverage, but that this efficiency effect is dominated by the "access" effect.

In the study about the impact of a Medicaid outreach program in California the late 1990s, Aizer (2007) tests the hypothesis that families responding to outreach efforts will sign their children up before they get sick, improving their access to outpatient care, and reducing their number of avoidable hospitalizations. Using California Medicaid administrative enrollment and claims data, she finds that increases in Medicaid take up resulted in lower hospitalization rates for avoidable conditions, but not others.

Using the HCUP NIS hospital discharge data from 2004 to 2008, KK examine the impact of the 2006 Massachusetts health insurance reform on avoidable hospitalizations for non-elderly adults. After controlling for illness severity, the authors estimate a statistically significant, negative impact of the Massachusetts reform on avoidable hospitalizations. They attributed the reduction in such hospitalizations to patients with less severe medical problems. Unlike the previous papers described here, KK employ avoidable hospitalization definitions developed by the AHRQ specifically for this type of analysis.

Taken as a whole, evidence from the literature suggests that expanding insurance coverage leads to more primary care utilization. Dafny and Gruber (2005), Aizer (2007), and KK all hypothesize that this could lead to a reduction in the need for avoidable hospitalizations. Dafny and Gruber (2005) refer to this as the efficiency effect. On the other hand, an increase in insurance coverage could lead to more hospitalizations as the price of hospital care falls. Dafny and Gruber (2005) call this the access effect. Both Aizer (2007) and KK find reductions in avoidable hospitalizations among the different populations gaining coverage in their studies. Their findings suggest that the efficiency effect dominates the access effect. Conversely, Dafny and Gruber (2005) find an increase in avoidable hospitalizations, though not as large as for total hospitalizations among children gaining Medicaid coverage in the mid-1980s through mid-1990s. Therefore, it is not obvious which effect would dominate for young adults gaining coverage through the ACA dependent coverage expansion. The conceptual model described in the next section formalizes this discussion and introduces moral hazard as a third potential channel through which insurance expansions can impact avoidable hospitalization demand.

III. Conceptual Model

Here I derive a conceptual model of avoidable hospitalizations that will guide my empirical work.

To start, I posit that the probability of an avoidable hospitalization is a function f of the price of an avoidable hospital stay (P_{AV}) and the consumer's health status H, so $Prob(AV) = f(P_{AV}, H)$. Further, I assume that the price of an avoidable hospital stay is a function of the ACA mandate or law (L) and that the consumer's health status is a function of their primary care consumption (PC) and their engagement in risky behaviors (B):

$$Prob(AV) = f(P_{AV}(L), H(PC, B)) \tag{1}$$

Primary care consumption (PC) is going to depend on the price of primary care (P_{PC}), which itself is a function of the ACA (L), and risky behaviors (B) are going to depend on the price of avoidable hospitalizations (P_{AV}), which itself is also a function of the ACA (L). Putting this all together gives me the following equation:

$$Prob(AV) = f\{P_{AV}(L), H\left(PC\left(P_{PC}(L)\right), B(P_{AV}(L))\right)\} \tag{2}$$

Since I am interested in the impact of the ACA dependent care coverage expansion on avoidable hospitalizations, I take the derivative of this function with respect to L:

$$\frac{dAV}{dL} = \frac{df}{dP_{AV}} * \frac{dP_{AV}}{dL} + \frac{df}{dH} * (\frac{dH}{dPC} * \frac{dPC}{dP_{PC}} * \frac{dP_{PC}}{dL} + \frac{dH}{dB} * \frac{dB}{dP_{AV}} * \frac{dP_{AV}}{dL}) \tag{3}$$

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Below each term I include my assumption about its sign based largely on the literature described in the previous section.

Since the ACA dependent care expansion increased insurance coverage among young adults, the partial derivatives of the change in health care prices with respect to the law should all be negative, so $\frac{dP_{AV}}{dL}$ and $\frac{dP_{PC}}{dL} < 0$. The law of demand suggests that as health care prices fall, we would expect health care consumption to increase, implying that $\frac{df}{dP_{AV}}$ and $\frac{dPC}{dP_{PC}} < 0$. These assumptions imply that the first term on the right hand side of equation (3) is positive and can be thought of as the **access effect**. The access effect suggests that as young adults gain insurance coverage and face lower prices for avoidable hospitalizations, their demand for avoidable hospitalizations will increase.

The second term on the right hand side formalizes two additional channels through which a coverage expansion can influence avoidable hospitalization consumption. The first channel is the **efficiency effect**. It suggests that as the price of primary care falls, young adults will consume more primary care ($\frac{dPC}{dP_{PC}} < 0$).[5] This in turn is assumed to improve their health ($\frac{dH}{dPC} > 0$) and reduce their demand for avoidable hospitalizations ($\frac{df}{dH} < 0$).[6] As mentioned in the previous section, both Aizer (2007) and KK find that the efficiency effect dominates the access effect since they estimate overall reductions in avoidable hospitalizations among the populations they study.

[5] Several studies have found that insurance expansions increase primary care consumption, including Manning et al. (1987), Currie and Gruber (1996a), Lichtenberg (2002), Card et al. (2008), and Finkelstein et al. (2012).

[6] Does more primary care really improve health? This can be a difficult question to answer with respect to insurance expansions as such expansions may increase primary care consumption, while at the same time also potentially increasing risky behavior, and both will affect health outcomes. The literature on the ACA dependent coverage example discussed in the previous section of this paper suggests mixed findings with respect to health outcomes. Brook et al. (1983) find that free care improves cholesterol levels, mental and physical health in certain sub-groups in the RAND health insurance experiment. Several studies suggest that Medicaid expansions reduce mortality and increase self-assessed overall, mental and physical health, while having no statistically significant effects on laboratory-measured health outcomes (Currie and Gruber, 1996b; Finkelstein et al., 2012; Sommers et al., 2012; Baicker et al., 2013). The Medicare program has been estimated to decrease mortality rates for Medicare inpatients (Card et al., 2009), but no significant impact of Medicare on the mortality rate for the elderly in general has been found (Finkelstein and McKnight, 2008). Unanimous evidence from the 2006 Massachusetts health insurance reform shows increases in self-assessed overall, mental and physical health, and decreases in functional limitations, joint disorders and mortality (Van der Wees et al., 2013; Courtemanche and Zapata, 2014; Sommers et al., 2014).

The other channel captured by the second term on the right hand side of equation (3) can be thought of as representing ***ex ante* moral hazard** (Ehrlick and Becker, 1972) through the term B in two ways. First, a reduction in the price of avoidable hospitalizations could lead to an increase in risky behaviors such as drinking and smoking. Second, a reduction in the price of avoidable hospitalizations could lead to a reduction in the demand for health promoting activities, such as flu vaccinations or smoking cessation program participation. Such behavior suggests $\frac{dB}{dP_{AV}} < 0$ and I assume that an increase in risky behavior leads to a reduction in health $\frac{dH}{dB} < 0$. The moral hazard effect would thus be predicted to lead to an increase in avoidable hospitalizations.

As this channel was not explicitly mentioned in the previous literature on avoidable hospitalizations, more discussion is warranted. First, is there evidence that reductions in the price of avoidable hospitalizations lead to increases in risky behaviors and reductions in health promoting activities? The empirical literature on these topics is mixed. Neither the RAND health insurance experiment nor the Oregon Medicaid study found a significant impact of insurance coverage on smoking or body weight (Brook et al., 1983; Finkelstein et al., 2012). While Dave and Kaestner (2009) find increases in smoking and drinking, and decreasing physical activity, associated with enrolling in the Medicare program, none of the effects are significant. Courtemanche and Zapata (2014) find no evidence on smoking or physical activity as a result of the 2006 Massachusetts health insurance reform, though they do find a significant reduction in body mass index.[7] As mentioned, Barbaresco et al. (2015) find no statistically significant impact of the ACA dependent coverage expansion on overall drinking, binge drinking, BMI, and obesity.

[7] Body mass index is a proxy of poor diets and sedentary lifestyles, and has been broadly used as one of the risky behaviors in the literature. However, it might not fully satisfy the narrow definition here as it can be affected through other channels (such as being suggested or reminded by the doctor during each physician visit) than the pure price effect of avoidable hospitalizations.

They did however, estimate a statistically significant decrease in flu vaccinations, which can be viewed as the reduction of the investment in health promoting activities as the price of flu shot is not very high even without health insurance.

As for the impact of risky behaviors on health, Mcginnis and Foege (1993) find in their influential study that half of the deaths in the United States in 1990 are from external modifiable risk behaviors. More recent studies by Mokdad et al. (2004 and 2005) also show similar results for the U.S. in 2000: smoking, diet, physical activity, and drinking are the main risky behaviors leading to death. Danaei et al. (2009) break dietary behavior into detailed categories and find high body mass index, physical inactivity, and high blood glucose are the three main risk factors leading to death, followed by a list of dietary risk factors. In general, the literature supports the notion that risky behaviors have an impact on health. However, young adults maybe more immune to the health effects of risky behaviors as compared to the elderly or to children.

Taken together, the evidence on these terms suggests that there may be a moral hazard effect associated with increased insurance coverage, which would lead to a higher demand for avoidable hospitalizations. My conceptual model predicts that the efficiency effect would lead to a reduction in avoidable hospitalizations, while the access effect and the moral hazard effect lead to increases in avoidable hospitalizations. Thus the overall effect is ambiguous, reinforcing the need to analyze this issue empirically.

IV. Methodology

I use a difference-in-differences strategy to examine the impact of the ACA dependent coverage expansion on the prevalence of avoidable hospitalizations among the treatment group of young adults relative to the control group of slightly older young adults before and after the mandate's implementation in late September of 2010. Because the group targeted by the mandate is 19-to-25 year olds, most previous studies on the ACA dependent coverage mandate use an age range of 19-25 to define their treatment group and typically use older young adults (sometimes including those as old as 34) as their control group.

The key identifying assumption in any difference-in-differences model is the assumption that both the treatment and control groups would have experienced the same changes in outcomes in the absence of the intervention of interest. Slusky (2015) calls into question the validity of the "common trends" assumption with respect to labor market outcomes for young adults in the age rage typically used in the literature. He replicates previous studies with "placebo" treatment dates occurring several years prior to the implementation of the mandate and finds significant "effects". This suggests that previous studies may be mistakenly attributing changes in young adult insurance coverage to the ACA that are actually driven by dynamics in the age structure of insurance and labor markets. He finds more reliable estimates after reducing the age bandwidth associated with the treatment group.

Like Barbaresco et al. (2015), I address this concern by defining my treatment group as young adults aged 23 to 25 and the control group as young adults aged 27 to 29.[8] Slusky's concerns are arguably less important for avoidable hospitalizations than they are for labor market outcomes, since avoidable hospitalizations are likely less directly impacted by cyclical economic fluctuations. In addition, narrowing the age bandwidth associated with the treatment and control groups, as done here and in Barbaresco et al. (2015), should also reduce the impact of any differential economic shocks. Finally, relative to other studies, I use a longer pre-reform period (starting from 2002) in my analysis to better test for differences in pre-reform trends between the treatment and control

[8] I follow the previous literature and exclude young adults aged 26, as it is difficult to determine whether or not the mandate is binding for them. It would be a function of their birthdate and the start date of their parents' insurance plan for the year.

groups.

Formally, I estimate the following equation:

$$Y_{ight} = \beta_0 + \beta_1(Treat_g * After_t) + \beta_2 \boldsymbol{X}'_{ight} + \theta_g + \varphi_t + \sigma_h + \varepsilon_{ight}, \tag{4}$$

where Y is a dummy variable equal to one if hospital discharge i is considered an avoidable hospitalization generated by a patient of age g in hospital h at time t. The primary parameter of interest is denoted by β_1. It measures the effect of the mandate after implementation on the targeted age group. $Treat_g$ is a dummy variable equal to one for any discharge generated by a patient in the age range of 23-25 (the treatment group). $After_t$ is a dummy variable equal to one for any discharge occurring in a time period t that is after the implementation of the ACA mandate (October 2010 or later). The vector X' includes a set of patient demographic characteristics and a set of risk adjusters to control for patient illness severity. The terms θ_g, φ_t and σ_h capture separately age, time, and the hospital fixed effects. Finally ε_{ight} represents the error term. In my estimation, I use heteroskedasticity-robust standard errors clustered at the treatment level age. NIS sampling weights, discussed below, are used in the analysis.

To verify the validity of my findings, I perform several placebo regressions using treatment dates occurring several years prior to the implementation of the mandate as in Slusky (2015). I also perform multiple additional robustness checks. The first two checks re-estimate equation (4) with shorter pre-reform time frames (15 and 23 quarters versus 35) to verify that my results are not driven by my chosen length of the pre-reform period. The third check excludes the time period of April 2010 to September 2010 (Q2 2010 – Q3 2010), which is the time period between when the law passed and its effective date, to avoid ambiguity about the treatment status of hospitalized young adults during this period.

V. Data

The dataset used for this analysis is the Nationwide Inpatient Sample (NIS), which is part of the Healthcare Cost and Utilization Project (HCUP) administered by the Agency for Healthcare Research and Quality (AHRQ). Each year of the NIS is a stratified sample of 20 percent of community hospitals in the U.S. and is nationally representative of all community hospitals.[9] If a hospital is sampled in a given year, it provides the universe of its discharges for that year, regardless of payer. As in KK, I take advantage of the fact that a large fraction of hospitals are sampled in each year to identify within hospital changes over time.

The NIS is a good data source to examine the impact of health insurance coverage reforms since it has complete payer information for each discharge. Detailed information on diagnoses and patients' point of admission (directly admitted or transferred from other facilities) allow me to create indicators for avoidable hospitalizations. One weakness of this data is that it only consists of hospitalized patients, which may introduce a selection problem with illness severity into the analysis. I use several patient-level risk adjusters to control for this problem.

The years I use for this analysis range from 2002 to 2011 (the most recent year available).[10] Since the mandate was implemented in late September 2010 and NIS is a quarterly data, I define the time from the first quarter of 2002 to the third quarter of 2010 as the pre-reform period, and

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[9] One caveat to note is that not every state participates in this endeavor. By 2011, there are 46 states reporting data to the HCUP database. Data from Alabama, Delaware, Idaho, and New Hampshire are not available in any year because they did not provide data to the NIS. Other states report incomplete data. I exclude the states of California, Maine and Texas from the analysis because detailed age information for patients is not available.

[10] The AHRQ redesigned the NIS sampling strategy in 2012. The new NIS is a sample of discharges from all hospitals participating in HCUP, rather than all discharges from a sample of participating hospitals, as in previous years. A consistent hospital identifier, allowing researchers to control for hospital fixed effects, will no longer be available.

from the fourth quarter of 2010 to the fourth quarter of 2011 as the post-reform period. My sample starts with 4,813,849 discharges from the NIS for young adults aged 23-29 over the 2002-2011 period of analysis. After excluding discharges with missing values for key variables (age, gender, principal diagnosis, quarter, year, and hospital), my sample is reduced to 3,845,814 discharges. A total of 3,363,241 discharges occur in the pre-reform time period and 482,573 occur in the post-reform time period.

The main outcome I consider in this analysis is the classification of a given discharge as an avoidable hospitalization, which implies that it is a hospitalization for a condition or treatment which could have been potentially prevented by effective community outpatient / primary care or other early medical intervention. Thus avoidable hospitalizations serve as a proxy for primary care quality. Such a hospitalization is also referred to as an ambulatory care sensitive (ACS) hospital admission.

One issue associated with this literature is that the definition of an avoidable hospitalization is often ad hoc and can differ from study to study. Given that I am using data from the AHRQ, I follow KK and use the AHRQ methodology for identifying avoidable hospitalizations. This methodology identifies twelve separate conditions / treatments considered to be avoidable for adults, such as an inpatient stay due to dehydration or uncontrolled diabetes.[11] The AHRQ provides software that creates flags for each of the twelve conditions / treatments, which they call Prevention Quality Indicators (PQIs).[12]

Table 1 provides the summary statistics of the pre- and post-reform and corresponding difference-in-differences calculations for all of the PQI avoidable hospitalization indicators, as

[11] Actually, this methodology identifies fourteen conditions, but I am not considering COPD / asthma admissions among older adults or low birth weight admissions.
[12] The AHRQ software generates these PQIs based on hospital discharge data by using complex algorithms. Essentially, the indicators first look for specific principal diagnoses, then exclude certain discharges based on their

well as AHRQ generated composites for acute and chronic PQIs, and an overall composite. The definition of the acute composite indicator, PQI 91, is the union of PQI indicators 10, 11, and 12 (dehydration, bacterial pneumonia, and urinary tract infections). Similarly, the definition of the chronic composite indicator, PQI 92, is the union of PQI indicators 1, 3, 7, 8, 13, 14, 15, and 16 (short-term and long-term diabetes complications, hypertension, congestive heart failure, angina, uncontrolled diabetes, adult asthma, and lower-extremity amputation). Thus it includes all PQIs except the previously defined acute indicators and PQI 2 (perforated appendix), because it has a different denominator. Finally, the overall PQI indicator (PQI 90) is defined as the union of all of the individual indicators except PQI 2.

The first row of table 1 suggests that in the pre-reform time period, the probability of a discharge among a young adult in the treated group being avoidable is 3.48 percent while the probability of a discharge among a young adult in the control group being avoidable is 3.55 percent. There is also a slightly lower probability of a discharge being chronic avoidable for young adults in the treated group than in the control group (1.81 vs 1.94 percent) in the pre-reform time period. For the acute PQI composite, the probability of a discharge being acute avoidable among the treated group is 1.67 percent, while it is 1.61 percent in the control group. For the twelve individual PQI indicators, most discharges have a slightly higher probability of being avoidable in the control group in the pre-reform time period, except short-term diabetes (PQI 1) and urinary tract infections (PQI 12).

The simple difference-in-differences calculations presented in the last column of table 1 compare the changes of the mean probability for the treatment relative to control group in the pre-

secondary and tertiary diagnoses. Transfers from other facilities are excluded to avoid double-counting. A diagnosis of pregnancy, if necessary, is also excluded in certain PQIs. For more information on the AHRQ PQI methodology, see: http://www.qualityindicators.ahrq.gov/Modules/PQI_TechSpec.aspx and post-reform periods, showing statistically significant increases in the overall PQI composite, the chronic PQI composite, as well as the PQIs for short-term diabetes complications (PQI 1), congestive heart failure (PQI 8), dehydration (PQI 10), angina without a procedure (PQI 13), and uncontrolled diabetes (PQI 14). The calculations also show statistically significant decreases in PQI 7 and 16. This is suggestive evidence that the ACA dependent coverage expansion may have led to an increase in avoidable hospitalizations.

Figure 1 shows trends in the probability that a given discharge is an overall, acute or chronic avoidable hospitalization separately for the treatment and control groups. The figures show similar trends for both groups before mandate, indicating that time-variant changes in observables and unobservables may not differ substantially between the two groups. This provides further support for implementing a difference-in-differences analysis.

In order to isolate the impact of the ACA dependent coverage mandate, I include in my regression analysis a set of demographic control variables. These are dummy variables for each year of age, gender, race/ethnicity, and patient's zip code in income quartile. In addition, I include the quarterly state unemployment rate, from the Bureau of Labor Statistics, to control for state level economic conditions. Following KK, I also utilize a set of risk adjusters to control for patient disease severity. These risk adjusters include the number of diagnoses on the discharge record, AHRQ comorbidity dummies for different diseases, All-Patient Refined Diagnosis Related Groups (APR-DRGs) classification, the APR-DRG severity of illness score, and the APR-DRG risk of mortality score.[13] All the risk adjusters are designed to measure some level of illness severity and are included in my discharge level regression.

[13] The number of diagnoses is calculated by counting the number of diagnoses on each discharge record. The AHRQ comorbidity dummies provide 29 categories of disease comorbidity (i.e. for congestive heart failure: 1 represents comorbidity and 0 shows comorbidity is not present). The APR-DRG related measures, developed by 3M, are used to classify patients according to their degree of potential mortality and illness severity.

Table 2 shows the pre-reform means and standard deviations for the demographic controls for the young adult discharges in the sample. Within both the treatment and the control group, the discharges are evenly distributed across the age categories. A larger share of discharges is generated by females (81.3 percent) than males, with similar percentages in both the treatment group and the control group. As for race and ethnicity, discharges from whites make up a slightly lower (40.9 percent vs. 43.5 percent) share for treatment group as compared to the control group. For the patient’s zip code income quartile, discharges associated with the age group 23-25 have a higher share (33.5 percent) in the two lowest quartiles, as compared to 30.6 percent among discharges from the age group 27-29.

VI. Results

A. Average Effects and Robustness Checks of the ACA Dependent Coverage Expansion on the Probability of Avoidable Hospitalizations

Column 1 of table 3 provides the results of difference-in-differences estimation of the baseline model. To control for potential changes in the patient population in the post-reform time period, I estimate the baseline model with risk adjusters, where I use severity of disease to control for observable changes in the health status of the patient pool. The baseline model suggests a 0.17 percentage point increase in the probability of a discharge being avoidable, which represents a 4.9 percent increase compared to the baseline rate of avoidable hospitalizations.[14] The composite indicator for chronic avoidable hospitalizations also shows a significant increase of 0.14 percentage points, which represents a 7.7 percent increase. The coefficient on the composite acute indicator, although not significant, is also positive.

[14] Compared to the pre-reform treatment mean of 3.48 percent, the increase of 0.12 percentage point represents an increase of 3.4 percent.

Column 2 to 5 are robustness checks. The estimates in column 2 (without risk adjusters) are similar to those generated by the baseline model, with slightly lower effects associated with overall (3.4 percent increase vs. 4.9 percent) and chronic avoidable hospitalizations (5 percent increase vs. 7.7 percent). This suggests that the illness severity of the inpatient population for young adults did not change much after the ACA mandate, which may due to the fact that young adults are relatively healthy in general.

Columns 3 and 4 restrict the period of analysis to 2007-2011 and 2005-2011 respectively. In each case the estimated impact of the ACA dependent coverage expansion on the likelihood that a young adult discharge is avoidable is very similar in terms of magnitude and statistical significance. The coefficient estimate in the baseline model suggests a 0.17 percentage point increase, while the coefficient estimate in the 2007-2011 (2005-2011) model suggests a 0.15 (0.16) percentage point increase. The results are similar for both the chronic and acute composite PQI indicators. This suggests the baseline results are not being driven by the length of the pre-reform period.

The next robustness check, presented in column 5, drops the time period between the passage of the ACA and its dependent coverage expansion implementation date, which I define as the second and third quarters of 2010. As above, making this change does not impact the coefficient estimates in a major way.

Additionally, table 3 lists results for each individual PQI indicator. Among the twelve individual indicators in the baseline model, four of them suggest statistically significant increases in a discharge being associated with that particular avoidable admission (short-term diabetes complications, congestive heart failure, dehydration, and uncontrolled diabetes); two exhibit statistically significant reductions (hypertension and lower-extremity amputation) and the remaining six have no statistical significance.

B. Placebo Tests

In order to test the validity of the difference-in-differences results presented in the previous sub-section, I estimate a series of four placebo tests that use artificial effective dates within the pre-reform period as in Slusky (2015). Following previous studies (Antwi Akosa et al., 2013; Barbaresco et al., 2015) which use a five-year period for their primary analyses, I use five-year windows pre-reform for my placebo tests spanning 2005-2009, 2004-2008, 2003-2007, and 2002-2006.[15] In my baseline model, there are five quarters in the post-reform time period, so I also use five quarters as the length of my artificial post-reform time period in each placebo test (e.g. the fourth quarter of 2008 is the start of the artificial post-reform time period for the 2005-2009 placebo test). I estimate a specification similar to my baseline model for all of the PQIs in each of the four placebo tests.

Table 4 reports the estimates from these tests. Fifteen PQI regressions in each of the four sets of placebo tests generate a total of 60 regressions. Theoretically, a small number of significant results are expected due to the large number of regressions. Around one estimate is expected to be significant at the 1 percent level, three at the 5 percent level, and six at the 10 percent level by chance. The number of significant results reported in table 4 is 0 at the 1 percent level, one (1.7 percent) at the 5 percent level, and five (8.3 percent) at the 10 percent level. Note that one particular PQI, PQI 13 (angina), accounted for two of the five significant results. Dropping PQI 13 from the definitions of the overall PQI avoidable hospital indicator and the chronic composite indicator

[15] In unreported placebo tests (available upon request), I estimate another five placebo tests with varying time windows of 2002-2009 (8 years), 2002-2008 (7 years), 2002-2007 (6 years), 2002-2006 (5 years), and 2002-2005 (4 years). The results are similar in terms of the number of significant estimates.

does not lead to major changes in my primary results. Overall, these placebo tests suggest that my primary difference-in-differences approach is sound and there does not appear to be any sustained differential pre-reform trends between the treatment and control groups. Moreover, these placebo test results also suggest that the standard errors, which are clustered at the age level, are not meaningfully understated.

C. Heterogeneity Tests

Having verified the validity of my empirical model and estimated the average effects of the ACA dependent coverage expansion, I next present the results of models that allow for heterogeneous effects for different sub-groups in my sample. There may be differences by gender or race in response to gaining insurance coverage. In addition, differences in socioeconomic status may also lead to different responses. Tables 5 and 6 present the results from heterogeneity regressions based on gender, race and patient's zip code income quartile.

The first two columns of table 5 illustrate differences by gender. These results suggest that the statistically significant increases in the probability of an overall avoidable hospitalization (PQI 90) or a chronic avoidable hospitalization (PQI 92) in my baseline model are being driven by young females, rather than young males. Young men do statistically significantly reduce their probability of a hospitalization for extremity amputation (PQI 16) after gaining coverage, but increase their probability of a hospitalization for heart failure (PQI 8).

The next three columns of table 5 present differences by race. Black, Hispanic, Asian, Native American and other races compose 28 percent of the sample and are grouped together as non-white. The remaining sample is classified as either unknown race (30 percent) or white (42 percent). These results suggest that the statistically significant increases in the probability of an overall avoidable hospitalization (PQI 90) or a chronic avoidable hospitalization (PQI 92) in my baseline model are being driven by whites, rather than non-whites or those with unknown race. Although I find no statistically significant impact on acute avoidable hospitalizations (PQI 91) in my baseline model, table 5 suggests that the ACA dependent coverage expansion lead to an increase in the probability of having such a hospitalization for non-whites.

Table 6 presents heterogeneity model results based on patient's zip code income quartile. These results suggest that the statistically significant increases in the probability of an overall avoidable hospitalization (PQI 90) and the probability of a chronic avoidable hospitalization (PQI 92) in the baseline model are being driven by patients coming from zip codes with income that fall in the third income quartile of the distribution. Taken together, this heterogeneity analysis suggests that there are important differences by gender, race, and income in response to gaining insurance through the ACA dependent coverage mandate.

D. Average Effects of the ACA Dependent Coverage Expansion on the Number of Avoidable Hospitalizations

One caveat of using the hospital discharge data is that the probability of avoidable hospitalizations obtained in the empirical work is conditional on all hospitalizations. Therefore, the increase in the probability of avoidable hospitalizations may indicate either increases in the number of both avoidable hospitalizations and total hospitalizations or decreases in the number of both hospitalizations, or a mix of increase in the number of avoidable hospitalizations and decrease in the number of total hospitalizations. Total hospitalizations are comprised of avoidable hospitalizations and unavoidable hospitalizations. Theoretically, increase in health insurance coverage will increase unavoidable hospital utilization or at least make no changes in such utilization if previous health care system was efficient that all the needs for unavoidable hospitalizations have been met. Thus, the number of avoidable hospitalizations as well as the number of total hospitalizations must increase.[16]

E. Increased Size for Avoidable Hospitalizations and Unavoidable Hospitalizations

The increase in the probability of avoidable hospitalizations indicates that the increase in avoidable hospitalizations grows faster than the increase in total hospitalizations, which is the sum of avoidable hospitalizations and unavoidable hospitalizations. Thus, the increased percent change in avoidable hospitalizations is greater than the increased percent change in unavoidable hospitalizations.[17] Increase in unavoidable hospitalizations represents access effect since those cannot be substituted by other types of health care utilization. As compared in Dafny and Gruber (2005), assuming access to hospital care increases the likelihood of all hospitalizations equally, the greater percent increase in avoidable hospitalizations indicates an extra positive effect besides the access effect, that is, the moral hazard effect in my conceptual model.

VII. Discussion

The overall increase in the probability of avoidable hospitalizations suggested by my empirical analysis implies that the access effect and the moral hazard effect dominate the efficiency effect for young adults gaining coverage through the ACA dependent coverage expansion. This is broadly consistent with the finding in Antwi Akosa et al. (2015) that ACA dependent coverage expansion increases non-birth hospital admissions and admissions associated with a mental health diagnosis. As previously discussed, my conceptual model suggests that if the probability of an

[16] For the both decrease situation, total hospitalizations (denominator) must decrease faster to insure the probability increase; however, the increase or no changes in unavoidable hospitalizations compensates the decrease of avoidable hospitalizations, and the total hospitalizations must decrease slower than the avoidable ones (numerator). Thus, this situation cannot hold. For the mix situation, increase in avoidable hospitalizations can only lead to an increase in total hospitalizations since unavoidable ones must increase or at least have no changes. So the last situation also cannot hold. For mathematical proof, see Appendix A1.
[17] For mathematical proof, see Appendix A2.

avoidable hospitalization increases as a result of a coverage expansion (as I find empirically), then this is likely being driven by the number of avoidable hospitalizations increasing more quickly than the number unavoidable hospitalizations. Suppose one further assumes:

- avoidable hospitalizations go up due to both the access effect and the moral hazard effect,
- unavoidable hospitalizations only go up due to the access effect, and
- the size of the access effect is equal for avoidable and unavoidable hospitalizations.

Under these additional assumptions, my empirical results and conceptual model imply that there is a moral hazard effect associated with the dependent coverage expansion.

I find some evidence of an efficiency effect for young adult avoidable hospitalizations as there are two individual indicators (hypertension and extremity amputation) that show reductions in probability after the ACA mandate. The evidence of efficiency effect echoes the results found in Dafny and Gruber (2005) for children gaining Medicaid coverage. Among those children there was some evidence of an efficiency effect, but this was dominated by the access effect. On the other hand, Aizer (2007) finds that when eligible, but not enrolled children formally enroll in Medicaid coverage in California they experience a reduction in avoidable hospitalizations. This would suggest the efficiency effect dominates.[18]

[18] Why do the results from Dafny and Gruber (2005) and Aizer (2007) regarding avoidable hospitalizations for children newly enrolled in Medicaid vary? One possible explanation is that Dafny and Gruber (2005) focus on children made newly eligible for Medicaid, while Aizer (2007) focuses on already eligible children who are now formally taking up Medicaid coverage. Presumably, children made newly eligible for Medicaid did not have a previous source of coverage for hospital or primary care. On the other hand, families of children who are eligible, but not formally enrolled in Medicaid may understand that hospital care would still be covered by Medicaid, as the hospital likely has experience assisting such families in the Medicaid enrollment process. This is less likely to be true with respect to primary care. Therefore, one could consider eligible, but not formally enrolled children as having "conditional hospital coverage" but not "conditional primary care coverage". Thus the children analyzed in Aizer (2007) experienced a greater increase in access to primary care as compared to hospital care. This increase in primary care access could explain why avoidable hospitalizations for this particular group of children fall.

Relative to my results, studies from the Massachusetts health insurance expansion tell a different story for older (non-elderly) adults. KK find that the Massachusetts reform leads to a reduction in the probability of avoidable hospitalizations, which they implicitly attribute to the efficiency effect dominating the access effect. This suggests that the older adults targeted by the reform responded by increasing their primary care consumption, thus reducing their rate of avoidable hospital stays. The difference in findings for young adults from ACA expansion and older (non-elderly) adults from Massachusetts reform may due to several potential reasons:

- **Information or experience:** Gaining health insurance coverage may lead to reductions in avoidable hospitalizations (i.e. the efficiency effect dominates), but that requires the newly insured to seek out and receive appropriate primary care. Young adults gaining coverage through the ACA dependent coverage expansion may not have enough experience with the health care system to successfully find such primary care services. Older adults are more likely to have this needed experience.
- **Risk attitudes:** Additionally, these older adults may be more risk averse than young adults, as they may realize that their overall health is no longer as good as when they were younger. Older adults may also need to protect themselves more diligently so that certain infectious disease (such as the flu) will not affect their family members. Therefore, even though the price of hospital care decreases due to expansions in insurance coverage, non-elderly adults do not want to face the risk of being hospitalized and so make sure they consume the necessary primary care.
- **Income constraints and Moral Hazard:** For financial reasons, young adults may be more likely than the older adults to forgo insurance coverage and instead focus on lower cost interventions such as flu vaccines and over-the-counter medications. However, receiving

insurance coverage alleviates the financing constraint, and as a result, young adults may engage in more risky behavior or invest less in their health, such as skipping their flu vaccine (Barbaresco et al., 2015). In other words, the *ex ante* moral hazard effect of obtaining coverage may be stronger for young adults than other adults.

On the other hand, dependent health insurance coverage may also increase young adults' disposable income, as some of them may no longer have to pay their own insurance premium. They may use this "extra" income to consume goods with adverse health consequences, such as cigarettes and alcohol. Barbaresco et al. (2015) show a significant increase in risky drinking; increases in drinking may lead to heart disease and diabetes in the long-run.

This discussion illustrates the benefits of using a conceptual model to think about how the impact of gaining coverage might differ for individuals of different ages. While my results might seem at first glance to contradict the results from Massachusetts, there are several plausible reasons why we might expect young adults to respond differently to a gain in insurance coverage than older adults.

VIII. Conclusion

A typical hospitalization may be characterized as an unavoidable because there is nothing that could have been done medically to avoid the stay, such as suffering a major injury in a car accident. In this paper I investigate whether or not there were changes in the probability of having an avoidable hospitalization – one that could have been prevented by the receipt of timely and appropriate primary medical care – among young adults gaining health insurance coverage through ACA dependent coverage expansion which was implemented in September 2010. Though several previous studies have examined the impact of coverage expansions on hospital utilization, there are many reasons why we might expect young adults to potentially respond differently than older adults or children. To answer this question I use HCUP NIS hospital discharge data and AHRQ avoidable hospitalization definitions to estimate a difference-in-differences model with a narrow age bandwidth of age 23-25 as the treatment group and age 27-29 as the control group. The results shown in the baseline model for the entire sample indicate increases in the probability of having any avoidable hospitalization as well as the chronic composite, but no clear effects on the acute composite index.

Specifically, the ACA dependent coverage mandate leads to an increases in the probability of PQI 1 (short-term diabetes), PQI 8 (congestive heart failure), acute PQI 10 (dehydration), and PQI 14 (uncontrolled diabetes). At the same time, I estimate decreases in the probability PQI 7 (hypertension) and PQI 16 (lower-extremity amputation). Controlling for patient illness severity does not lead to major changes in these results. Then I implement another three robustness checks to confirm the effects shown in the baseline model are not driven by my choice of the length of the pre-reform period in my analysis. Next, I utilize several placebo regressions with pre-reform periods to validate the model with a narrow age range treatment group. Finally, I estimate the model on sub-samples of different gender, race, and zip code income quartiles. There are important differences by gender, race, and income in response to the ACA dependent coverage mandate.

One inference derived from my empirical results is evidence of a positive effect increasing avoidable hospitalizations for young adults. By referring to the conceptual model created in this paper, this is consistent with the previous literature of regarding the moral hazard effects associated with health insurance expansions, although it has not been discussed in the previous avoidable hospitalization literature or directly empirically tested in this paper. Further research is needed to empirically estimate the moral hazard effect and its size in this context.

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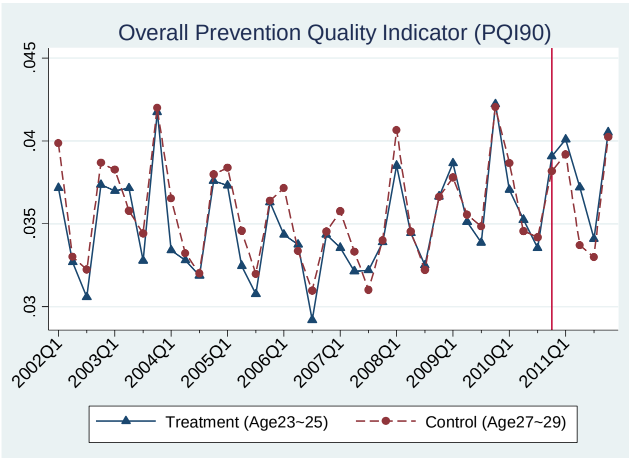
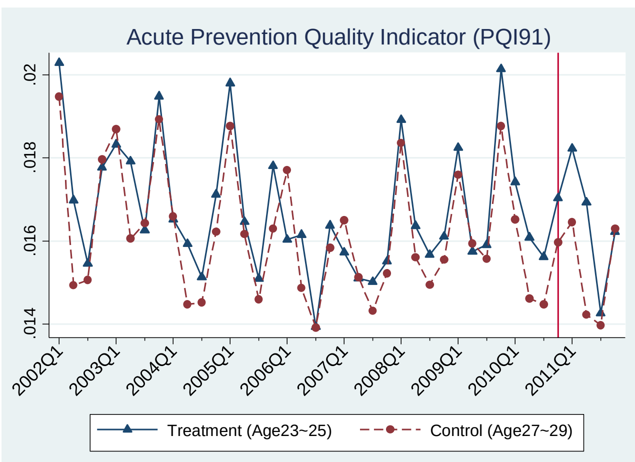
Figure 1 – Trends in Prevention Quality Indicators by Age Group

(a) Overall Prevention Quality Indicator



(b) Acute Prevention Quality Indicator



(c) Chronic Prevention Quality Indicator

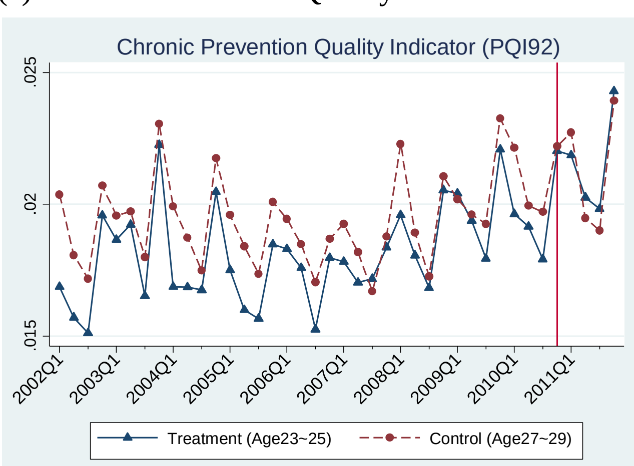


Table 1 – Means and Standard Deviations for Outcome Variables

Quality Indicators	Pre-reform Period Treatment (Ages 23-25)	Pre-reform Period Control (Ages 27-29)	Post-reform Period Treatment (Ages 23-25)	Post-reform Period Control (Ages 27-29)	Difference-in-Difference
Overall Prevention Quality Indicators					
PQI 90 Overall Composite	0.0348 (0.1832)	0.0355 (0.1851)	0.0381 (0.1916)	0.0368 (0.1883)	0.0021 (0.0005)**
PQI 91 Acute Composite	0.0167 (0.1281)	0.0161 (0.1260)	0.0165 (0.1274)	0.0154 (0.1230)	0.0006 (0.0005)
PQI 92 Chronic Composite	0.0181 (0.1332)	0.0194 (0.1379)	0.0216 (0.1455)	0.0214 (0.1448)	0.0015 (0.0002)***
Individual Component Measures of Prevention Quality Indicators					
PQI 01 Diabetes short-term comp.	0.0079 (0.0885)	0.0067 (0.0814)	0.0108 (0.1033)	0.0085 (0.0917)	0.0011 (0.0004)**
PQI 02 Perforated appendix	0.1717 (0.3771)	0.1748 (0.3798)	0.1763 (0.3812)	0.1853 (0.3887)	-0.0059 (0.0140)
PQI 03 Diabetes long-term comp.	0.0020 (0.0446)	0.0030 (0.0550)	0.0027 (0.0523)	0.0039 (0.0622)	-0.0001 (0.0003)
PQI 07 Hypertension	0.0005 (0.0222)	0.0009 (0.0305)	0.0005 (0.0234)	0.0012 (0.0348)	-0.0002 (0.0001)**
PQI 08 Congestive heart failure	0.0009 (0.0303)	0.0015 (0.0390)	0.0009 (0.0307)	0.0013 (0.0356)	0.0003 (0.0001)*
PQI 10 Dehydration	0.0041 (0.0642)	0.0043 (0.0655)	0.0034 (0.0585)	0.0032 (0.0561)	0.0005 (0.0002)**
PQI 11 Bacterial pneumonia	0.0053 (0.0728)	0.0058 (0.0757)	0.0057 (0.0752)	0.0060 (0.0772)	0.0001 (0.0003)
PQI 12 Urinary tract infection	0.0072 (0.0847)	0.0061 (0.0776)	0.0074 (0.0857)	0.0062 (0.0786)	0.00001 (0.0002)
PQI 13 Angina without procedure	0.0001 (0.0096)	0.0002 (0.0134)	0.0001 (0.0081)	0.0001 (0.0101)	0.0001 (0.00004)
PQI 14 Uncontrolled diabetes	0.0008 (0.0277)	0.0009 (0.0299)	0.0008 (0.0280)	0.0007 (0.0272)	0.0002 (0.00003)***
PQI 15 Asthma in younger adults	0.0059 (0.0767)	0.0062 (0.0782)	0.0058 (0.0756)	0.0057 (0.0753)	0.0003 (0.0002)
PQI 16 Lower-extremity amputation	0.00003 (0.0053)	0.0001 (0.0082)	0.00002 (0.0042)	0.0001 (0.0113)	-0.00007 (0.00002)**
Sample Size	1,620,088	1,743,153	225,861	256,712	--

Notes: Means are reported, with standard deviations in parentheses. Standard errors, heteroskedasticity-robust and clustered at the age level, are in parentheses for difference-in-differences calculations. NIS sampling weights are used. *** indicates the difference-in-differences is significant at the 1% level; ** 5%; * 10%.

Table 2 – Pre-reform Means and Standard Deviations for Control Variables

Control Variables	Total (Ages 23-29)	Treatment (Ages 23-25)	Control (Ages 27-29)
Age dummies (age=23 is omitted)			
Age=24	0.161 (0.367)	0.334 (0.472)	--
Age=25	0.164 (0.371)	0.341 (0.474)	--
Age=27	0.173 (0.378)	--	0.333 (0.471)
Age=28	0.173 (0.378)	--	0.333 (0.471)
Age=29	0.173 (0.378)	--	0.334 (0.471)
Female	0.813 (0.390)	0.813 (0.390)	0.812 (0.391)
Race/ethnicity dummies (non-Hispanic white is omitted)			
Black	0.130 (0.336)	0.139 (0.346)	0.121 (0.327)
Hispanic	0.089 (0.285)	0.094 (0.291)	0.085 (0.279)
Asian	0.018 (0.131)	0.015 (0.121)	0.020 (0.140)
Native American	0.006 (0.079)	0.007 (0.081)	0.006 (0.077)
Other than black, Hispanic, Asian, Native, or white	0.036 (0.185)	0.035 (0.184)	0.036 (0.186)
Unknown Race	0.299 (0.458)	0.301 (0.459)	0.297 (0.457)
Patient's Zip Code in Income Quartile dummies (First (Lowest) is omitted)			
Second Income Quartile	0.154 (0.361)	0.158 (0.365)	0.150 (0.357)
Third Income Quartile	0.133 (0.340)	0.127 (0.333)	0.139 (0.346)
Fourth Income Quartile	0.099 (0.299)	0.084 (0.277)	0.113 (0.317)
Unknown Income	0.448 (0.497)	0.454 (0.498)	0.442 (0.497)
State Unemployment Rate	6.059 (2.056)	6.041 (2.048)	6.077 (2.064)
Prior State Law	0.824 (0.381)	0.819 (0.385)	0.828 (0.377)
Sample Size	3,363,241	1,620,088	1,743,153

Notes: Means are reported, with standard deviations in parentheses. NIS sampling weights are used.

Table 3 Difference-in-Differences Estimates and Robustness Checks

Quality Indicators	Baseline Model	Controls Only	2007-2011	2005-2011	Drop periods 2010 Q2 - 2010 Q3
Overall Prevention Quality Indicators					
PQI 90	0.0017 (0.0005)**	0.0012 (0.0004)**	0.0015 (0.0004)**	0.0016 (0.0005)**	0.0018 (0.0005)**
PQI 91	0.0003 (0.0004)	0.0004 (0.0005)	0.0004 (0.0005)	0.0004 (0.0005)	0.0004 (0.0004)
PQI 92	0.0014 (0.0002)***	0.0009 (0.0002)***	0.0011 (0.0003)**	0.0012 (0.0002)***	0.0014 (0.0002)***
Individual Component Measures of Prevention Quality Indicators					
PQI 01	0.0010 (0.0005)*	0.0009 (0.0004)*	0.0009 (0.0004)*	0.0009 (0.0005)*	0.0010 (0.0005)*
PQI 02	0.0003 (0.0060)	-0.0021 (0.0121)	0.0001 (0.0053)	-0.0012 (0.0063)	-0.0019 (0.0061)
PQI 03	-0.00003 (0.0002)	-0.0003 (0.0003)	-0.0001 (0.0002)	-0.0002 (0.0002)	-0.0001 (0.0002)
PQI 07	-0.0003 (0.0001)**	-0.0003 (0.0001)**	-0.0003 (0.0001)*	-0.0003 (0.0001)*	-0.0003 (0.0001)**
PQI 08	0.0003 (0.0001)*	0.0002 (0.0001)	0.0002 (0.0002)	0.0003 (0.0002)	0.0003 (0.0001)*
PQI 10	0.0005 (0.0002)**	0.0004 (0.0001)**	0.0005 (0.0001)***	0.0005 (0.0002)**	0.0005 (0.0002)**
PQI 11	-0.0001 (0.0003)	0.00002 (0.0003)	-0.0001 (0.0003)	-0.0001 (0.0003)	-0.00003 (0.0002)
PQI 12	-0.0001 (0.0002)	-0.00004 (0.0002)	-0.0001 (0.0002)	-0.00003 (0.0003)	-0.00003 (0.0002)
PQI 13	0.0001 (0.00004)	0.0001 (0.00004)	0.00001 (0.00003)	0.00002 (0.00003)	0.0001 (0.00004)
PQI 14	0.0002 (0.00003)***	0.0002 (0.00003)***	0.0002 (0.0001)**	0.0002 (0.0001)**	0.0002 (0.00003)***
PQI 15	0.0003 (0.0002)	0.0001 (0.0002)	0.0002 (0.0003)	0.0003 (0.0002)	0.0003 (0.0002)
PQI 16	-0.0001 (0.00002)**	-0.0001 (0.00003)**	-0.0001 (0.00003)*	-0.0001 (0.00003)**	-0.0001 (0.00003)**
Sample Size[a]	3,812,595	3,845,814	1,975,809	2,749,374	3,612,359

Notes: [a] For PQI 2, the sample sizes are 48,275, 48,748, 24,018, 34,071, and 45,897 separately. *** indicates the difference-in-difference is significant at the 1% level; ** 5%; * 10%. Standard errors, heteroskedasticity-robust and clustered at the age level, are in parentheses. All regressions include the controls plus age, hospital and time fixed effects. NIS sampling weights are used.

Table 4 Placebo Regressions

Quality Indicators	2005-2009 Treatment 2008 Q4	2004-2008 Treatment 2007 Q4	2003-2007 Treatment 2006 Q4	2002-2006 Treatment 2005 Q4
PQI 90	0.0005 (0.0009)	0.0006 (0.0004)	0.0009 (0.0006)	0.0007 (0.0008)
PQI 91	-0.0001 (0.0004)	0.0001 (0.0007)	-0.0002 (0.0006)	-0.0002 (0.0004)
PQI 92	0.0006 (0.0007)	0.0005 (0.0003)	0.0011 (0.0004)**	0.0008 (0.0007)
PQI 01	0.0001 (0.0005)	0.00001 (0.0002)	0.0002 (0.0003)	0.0001 (0.0004)
PQI 02	0.0091 (0.0076)	-0.0128 (0.0070)	0.0091 (0.0044)*	0.0033 (0.0065)
PQI 03	0.0003 (0.0002)	-0.0003 (0.0002)	0.0002 (0.0002)	0.0002 (0.0001)
PQI 07	-0.0001 (0.0001)	-0.00002 (0.00002)	0.0001 (0.0001)	0.00003 (0.0001)
PQI 08	0.0001 (0.0001)	0.0002 (0.0002)	0.0002 (0.0001)	0.0002 (0.0002)
PQI 10	0.0001 (0.0001)	-0.0002 (0.0003)	-0.0001 (0.0002)	0.0001 (0.0002)
PQI 11	-0.0002 (0.0002)	0.0001 (0.0003)	0.0002 (0.0003)	-0.0001 (0.0001)
PQI 12	-0.0001 (0.0003)	0.0001 (0.0002)	-0.0003 (0.0004)	-0.0002 (0.0002)
PQI 13	0.0001 (0.00003)*	0.0001 (0.00003)*	-0.00001 (0.00002)	0.0001 (0.00004)
PQI 14	-0.0001 (0.0001)	-0.00003 (0.0001)	0.0002 (0.0001)	0.00002 (0.0001)
PQI 15	0.0002 (0.0002)	0.0005 (0.0003)*	0.0002 (0.0003)	0.0002 (0.0003)
PQI 16	0.00000 (0.00001)	0.00003 (0.00003)	0.00001 (0.00002)	-0.00001 (0.00002)
Sample Size[a]	1,971,669	1,970,130	1,908,626	1,870,005

Notes: [a] For PQI 2, the sample sizes are 25,231, 25,403, 24,749 and 24,257 separately. *** indicates significant at the 1% level; ** 5%; * 10%. Standard errors, heteroskedasticity-robust and clustered at the age level, are in parentheses. All regressions include the controls plus age, hospital and time fixed effects. NIS sampling weights are used.

Table 5 Heterogeneity Tests by Gender and Race

Quality Indicators	Female	Male	White	Non-white	Unknown Race
PQI 90	0.0018 (0.0005)**	0.0017 (0.0014)	0.0020 (0.0009)*	0.0015 (0.0007)*	0.0008 (0.0012)
PQI 91	0.0004 (0.0004)	0.0001 (0.0009)	-0.0003 (0.0008)	0.0011 (0.0004)**	-0.0001 (0.0009)
PQI 92	0.0014 (0.0002)***	0.0017 (0.0009)	0.0023 (0.0005)***	0.0004 (0.0006)	0.0009 (0.0009)
PQI 01	0.0011 (0.0002)***	0.0007 (0.0012)	0.0013 (0.0005)**	0.0007 (0.0005)	0.00001 (0.0010)
PQI 02	0.0071 (0.0093)	-0.0040 (0.0024)	0.0017 (0.0085)	0.0081 (0.0100)	-0.0128 (0.0160)
PQI 03	0.00001 (0.0001)	-0.0001 (0.0009)	0.0002 (0.0003)	-0.0006 (0.0003)	0.0007 (0.0004)*
PQI 07	-0.0002 (0.0001)	-0.0005 (0.0003)	-0.0001 (0.0001)	-0.0004 (0.0003)	-0.0003 (0.0003)
PQI 08	0.0001 (0.0001)	0.0013 (0.0004)**	0.0001 (0.0001)	0.0008 (0.0004)*	0.0001 (0.0003)
PQI 10	0.0006 (0.0001)***	-0.0005 (0.0004)	0.00002 (0.0004)	0.0007 (0.0004)	0.0011 (0.0003)***
PQI 11	-0.0002 (0.0002)	0.0006 (0.0005)	-0.00001 (0.0003)	0.00003 (0.0004)	-0.0005 (0.0004)
PQI 12	0.00002 (0.0003)	-0.0001 (0.0001)	-0.0003 (0.0003)	0.0004 (0.0002)**	-0.0007 (0.0004)
PQI 13	0.00004 (0.00002)	0.0001 (0.0001)	0.00003 (0.00004)	0.0001 (0.0001)	0.0001 (0.00003)***
PQI 14	0.0002 (0.00004)***	0.0002 (0.0002)	0.0001 (0.0001)	0.0003 (0.0002)	0.0003 (0.0001)***
PQI 15	0.0003 (0.0002)	0.0001 (0.0005)	0.0007 (0.0003)**	-0.0004 (0.0003)	0.0001 (0.0005)
PQI 16	-0.00003 (0.00002)	-0.0002 (0.00004)***	-0.00004 (0.00003)	-0.0001 (0.0001)	-0.0001 (0.00004)**
Sample Size[a]	3,096,019	716,576	1,646,963	1,100,320	1,065,312

Notes: [a] For PQI 2, the sample sizes are 20,512, 27,763, 22,813, 13,145 and 12,317 separately. *** indicates significant at the 1% level; ** 5%; * 10%. Standard errors, heteroskedasticity-robust and clustered at the age level, are in parentheses. All regressions include the controls plus age, hospital and time fixed effects. NIS sampling weights are used.

Table 6 Heterogeneity Tests by Patient's Zip Code Income Quartile

Quality Indicators	First (Lowest) Income Quartile	Second Income Quartile	Third Income Quartile	Fourth Income Quartile	Unknown Income Quartile
PQI 90	0.0001 (0.0005)	0.0022 (0.0016)	0.0035 (0.0010)**	0.0009 (0.0011)	0.0008 (0.0030)
PQI 91	0.00003 (0.0009)	0.0014 (0.0013)	0.0008 (0.0010)	-0.0002 (0.0005)	-0.0015 (0.0011)
PQI 92	0.0001 (0.0006)	0.0008 (0.0008)	0.0028 (0.0007)***	0.0011 (0.0013)	0.0023 (0.0032)
PQI 01	0.0012 (0.0009)	-0.0006 (0.0009)	0.0013 (0.0007)	0.0017 (0.0005)**	0.0022 (0.0011)*
PQI 02	-0.0169 (0.0132)	0.0097 (0.0163)	0.0415 (0.0124)**	-0.0364 (0.0178)	0.0484 (0.0984)
PQI 03	-0.0008 (0.0003)**	-0.0002 (0.0004)	0.0011 (0.0004)**	-0.0003 (0.0004)	0.0003 (0.0009)
PQI 07	-0.0004 (0.0002)	-0.0002 (0.0001)	-0.0003 (0.0002)	0.0001 (0.0002)	-0.0005 (0.0005)
PQI 08	0.0008 (0.0004)*	0.0004 (0.0003)	-0.0002 (0.0001)	-0.0002 (0.0002)	-0.0011 (0.0012)
PQI 10	0.0005 (0.0002)*	0.0006 (0.0005)	0.0005 (0.0004)	0.0001 (0.0002)	0.0009 (0.0007)
PQI 11	-0.0005 (0.0005)	0.0006 (0.0006)	-0.00002 (0.0004)	0.0002 (0.0003)	-0.0013 (0.0010)
PQI 12	0.00003 (0.0006)	0.0002 (0.0004)	0.0003 (0.0005)	-0.0005 (0.0006)	-0.0011 (0.0013)
PQI 13	0.0001 (0.0001)	-0.0001 (0.0001)	0.00003 (0.00003)	-0.00004 (0.00004)	0.0003 (0.0001)*
PQI 14	-0.0001 (0.0001)	0.0004 (0.0002)*	0.0004 (0.0001)***	-0.0001 (0.0001)	0.0006 (0.0009)
PQI 15	-0.0007 (0.0006)	0.0011 (0.0005)*	0.0004 (0.0004)	-0.0001 (0.0008)	0.0004 (0.0013)
PQI 16	-0.0001 (0.0001)	0.00000 (0.00003)	-0.00004 (0.00001)***	-0.0001 (0.00002)*	0.00001 (0.00002)
Sample Size[a]	698,365	639,567	565,782	409,215	1,499,666

Notes: [a] For PQI 2, the sample sizes are 7,196, 7,364, 7,314, 6,509 and 19,892 separately. *** indicates significant at the 1% level; ** 5%; * 10%. Standard errors, heteroskedasticity-robust and clustered at the age level, are in parentheses. All regressions include the controls plus age, hospital and time fixed effects. NIS sampling weights are used.

Appendix A1

Notation: $P(AV)$: the probability of avoidable hospitalizations, short as P; AV: number of avoidable hospitalizations; UA: number of unavoidable hospitalizations; TH: number of total hospitalizations.

$$P(AV) = \frac{AV}{TH} = \frac{AV}{AV + UA}$$

Since $P,\ AV,\ UA$ are all affected by law L, I take total derivatives with respect to L to the above equation:

$$\text{Let } F(P,\ AV,\ UA) = P - \frac{AV}{AV+UA} = 0, \tag{A1.1}$$

$$\frac{dF}{dL} = \frac{\partial F}{\partial P} * \frac{\partial P}{\partial L} + \frac{\partial F}{\partial AV} * \frac{\partial AV}{\partial L} + \frac{\partial F}{\partial UA} * \frac{\partial UA}{\partial L} = 0, \tag{A1.2}$$

From (A1.1), I calculate the following pieces: $\frac{\partial F}{\partial P} = 1$, $\quad \frac{\partial F}{\partial AV} = -\frac{UA}{(AV+UA)^2}$, $\quad \frac{\partial F}{\partial UA} = \frac{AV}{(AV+UA)^2}$,

Putting all the calculated pieces into (A1.2):

$$1 * \frac{\partial P}{\partial L} - \frac{UA}{(AV+UA)^2} * \frac{\partial AV}{\partial L} + \frac{AV}{(AV+UA)^2} * \frac{\partial UA}{\partial L} = 0, \tag{A1.3}$$

Empirical result indicates that $\frac{\partial P}{\partial L} > 0$, rearrange the equation (A1.3):

$$\frac{UA}{(AV+UA)^2} * \frac{\partial AV}{\partial L} > \frac{AV}{(AV+UA)^2} * \frac{\partial UA}{\partial L}, \tag{A1.4}$$

Since $UA > 0$, and $(AV + UA)^2 > 0$, inequation (A1.4) can be written as:

$$\frac{\partial AV}{\partial L} > \frac{AV}{UA} * \frac{\partial UA}{\partial L},$$

Since $\frac{\partial UA}{\partial L} \geq\ 0$ (Having access to health insurance leads to increase or at least no changes in unavoidable hospitalizations),

$$\frac{\partial \mathrm{AV}}{\partial \mathrm{L}} > 0.$$

That is, the change in the number of avoidable hospitalizations must increase.

Appendix A2

Assume the percent change in AV is x $(x > 0)$, and the percent change in UA is y $(y > 0)$, so

$$P' = \frac{AV(1+x)}{AV(1+x)+UA(1+y)};$$

Since P increases after law L,

$$\Delta P = P' - P = \frac{AV(1+x)}{AV(1+x)+UA(1+y)} - \frac{AV}{AV+UA} > 0, \tag{A2.1}$$

Since $AV > 0$, and $UA > 0$, rearrange (A2.1):

$$(AV + UA) * (1 + x) > AV(1 + x) + UA(1 + y),$$

Further $$UA * (1 + x) > UA(1 + y),$$

Then $$x > y.$$

That is, the percent increase $(x > 0)$ in the number of avoidable hospitalization is greater than the percent increase $(y > 0)$ in the number of unavoidable hospitalization.

Note that, even releasing the constraint of $(x > 0)$ and $(y > 0)$, the conclusion still holds. Also, if $\Delta P = P' - P < 0$, then $x < y$.