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Hospital and Patient Responses to Medicare Policy

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ABSTRACT

HOSPITAL AND PATIENT RESPONSES TO MEDICARE POLICY

By

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In chapter 1 of this work, I estimate the causal impact of Section 3008 of the Affordable Care Act (ACA) on its targeted infection outcomes. This policy, implemented in October 2014, imposes a 1% reduction in the Medicare reimbursements of hospitals that perform poorly based on a hospital-acquired infection (HAI) measure. A limited body of literature evaluates the impact of this policy in a primarily descriptive manner. Using patient discharge data from the National Inpatient Sample (NIS), Healthcare Cost and Utilization Project (HCUP), Agency for Healthcare Research and Quality and a difference-in-differences identification strategy, I contribute to the literature by estimating the causal effects this ACA provision had on the incidence of HAIs. Results suggest that the policy reduced the likelihood of acquiring an infection, with effects varying by HAI type. In addition, I find a general reduction in the likelihood of a HAI for whites, while the effects by gender or age vary on HAI type.

In chapter 2, I look at the causal effects of expanding prescription drug coverage on hospital admissions due to antimicrobial resistance. Antimicrobial resistance has been growing rapidly in the United States in recent years despite government efforts to control its outbreak. Both under and overutilization of prescribed medications can lead to an increase in antimicrobial resistance. The introduction of Medicare Part D in 2006 led to an increase in prescription drug

coverage, including antimicrobials, for the elderly. If cost barriers had led to underutilization of prescriptions among those without previous prescription coverage, then Medicare Part D may reduce antimicrobial resistance. On the other hand, if Medicare Part D encourages over-utilization of prescriptions, then an unintended consequence may be an increase in antimicrobial resistance. Using data from the Nationwide Inpatient Sample (NIS), Healthcare Cost and Utilization Project (HCUP), Agency for Healthcare Research and Quality for years 2004 to 2011 and a difference-in-differences identification strategy, I estimate the net effect of Medicare Part D on the incidence of inpatient discharges due to antimicrobial resistance among the Medicare-eligible population. Results show that the incidence of antimicrobial resistance among the elderly as measured by inpatient discharges decreased after Medicare Part D implementation.

Finally in chapter 3, I estimate the causal effects of expanding prescription drug coverage on opioid use disorder-related hospital admissions. Opioid misuse is an ongoing public health concern in the United States. Each year, an increasing number of individuals continue to suffer from opioid use disorders (OUD) and fatalities despite government efforts to control the epidemic. Medicare Part D went into effect in January 2006, mandating Medicare plans to cover prescription drugs, including those intended for medication-assisted treatment (MAT) of OUD. To date, there is no estimate available in the literature regarding the causal effects the policy had on the incidence of OUD among its beneficiaries, especially on associated hospital admissions. To help fill this gap, I use a nationally representative sample of hospital discharges from the Nationwide Inpatient Sample (NIS), Healthcare Cost and Utilization Project (HCUP), Agency for Healthcare Research and Quality together with a difference-in-differences strategy comparing OUD-related discharges between the Medicare-eligible adults aged 65 to 69 and ineligible adults

age 60 to 64. I find that after the policy went into effect, the incidence of OUD-related hospital discharges decreased among the Medicare-eligible population.

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ACCEPTANCE

This dissertation was prepared under the direction of the candidate's Dissertation Committee. It has been approved and accepted by all members of that committee, and it has been accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy in Economics in the Andrew Young School of Policy Studies of Georgia State University.

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Dedication

To my parents Ric and Bess, for allowing me to do everything that I want to do.

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Chapter 1: The Affordable Care Act and Hospital-Acquired Infections

1.1. Introduction

Each year, one in every 31 hospitalized patients in the United States is diagnosed with at least one hospital-acquired infection (HAI), amounting to $28.4 billion in direct medical costs and $12.4 billion in costs arising from early deaths and lost productivity (CDC, 2021c). While measuring the cost of HAIs is difficult, they generally include the following: "hotel" costs as a result of delayed patient discharge, opportunity costs for missed work, and treatment costs associated with increased number of laboratory and diagnostic investigations (Friedman, 2016).

These HAIs are correlated with patient characteristics such as sex, age, comorbidities, length of stay in the hospital, frequent visits to healthcare facilities, mechanical ventilatory support, recent invasive procedures, indwelling devices, and stay in an intensive care unit (ICU) (Kaye et al., 2011; Greene et al., 2012; Monegro et al., 2022), and hospital factors such as the type and duration of catheters left on a patient, and pathogens in hospitals acquired from other patients, hospital staff, or the hospital facility (Apisarnthanarak et al., 2007; Johnson et al., 2006; Monegro et al., 2022).

To mitigate the environmental risks (i.e., those that are external to patients), practices such as hand hygiene, environmental cleanliness, good hospital leadership, proper use of personal protective equipment, consistent evident-based practices, antimicrobial-resistance campaign, respiratory hygiene and cough etiquette, and constant evaluation of existing guidelines are implemented (Collins, 2008). However, following such guidelines sometimes requires financial investments that are more costly than the possible losses hospitals face that are associated with HAIs (Lee et al., 2012).

In October 2014, the United States government implemented Section 3008 of the Affordable Care Act (ACA), more commonly known as the Hospital-Acquired Condition Reduction Program (HACRP), which imposes a 1% reduction in the Medicare reimbursements of hospitals that perform poorly based on a HAC metric.[1] While it may seem that this policy incentivizes hospitals to lower HAIs, there's only a limited body of literature evaluating the impacts of this change.

The existing work suffers from a number of limitations. First, most of the previous studies (Arntson et al., 2021; Alrawashdeh et al., 2021; Hsu et al., 2019, 2020) are descriptive in nature and do not attempt to estimate the causal impact of this policy. Second, many are limited in scope by focusing on specific age groups like the elderly (Arntson et al., 2021) or specific hospital departments like the intensive care unit (Hsu et al., 2019). Others are limited by focusing on a specific state (Sheetz et al., 2019). Third, with the exception of (Sheetz et al., 2019), every paper cited above focuses on one or two infections at most, despite the fact that there are several more that are subject to the policy. Some of these descriptive studies suggest that the incidence of some conditions targeted by the program declined after the policy was announced. However, the absence of counterfactuals in their study designs makes it difficult for their findings to be directly linked to HACRP.

One paper that attempts causal analysis is Sheetz et al. (2019), which used data from the Michigan Surgical Quality Collaborative and a difference-in-differences (DD) model to analyze changes in CAUTI, CDI, and CLABSI outcomes. The control group that they used included hospital-acquired conditions that were not targeted by HACRP. However, it is highly possible that there may have been spillover effects on these conditions, and so the observed differences in

[1] Section 3008 is a component of the ACA specifically targeting hospital-acquired conditions, which is broader than just HAIs.

trends may not reflect the true effect of the policy. Another limitation their work faces is that their data does not satisfy the parallel trends assumption required in the DD approach. Finally, they mention that Michigan has a "unique and robust quality improvement infrastructure", making it difficult to assume that the estimated effects of the policy affects other states in the same way.

The primary goal of this paper is to estimate the causal impacts of HACRP on the incidence of different types of HAIs using data from the National Inpatient Sample (NIS), Healthcare Cost and Utilization Project (HCUP), Agency for Healthcare Research and Quality for years 2012 to 2019. The NIS contains the largest publicly available all-payer inpatient care data in the United States. To the best of my knowledge, no existing work uses a nationally representative sample of adults in the United States to estimate the causal impact of the policy on the incidence of four types of HAIs, namely, catheter-associated urinary tract infections (CAUTI), central-line associated bloodstream infection (CLABSI), *Clostridium difficile* infection (CDI), and methicillin-resistant *Staphylococcus aureus* (MRSA) infection. Thus unlike the previous literature, my sample includes discharges generated by individuals from different age groups, different hospital departments, and different parts of the country. Another contribution I make is by exploiting variation in hospital exposure to the policy as proxied by their Medicare revenue shares in a difference-in-differences framework. By using this approach, I establish causal relationships between HACRP and my HAI outcomes of interest. Finally, I consider alternate specifications of when the post-implementation period should begin given the rollout of the policy.

My results suggest that the policy reduced the likelihood of acquiring an infection, with the effect observed to be the largest for CLABSI (-11.17% reduction in the likelihood of

infection for a one standard deviation increase in Medicare share), followed by MRSA (-6.59%), CAUTI (-5.56%), and CDI (-1.58%), respectively. In addition, I find a general reduction in the likelihood of HAI for whites, with statistically significant reductions for CLABSI, CAUTI, and MRSA. The effects by gender or age vary by HAI type. For example, I estimated significant declines in the likelihood of CLABSI and MRSA in both the men and women subsamples, but decreases in the likelihood of CAUTI are significant only for men, while decreases in the likelihood of CDI are significant only for women. Similarly, I estimated significant declines in the likelihood of CLABSI and MRSA in both the elderly and non-elderly subsamples, but decreases in the likelihood of CDI are significant only in the non-elderly population. There is no significant decrease in the likelihood of CAUTI for both elderly and non-elderly. I also find that my results are robust under different alternative specifications.

The rest of this paper is organized as follows: Section 1.2 provides some institutional background on policies related to reducing HAIs. Section 1.3 layouts my conceptual framework. Section 1.4 discusses my dataset. Section 1.5 discusses the methodology used in my analysis. Section 1.6 presents my results, while Section 1.7 concludes the paper with some discussion.

1.2. Institutional Background

1.2.1. Pre-ACA Infection Prevention Program HAI Landscape

Prior to the ACA, the biggest policy implemented to reduce HAIs was included in the Deficit Reduction Act of 2005 (DRA). Beginning in October 2008, Section 5001(c) of the DRA, otherwise known as the Hospital-Acquired Conditions–Present on Admission (HAC-POA) Reporting Provision, mandated CMS to stop reimbursing hospitals for charges related to hospital-acquired, secondary diagnoses that were considered high cost and preventable. As a response to the policy, Sorensen et al. (2014) reported that hospitals adapted several key changes

such as "cultural shifts involving attention, commitment, and support from hospital leadership for patient safety, hiring new staff to assure the accuracy of clinical documentation and POA oversight structures, increased time burden for physicians, nurses, and coders, need to upgrade or purchase new software, and need to collaborate with hospital departments or staff that did not interface directly in the past." In fact, in a survey of hospital CEOs, Peasah et al. (2013) find that 70% considered making financial investments by introducing new technologies to help improve infection rates due to the HAC-POA reporting provision.

Works that look into the effects of this earlier policy on selected HAI outcomes find mixed results. Lee et al. (2012), using primarily a before-and-after analysis find that there were no significant changes in the rates of CLABSI and CAUTI after the policy's implementation. They used ventilator-associated pneumonia as control group to determine the significance of changes in the rates of CLABSI and CAUTI in the post period. However, their work did not consider the possibility of the policy having spillover effects on this condition.

Meddings et al. (2012) also find that there was no significant decrease in CAUTI events from 2007 to 2009 across Michigan hospitals. They used the Healthcare Cost & Utilization Project (HCUP) State Inpatient Database (SID) in their before-and-after analysis, but note that CAUTI rates in this dataset appear to be inaccurate and are underestimated compared to epidemiologic surveillance data. Peasah et al. (2013) also show that CAUTI outcomes did not improve in Florida after the HAC-POA reporting provision was implemented, but saw significant improvements in CLABSI outcomes in terms of declines in quarterly incidence and the probability of acquiring CLABSI post-policy. They used 2007 to 2011 administrative discharge data from the Florida Agency for Healthcare Administration and a pre-post design to arrive at these results.

1.2.2. The Affordable Care Act's Section 3008 or "HACRP"

In response to the continuing public health concern about HAIs, the US government included a provision in the Affordable Care Act (through its Section 3008) which directs the Centers for Medicaid and Medicare Services (or CMS) to reduce the total Medicare reimbursements of "poor-performing" hospitals by 1% (CMS, 2015a). These "poor-performing" hospitals are those with a total HAC score greater than the 75th percentile of all Total HAC Scores (CMS, 2023a).[2] One of its main objectives is to encourage hospitals to improve their HAI outcomes to avoid penalties. Once finalized, the scores used to rank hospitals are publicly released by CMS, together with each hospital's total Medicare reimbursement reductions.

Understanding the timing of this policy is complicated since there are several "key dates" that need to be considered which vary by HAI type. These key dates can be generally described as (i) when the financial penalties started to get imposed, (ii) when the rule containing these penalties was first announced/circulated for comments, (iii) when the rule mentioned in (ii) was finalized, and (iv) when the performance of hospitals were evaluated. HACRP was first implemented in Fiscal Year 2015 (i.e., October 2014 to September 2015), but the scores that were used to rank hospitals in this period only considered two HAIs, namely CAUTI and CLABSI. In this fiscal year, "poor-performing" hospitals received a financial penalty on their Medicare reimbursements. It is important to note that the performance of hospitals mentioned in this case refers to a lookback period of January 2012 to December 2013. Thus it may seem as though hospitals had no way of influencing their performance in this lookback period. However, there is also a question of when hospitals became aware of the policy and thus when they started changing their behavior. In May 2013, the rule containing all these information was initially

[2] The Total HAC Score scoring methodology as well as an example on how to compute it can be found in CMS (2022a).

circulated for feedback and in August 2013 the rule was finalized. This information is presented chronologically both in the top half of Table 1.1 and in Figure 1.1.

Table 1.1. Relevant Dates by HAI Type

Infection Type	First Performance Period	Proposed Rule Circulated	Rule Finalized and Published
CAUTI, CLABSI	January 2012 to December 2013	May 2013	August 2013
CDI, MRSA	January 2014 to December 2015	April 2015	August 2015

Sources: CMS (2013a, 2013b, 2015b, 2015c).

In the case of CDI and MRSA, these infections only affected hospital HAC Score rankings starting in Fiscal Year 2017 (i.e., October 2016 to September 2017). Hospitals were first made aware of this inclusion in August 2013. For these infections, the initial lookback period was January 2014 to December 2015, while the policy rule containing all these information was initially circulated for feedback in April 2015 and finalized in August 2015. This information is presented in the bottom half of Table 1.1 as well as in Figure 1.1.

An implication of Table 1.1 is that conditional on HAI type and when we think hospitals may have started changing their behavior, what we can consider as the appropriate "post period" for analyzing the impact of the policy will differ. Generally, hospitals may respond to the policy (i.e., put in place measures to improve their outcomes) proactively if they knew ahead what time period will be used to evaluate them ("Perfect Foresight "), only when they read about the proposed rule relevant to the policy ("Partial Foresight "), or not until they read the final and published rule for the upcoming fiscal year ("Zero Foresight "). Table 1.2 presents these different types of foresight (i.e. different potential timing for when we might think hospitals will start changing their behavior) and the corresponding quarters when the associated post-period would begin.

Figure 1.1. Important Dates in the Early Implementation of the HACRP

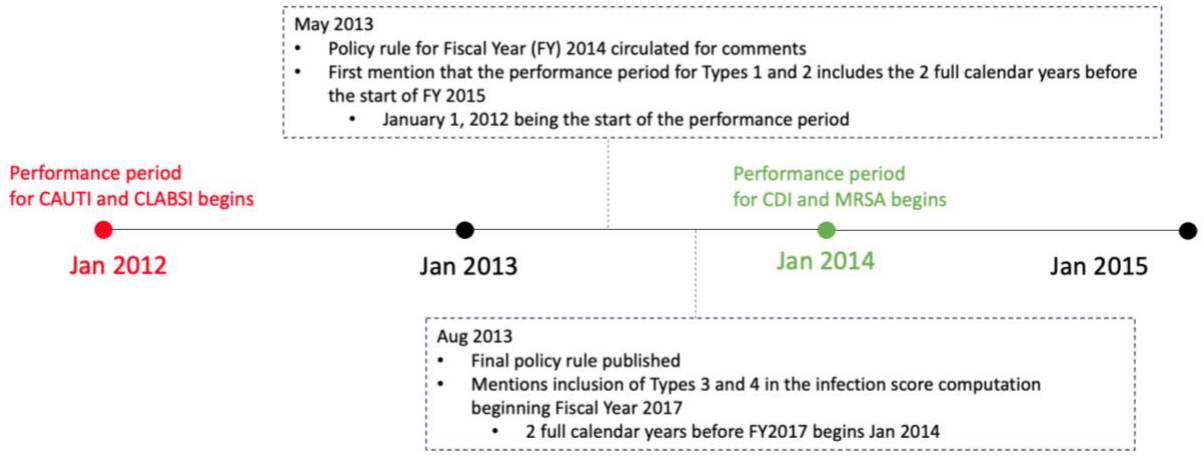


Table 1.2. Types of Foresights and Corresponding Quarters When the Post-Period Begins

Infection Type	Perfect Foresight	Partial Foresight	Zero Foresight
CAUTI, CLABSI	2012 Q1	2013 Q2	2013 Q3
CDI, MRSA	2014 Q1	2015 Q2	2015 Q3

Note: Quarters based on months as indicated in Table 1.1.

1.3. Conceptual Framework

In this section, I describe an informal conceptual framework to help better understand how a hospital might respond to the policies described in Section 1.2. A hospital's response is conditional on their Medicare revenue shares, the infection outcome considered, as well as the timing of the policies (i.e. the response to the 2014 policy may be a function of the previous response to the 2008 policy). There are two primary considerations: first is the cost associated with implementing outcome enhancement measures, and second is the potential penalties they might face based on the measures they do or do not implement.

If the cost of implementing these measures exceeds the potential penalties, it's reasonable to anticipate that hospitals would opt to accept the penalties. Conversely, when the potential penalties outweigh the associated costs, it's expected that hospitals would prioritize the implementation of improvement measures. In Appendix A, I layout a more detailed framework outlining the decision-making processes hospitals follow in this regard.

1.3.1. Responses to the HAC-POA Reporting Provision

The HAC-POA reporting provision ("2008 policy") directly impacts outcomes related to CAUTI and CLABSI. This policy mandates that CMS stop reimbursing hospitals for any Medicare charges linked to these two types of infections. Conceptually, I assume there are two types of hospitals. First, hospitals with sufficiently low Medicare revenue shares ("Type L") whose penalties stemming from this policy if they do nothing are relatively insignificant as compared to the expenses involved in implementing improvement initiatives (Figure A1). Second, hospitals with substantial Medicare revenue shares ("Type H") for whom the penalty costs associated with doing nothing likely exceed the cost associated with implementing improvement programs (Figure A2). We would expect Type L hospitals to do nothing and pay the penalties associated with CAUTI and CLABSI infections, while we would expect Type H hospitals to implement improvement programs in order to avoid the penalties for CAUTI and CLABSI infections. Analysis presented in Appendix B tests these hypotheses directly. The results suggest that after the 2008 policy's implementation, Type H hospitals indeed saw greater decrease in the incidence of CAUTI and CLABSI.

1.3.2. Responses to HACRP

Differential responses by Type L and Type H hospitals to the 2008 policy are likely to generate differential responses to HACRP ("2014 policy"). This is because the 2014 policy impacted both CAUTI and CLABSI as well as two new infections, CDI and MRSA. This framework generates one set of predictions for CAUTI and CLABSI and a different set of predictions for CDI and MRSA.

First, we consider CAUTI and CLABSI. Type L hospitals were not predicted to respond to the 2008 policy, so in 2014 they have to decide again whether or not to implement

improvement programs for these two infections (Figure A3). We would expect the cost of implementing an improvement program to be less than the penalties they would face for doing nothing. This is because the 2014 penalties (which impact all Medicare reimbursements) are more imposing than the 2008 penalties (which only impact Medicare reimbursements related to these infections). Type H hospitals were predicted to implement improvement programs for CAUTI and CLABSI in 2008, so they may not need to implement additional programs to impact those infection rates if their initial efforts were successful (Figure A4). Thus, the framework predicts a smaller response to the 2014 policy by Type H hospitals in improving CAUTI and CLABSI outcomes.

As mentioned above the dynamics differ when considering CDI and MRSA outcomes. Neither of these infection types falls under the scope of the 2008 policy, implying that neither Type L nor Type H hospitals were previously incentivized to implement practices directly aimed at managing these outcomes (Figure A5 and Figure A6). In this case we still expect the cost of implementing an improvement program to be less than the penalties they would face for doing nothing. However, Type H hospitals are exposed to larger financial loses if they get penalized, as they have larger Medicare reimbursements compared to Type L hospitals. Thus, the framework predicts a larger response to the 2014 policy by Type H hospitals in improving CDI and MRSA outcomes (Figure A7 and Figure A8).

1.4. Data

The main data source that I use to conduct this study is the National Inpatient Sample (NIS), Healthcare Cost and Utilization Project (HCUP), Agency for Healthcare Research and Quality for years 2012 to 2019. Prior to 2012, the NIS consisted of all discharges from a sample of hospitals, while from 2012 onwards, the NIS consists of sample of discharges from all

hospitals (AHRQ, 2024b). To make the sampling methodology consistent across all years in my analysis, I only use discharges recorded from 2012 onwards. The NIS is "*the largest publicly available all-payer inpatient healthcare database designed to produce U.S. regional and national estimates of inpatient utilization, access, cost, quality, and outcomes. Unweighted, it contains data from more than 7 million hospital stays each year. Weighted, it estimates more than 35 million hospitalizations nationally* " (AHRQ, 2024b).

One contribution on this paper is to examine a relatively large number of HAIs. In particular, my analysis includes the following HAIs that enter into the Total HAC Score computation described earlier: catheter-associated urinary tract infection (CAUTI), central line-associated bloodstream infection (CLABSI), *Clostridium difficile* infection (CDI), and methicillin-resistant *Staphylococcus aureus* (MRSA).

CAUTI is a type of infection arising in patients who require a urinary catheter during their hospital stay. When these devices are used for a prolonged period, the likelihood of organisms to pass from the opening of the urethra into the rest of the urinary tract system increases (Johnson et al., 1990; Lo et al., 2014). CLABSI, another device-related infection, is commonly caused by the prolonged use of a central line, together with other factors such as poor central line insertion and maintenance practices (California Department of Public Health, 2020). CDI is an infection caused by the *Clostridium difficile* bacteria which primarily occurs in the large intestine and happens as a side-effect of taking antibiotics (Mayo Clinic, 2023b; CDC, 2019a). One of its common modes of transmission in hospitals is through contaminated hands of healthcare workers (Public Health Agency of Canada, 2014). MRSA infections are caused by the methicillin-resistant *Staphylococcus aureus*, a type of bacteria that is resistant to several

antibiotics (CDC, 2019c). Similar with CDI, MRSA is commonly spread through physical contact.

To determine if a discharge records a particular HAI, I look for the HAI's associated International Classification of Diseases (ICD) code among the set of the patient's diagnoses. A limitation of the NIS is that it does not have an indicator as to whether a particular diagnosis is present upon admission or not. This poses some challenge in identifying if the recorded diagnosis is hospital-acquired or if the patient already had it prior to admission. In HCUP databases, however, diagnoses are recorded such that the "first listed diagnosis is the principal diagnosis defined as the condition established after study to be chiefly responsible for occasioning the admission of the patient to the hospital for care" (AHRQ, 2008). Thus, I assume that all first-listed diagnoses in the NIS are present on admission, while diagnoses entered further down the list are more likely to be hospital-acquired.[3]

From 2012 until the third quarter of 2015, the NIS uses ICD, Ninth Revision, Clinical Modification (ICD-9-CM) codes to record diagnoses, while from the fourth quarter of 2015 until 2019, the NIS uses ICD, Tenth Revision, Clinical Modification (ICD-10-CM) codes. These changes were accounted for in determining the relevant HAIs for each discharge entry, with the corresponding ICD-9-CM and ICD-10-CM codes for each type of HAI summarized in Table 1.3. To summarize, my set of outcome variables consists of four individual discharge-level indicators for the presence of the different HAIs of interest.

Using both the Core and Hospital files of the NIS, I use the following discharge characteristics as covariates: patient age at time of admission, sex, race, and median household income for the patient's ZIP Code (based on current year). I also use the following hospital

[3] I also estimate alternative specifications where I treat the first two and first three diagnoses as present on admission. This is discussed further in Section 1.6.2.

characteristics to further improve my model: control/ownership of hospital (i.e., government & nonfederal, private & non-profit, private & investor-owned), bed size (i.e., small, medium, large), region (i.e., New England, Middle Atlantic, East-North Central, West-North Central, South Atlantic, East-South Central, West-South Central, Mountain, Pacific), and location/teaching status (i.e., rural, urban-nonteaching, urban-teaching). I drop all observations with missing values for any of the mentioned variables.

Table 1.3. Corresponding ICD-9 and ICD-10 Codes of Each HAI Type

HAI Type	ICD-9	ICD-10
CAUTI	996.64	T83.51XA, T83.511A, T83.518A
CLABSI	999.31, 999.32, 999.33	T80.211A, T80.212A, T80.218A, T80.219A
CDI	008.45	A04.7, A04.71, A04.72
MRSA	038.12, 482.41, 482.42, 041.12	A41.02, J15.212, B95.62, A49.02, A41.01, J15211

Sources: Clements (2023), CMS (2023b, 2024), Dubberke et al. (2006), Jones et al. (2012), Schweizer et al. (2011).

To compute a hospital's within-sample Medicare revenue share, I add all charges whose expected primary payer is Medicare, then divide that by the total charges, regardless of payer, recorded for each hospital within the HCUP year. One limitation that the NIS poses is that it is designed to be representative of discharges at the national level, and not at the hospital level. Hence, it is possible that the share of each hospital's Medicare reimbursements derived from the dataset is an inaccurate estimate of the actual share.

In Table 1.4 and Table 1.5, I present the summary statistics of my HAI outcomes using the full sample, as well as by stratifying hospitals into two groups: those with within-sample Medicare revenue shares of at least 50%, and those with within-sample Medicare revenue shares less than 50%. Table 1.4 suggests that hospitals with within-sample Medicare revenue shares less than 50%, which I hypothesized to be more strongly impacted by the policy with respect to CAUTI and CLABSI, had slightly smaller increases in CAUTI (35.65% vs. 35.11%) and smaller decreases in CLABSI (-32.54% vs. -34.18%) relative to hospitals with within-sample Medicare revenue shares of at least 50%. Thus these descriptive findings with respect to CAUTI and

CLABSI are mixed. While in Table 1.5, hospitals with within-sample Medicare revenue shares of at least 50%, which I hypothesized to be more strongly impacted by the policy with respect to CDI and MRSA, had larger decreases in both CDI (-5.27% vs. -3.66%) and MRSA (-9.52% vs. -2.19%) after the policy's implementation. Thus, these descriptive results for CDI and MRSA better align with our intuition that the policy would lead to larger reductions in infection rates.[4] Of course, Table 1.4 and Table 1.5 are not controlling for any other factors that will be included in my formal analysis. Table C.3 provides the summary statistics of the covariates.

Graphical illustrations of how the outcomes changed over time (between these two hospital types) are given in Figure 1.2 and Figure 1.3. In the left panel of Figure 1.2, we see that CAUTI per 100k discharges have been increasing, with the incidence consistently higher among Type H hospitals (i.e. the control group for CAUTI and CLABSI). The right panel illustrates that CLABSI per 100k discharges have been decreasing, with the gap getting smaller in the post period. This is consistent with our expectation. The left panel of Figure 1.3 shows that while CDI started to generally decrease in the middle part of the post period, there seems to be no differential changes by Medicare revenue shares. Finally, the right panel suggests that MRSA per 100k discharges is decreasing, with the gap getting smaller in the post period. This is also consistent with our expectation.

[4] I also look at the summary statistics of the outcome variables using smaller Medicare revenue ranges, namely, hospitals with 0 to 25%, 25 to 50%, 50 to 75%, and 75 to 100% Medicare revenue shares. Table C.1 suggests that hospitals with lower Medicare revenue shares, which I hypothesized to be more strongly impacted by the policy with respect to CAUTI, saw incidence grow proportionally across the quartiles (14.86% in Q1, 35.42% in Q2, 35.65% in Q3, and 40.00% in Q4). For CLABSI we see a similar pattern in terms of a reduction, with proportional growth in the size of the reduction between Q1 (-25.71%) and Q4 (-40.3%). The results for CDI and MRSA in Table C.2 are somewhat more mixed.

Table 1.4. Summary Statistics of CAUTI and CLABSI (per 100 Thousand Discharges)

Outcome variable (per 100k discharges)	Full			Within-sample Medicare revenue shares of at least 50% ("Control")			Within-sample Medicare revenue shares less than 50% ("Treatment")		
	Pre	Post	Percent change	Pre	Post	Percent change	Pre	Post	Percent change
CAUTI	108 (3282)	146 (3816)	35.19%	116 (3404)	155 (3939)	33.62%	92 (3035)	127 (3559)	38.04%
CLABSI	95 (3087)	64 (2522)	-32.63%	80 (2819)	53 (2300)	-33.75%	126 (3547)	85 (2912)	-32.54%
No. of obs.	6,938,796	37,749,007		4,566,961	25,089,837		2,371,835	12,659,170	

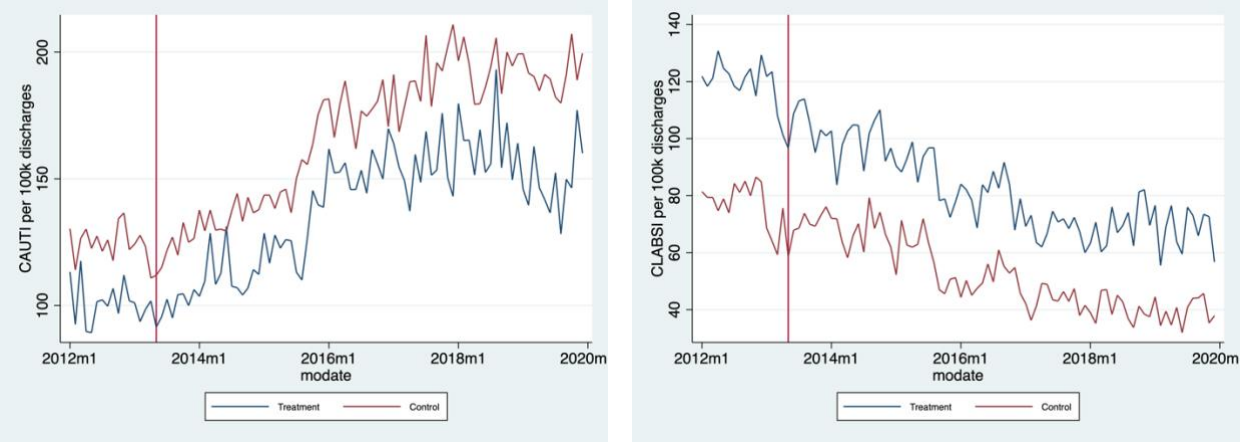
Notes: Post period begins 2013 Q2. Type H = Medicare revenues at least 50% of total revenues. Type L = Medicare revenues less than 50% of total revenues. HCUP discharge weights used. Standard deviations in parentheses. We expect that hospitals in the treatment group see smaller increases in infections or larger decreases in infections.

Table 1.5. Summary Statistics of CDI and MRSA (per 100 Thousand Discharges)

Outcome variable (per 100k discharges)	Full			Within-sample Medicare revenue shares of at least 50% ("Treatment")			Within-sample Medicare revenue shares less than 50% ("Control")		
	Pre	Post	Percent change	Pre	Post	Percent change	Pre	Post	Percent change
CDI	729 (8509)	696 (8312)	-4.53%	740 (8573)	702 (8351)	-5.14%	708 (8385)	683 (8236)	-3.53%
MRSA	1032 (10104)	958 (9742)	-7.17%	1070 (10288)	970 (9801)	-9.35%	958 (9742)	935 (9624)	-2.40%
No. of obs.	10,972,214	33,715,589		7,196,999	22,459,799		3,775,215	11,255,790	

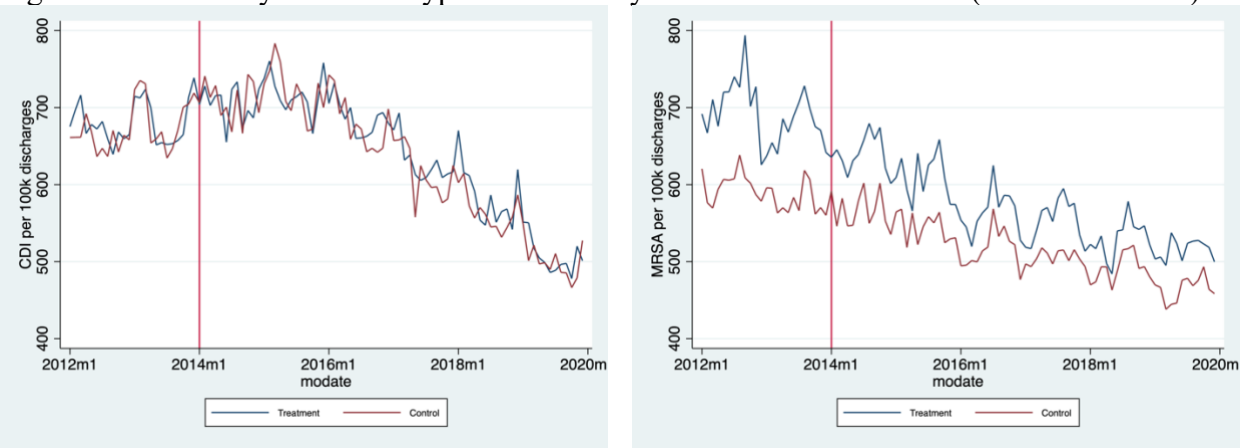
Notes: Post period begins 2014 Q1. Type H = Medicare revenues at least 50% of total revenues. Type L = Medicare revenues less than 50% of total revenues. HCUP discharge weights used. Standard deviations in parentheses. We expect that hospitals in the treatment group see smaller increases in infections or larger decreases in infections.

Figure 1.2. Trends by Infection Type from January 2012 to December 2020 (CAUTI and CLABSI)



Notes: Red vertical lines indicate the beginning of the post period. HCUP discharge weights used.

Figure 1.3. Trends by Infection Type from January 2012 to December 2020 (CDI and MRSA)



Notes: Red vertical lines indicate the beginning of the post period. HCUP discharge weights used.

1.5. Methodology

Adapting Finkelstein (2007) and Miller (2012), I analyze the likelihood of a patient getting a HAI based on the admitting hospital's exposure to the policy as measured by their admitting hospitals' respective Medicare revenue shares (Medicare revenues as percent of their total revenues).[5] The identification strategy relies on the assumption that in the absence of the policy, changes in the likelihood of patients getting a HAI would not vary by the admitting

[5] I also consider exposure as measured by hospitals' Medicare patient shares (number of Medicare patients as percent of total patients) and find that results do not significantly change.

hospital's Medicare revenue shares. I differentiate my identification strategy for CAUTI and CLABSI vs. that for CDI and MRSA following the conceptual framework in Section 1.3.

1.5.1. Estimating Equation for CAUTI and CLABSI

From the framework in Section 1.3, I argued that Type L hospitals are the ones most likely to implement more measures to control CAUTI and CLABSI outcomes following HACRP's (2014 policy) implementation. Thus in my identification strategy, I consider them to belong to the "treatment group", while Type H hospitals fall into the "control group". In a standard difference-in-differences model with a continuous treatment running from 0 to 100, observations with $TREAT = 100$ are considered as "pure treatment" while those with $TREAT = 0$ are considered as "pure control". To use this approach in analyzing HACRP's effect on the incidence of CAUTI and CLABSI, the continuous treatment variable is redefined such that $TREAT = (100 - MEDICAREShare)$, since Type H hospitals are considered as part of the control group. This means that the difference-in-differences model takes on the form

$$y_{iht} = \alpha_0 + \alpha_1 \mathbf{1}(Post)_t + \alpha_2(100 - MEDICAREShare_{ht}) + \alpha_3 \mathbf{1}(Post)_t \times (100 - MEDICAREShare_{ht}) + \mathbf{X}'_{iht}\boldsymbol{\alpha}_4 + \delta_s + \tau_t + \varepsilon_{iht}, \quad (1)$$

where α are coefficients, $y_{iht} = 1$ if discharge i in hospital h records a HAI in year-quarter t, and 0 otherwise, $\mathbf{1}(Post)_t = 1$ in year-quarters after the policy was implemented, and 0 otherwise, $MEDICAREShare_{ht}$ = hospital h's within-sample Medicare revenue share in quarter-year t, $\mathbf{X}$ = vector of controls, δ_s = region of country FE, τ_t = year-quarter FE, and ε_{iht} = error term. Since the relevant performance period for CAUTI and CLABSI (which begins in January 2012) was not mentioned by CMS prior to the proposed rule that they circulated in May 2013, I assume that hospitals only had $Partial\ Foresight$ for these HAI types (i.e., post period begins in 2013 Q2). The primary coefficient of interest here is α_3, which tells us how

much the incidence of HAIs changed following the implementation of HACRP for CAUTI and CLABSI. A negative coefficient implies that the policy reduced the incidence of these particular HAIs.

1.5.2. Estimating Equation for CDI and MRSA

CDI and MRSA were not affected by the 2008 policy discussed in Section 1.2, creating treatment and control groups that are the inverse of those for CAUTI and CLABSI. As we expect to see a stronger impact of the 2014 policy on CDI and MRSA among Type H hospitals, these hospitals would be considered as the treatment group for these HAIs. The control group would then consist of Type L hospitals.

Accordingly, the estimating equations for these two types are modified such that

$$y_{iht} = \beta_0 + \beta_1 \mathbf{1}(Post)_t + \beta_2(100 - MEDICAREShare_{ht}) + \beta_3 \mathbf{1}(Post)_t \times (100 - MEDICAREShare_{ht}) + \mathbf{X}'_{iht}\boldsymbol{\beta}_4 + \delta'_s + \tau'_t + \varepsilon'_{iht}, \quad (2)$$

where β are coefficients, $y_{iht} = 1$ if discharge i in hospital h records a HAI in year-quarter t, and 0 otherwise, $\mathbf{1}(Post)_t = 1$ in year-quarters after the policy was implemented, and 0 otherwise, $MEDICAREShare_{ht}$ = hospital h's within-sample Medicare revenue share in quarter-year t, $\mathbf{X}$ = vector of controls, δ'_s = region of country FE, τ'_t = year-quarter FE, and ε'_{iht} = error term. In the case of CDI and MRSA, it was mentioned as early as August 2013 that these two HAI types will be included in the FY 2017 Total HAC Score, so in this case it can be argued that hospitals had Perfect Foresight (i.e., post period begins in 2014 Q1).[6] The primary coefficient of interest here is β_3, which tells us how much the incidence of HAIs changed

[6] While I focus on Partial Foresight for CAUTI and CLABSI, and Perfect Foresight for CDI and MRSA, I also estimate models assuming other types of foresight. These results are found in Table 1.15 to Table 1.18.

following the implementation of HACRP for CDI and MRSA. A negative coefficient implies that the policy reduced the incidence of these particular HAIs.

1.5.3. Event Study

I also estimate an event study model using the following specification:

$$y_{iht} = \gamma_0 + \sum_{YQ \neq PreQuarter} \gamma_{YQ} \mathbf{1}(YQ)_t \times MEDICAREShare_{ht} + \mathbf{X}'_{iht}\gamma_4 + \delta''_s + \tau''_t + \nu_{iht}, \quad (3)$$

where γ are coefficients, YQ consist of the year-quarters from 2012 Q1 until 2019 Q4, except the quarter prior to the program implementation ($PreQuarter$), $\mathbf{1}(YQ)_t$ are year-quarter dummies for each YQ, and other variables as previously defined.

It is important to show that the parallel trends assumption is sufficiently supported based on the event study analysis, so that the causal interpretations from the differencein-differences model can be established. If the estimates of the $MEDICAREShare_{ht}$ interactions with each of the pre-$PreQuarter$ dummies in Equation 3 are insignificant, this provides support for the parallel trends assumption.

1.6. Results

1.6.1. Baseline Results and Event Study

My estimates based on Equations 1 and 2 suggest that the probability of having a HAI statistically significantly decreased after the policy was implemented. As seen in Table 1.6, for every 1 standard deviation decrease in a hospital's Medicare share (as % of total revenues), we see a -5.56% and -11.17% decrease in the probability of a patient acquiring CAUTI and CLABSI, respectively. Similarly, for every 1 standard deviation increase in a hospital's Medicare share (as % of total revenues), we see a -1.58% and -6.59% decrease in the probability of acquiring CDI and MRSA, respectively.

Table 1.6. Difference-in-Difference Coefficients for Equations 1 and 2

	HAI Type			
	CAUTI	CLABSI	CDI	MRSA
DD coeff.	-0.30***	-0.53***	-0.46**	-2.72***
(Std. Err.) *per 100k*	(0.11)	(0.11)	(0.23)	(0.29)
Pre-policy implementation mean of dep. var. *per 100k*	108	95	729	1032
Change in probability of infection for every 1 SD decrease/increase in Medicare share	-5.56%	-11.17%	-1.58%	-6.59%
No. of obs.	44,687,803	44,687,803	44,687,803	44,687,803

Notes: *, **, *** denote significance levels of 10%, 5%, and 1%, respectively. HCUP discharge weights used. Discharge-level characteristics, hospital-level characteristics, stratum fixed effects, and year-quarter fixed effects included in the models. Robust standard errors in parentheses.

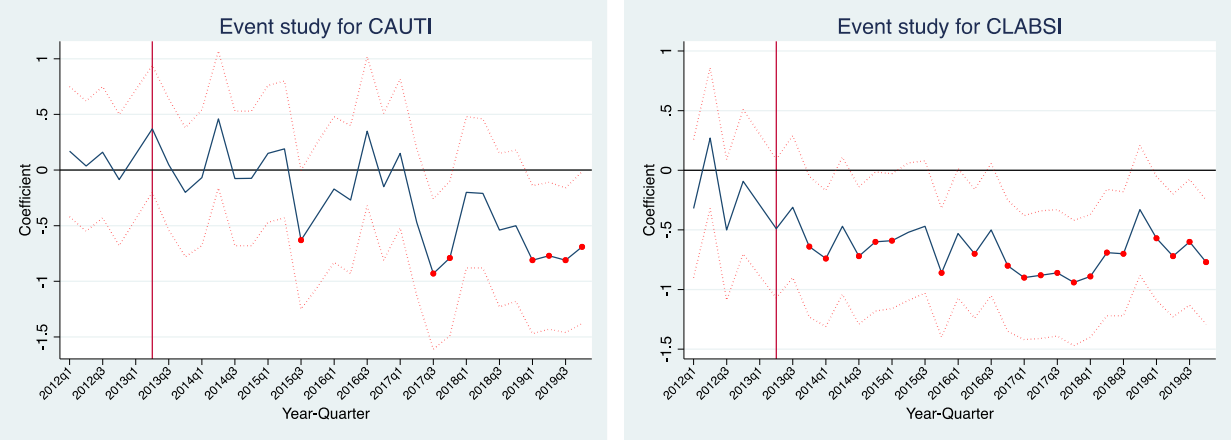
Haque et al. (2020) notes that hand hygiene is the "most effective, simplest, and cheapest" measure to prevent HAIs. However, not all healthcare workers wash their hands properly, with some washing their hands less than half of the times they should (CDC, 2023). In some cases, healthcare workers only use alcohol-based hand sanitizers instead of washing their hands with soap and water. This could potentially explain the difference in the estimated effects, as in most cases, the bacteria causing CAUTI, CLABSI, and MRSA can be killed by the use of alcohol-based hand sanitizers alone, while the bacteria causing CDI requires thorough washing with soap and water.

Together with Figure 1.2 and Figure 1.3, these DD results can be interpreted as follows. For CAUTI, the incidence in low Medicare hospitals ("treatment") increased at a slower rate compared to the incidence in high Medicare hospitals ("control"). For CLABSI, the incidence in low Medicare hospitals ("treatment") decreased at a faster rate compared to the incidence in high Medicare hospitals ("control"). For MRSA and CDI, the incidence in high Medicare hospitals ("treatment") decreased at a faster rate compared to the incidence in low Medicare hospitals ("control").

Figure 1.4 and Figure 1.5 graphically present estimates from my event study model specified in Equation 3. Here, we see that none of the interactions with each of the pre-

$PreQuarter$ dummies for CAUTI and CLABSI are significant, while for CDI and MRSA, only 1 out of 7 are significant (i.e. 14%). Having 14% significant for CDI and MRSA is about what you would expect by chance. This gives me more confidence in a causal interpretation of my baseline results. Additionally, Figure 1.4 and Figure 1.5 suggest that the reductions in the different HAIs followed different patterns over time.

Figure 1.4. Event Study Results for CAUTI and CLABSI



Notes: Significant coefficients are marked with solid red dots for emphasis. Dotted lines indicate 95% confidence interval.

Figure 1.5. Event Study Results for CDI and MRSA

Notes: Significant coefficients are marked with solid red dots for emphasis. Dotted lines indicate 95% confidence interval.

From these figures, we see that the reductions in CLABSI and MRSA were pretty uniform across the post period, with more of a consistent downward trend for MRSA. The reduction for CDI that I see in my baseline results seems to be driven by the beginning of the

post-period, while the reduction for CAUTI seems to be driven more by the later part of the post-period.

1.6.2. Specification Tests

I also consider longer pre-policy implementation time periods (starting in 2009, 2010, or 2011 instead of 2012) in Table 1.7 to Table 1.10. For CAUTI, we see that depending on the starting year that we choose, the effects could be as small as -3.60% and as big as -7.81% (Table 1.7). For CLABSI, these values range from -8.61% to -15.95% (Table 1.8). For CDI, we observe that the estimated coefficients could be as small as -1.58% and as big as -4.48% (Table 1.9). For MRSA, the results are more consistent with estimated effects ranging from -6.34% to -6.59% (Table 1.10). In general, the results with a longer pre-implementation period yield coefficients with similar signs, and slightly different magnitudes.

Table 1.7. Difference-in-Difference Coefficients Using Data with Longer Pre-Policy Implementation Periods (Outcome of Interest: CAUTI)

	Beginning in year			
	2012	2011	2010	2009
DD coeff.	-0.30***	-0.37***	-0.16*	-0.17**
(Std. Err.) *per 100k*	(0.11)	(0.092)	(0.081)	(0.074)
Pre-policy implementation mean of dep. var. *per 100k*	108	106	105	103
Change in probability of infection for every 1 SD decrease in Medicare share	-5.56%	-7.81%	-3.60%	-4.01%
No. of obs.	44,687,803	49,910,248	54,764,930	59,362,531

Notes: *, **, *** denote significance levels of 10%, 5%, and 1%, respectively. HCUP discharge weights used. Discharge-level characteristics, hospital-level characteristics, stratum fixed effects, and year fixed effects included in the models. Robust standard errors in parentheses.

Another specification check I perform considers more conservative definition of what can be considered a hospital-acquired infection. As explained in Section 1.4, a limitation that NIS poses is that it does not have an indicator as to whether a particular diagnosis is present upon admission or not. So far, I considered an infection in the NIS as hospital-acquired if it is not the first-listed diagnosis (e.g., second-listed onwards). To check the robustness of my results, I also estimate models that exclude the second-listed and third-listed diagnoses in classifying if an

infection is likely to be hospital-acquired or not. However, the following results must be interpreted with caution as these could just be driven by mechanical changes in the definition, and not by the diagnoses being misclassified as present on admission, per se.

Table 1.8. Difference-in-Difference Coefficients Using Data with Longer Pre-Policy Implementation Periods (Outcome of Interest: CLABSI)

	Beginning in year			
	2012	2011	2010	2009
DD coeff.	-0.53***	-0.70***	-0.63***	-0.37***
(Std. Err.) *per 100k*	(0.11)	(0.089)	(0.078)	(0.073)
Pre-policy implementation mean of dep. var. *per 100k*	95	101	107	110
Change in probability of infection for every 1 SD decrease in Medicare share	-11.17%	-15.95%	-14.35%	-8.61%
No. of obs.	44,687,803	49,910,248	54,764,930	59,362,531

Notes: *, **, *** denote significance levels of 10%, 5%, and 1%, respectively. HCUP discharge weights used. Discharge-level characteristics, hospital-level characteristics, stratum fixed effects, and year fixed effects included in the models. Robust standard errors in parentheses.

Table 1.9. Difference-in-Difference Coefficients Using Data with Longer Pre-Policy Implementation Periods (Outcome of Interest: CDI)

	Beginning in year			
	2012	2011	2010	2009
DD coeff.	-0.46**	-0.56***	-0.58***	-1.09***
(Std. Err.) *per 100k*	(0.23)	(0.21)	(0.19)	(0.18)
Pre-policy implementation mean of dep. var. *per 100k*	729	722	698	675
Change in probability of infection for every 1 SD increase in Medicare share	-1.58%	-2.06%	-2.27%	-4.48%
No. of obs.	44,687,803	49,910,248	54,764,930	59,362,531

Notes: *, **, *** denote significance levels of 10%, 5%, and 1%, respectively. HCUP discharge weights used. Discharge-level characteristics, hospital-level characteristics, stratum fixed effects, and year fixed effects included in the models. Robust standard errors in parentheses.

Table 1.10. Difference-in-Difference Coefficients Using Data with Longer Pre-Policy Implementation Periods (Outcome of Interest: MRSA)

	Beginning in year			
	2012	2011	2010	2009
DD coeff.	-2.72***	-2.50***	-2.40***	-2.43***
(Std. Err.) *per 100k*	(0.29)	(0.26)	(0.24)	(0.22)
Pre-policy implementation mean of dep. var. *per 100k*	1032	1040	1036	1057
Change in probability of infection for every 1 SD increase in Medicare share	-6.59%	-6.39%	-6.34%	-6.38%
No. of obs.	44,687,803	49,910,248	54,764,930	59,362,531

Notes: *, **, *** denote significance levels of 10%, 5%, and 1%, respectively. HCUP discharge weights used. Discharge-level characteristics, hospital-level characteristics, stratum fixed effects, and year fixed effects included in the models. Robust standard errors in parentheses.

I find that using stricter definitions, the results for CAUTI and CLABSI do not significantly change (Table 1.11 and Table 1.12). However, we see different results for the CDI model wherein the coefficients change from -1.58% (Table 1.13, Column 1) to -1.74% and -2.38%, depending on the level of exclusion that we adapt (Table 1.13, Columns 2 and 3). For MRSA, we see that the estimates become weaker going from -6.59% if I only exclude the first-listed diagnosis to -3.45% and -2.37% when the second and third listed diagnoses are excluded, respectively (Table 1.14).

Table 1.11. Difference-in-Difference Coefficients Using More Conservative Definitions of an HAI (Outcome of Interest: CAUTI)

	Excluded diagnosis		
	Up to 1st listed	Up to 2nd listed	Up to 3rd listed
DD coeff.	-0.30***	-0.23**	-0.23**
(Std. Err.) *per 100k*	(0.11)	(0.10)	(0.098)
Mean of dep. Var. *per 100k*	108	98	88
Change in probability of infection for every 1 SD decrease in Medicare share	-5.56%	-4.70%	-5.23%
No. of obs.	44,687,803	44,687,803	44,687,803

Notes: *, **, *** denote significance levels of 10%, 5%, and 1%, respectively. HCUP discharge weights used. Discharge-level characteristics, hospital-level characteristics, stratum fixed effects, and year fixed effects included in the models. Robust standard errors in parentheses.

Table 1.12. Difference-in-Difference Coefficients Using More Conservative Definitions of an HAI (Outcome of Interest: CLABSI)

	Excluded diagnosis		
	Up to 1st listed	Up to 2nd listed	Up to 3rd listed
DD coeff.	-0.53***	-0.52***	-0.54***
(Std. Err.) *per 100k*	(0.11)	(0.10)	(0.096)
Mean of dep. Var. *per 100k*	95	89	80
Change in probability of infection for every 1 SD decrease in Medicare share	-11.17%	-11.70%	-13.51%
No. of obs.	44,687,803	44,687,803	44,687,803

Notes: *, **, *** denote significance levels of 10%, 5%, and 1%, respectively. HCUP discharge weights used. Discharge-level characteristics, hospital-level characteristics, stratum fixed effects, and year fixed effects included in the models. Robust standard errors in parentheses.

These big differences in the estimates for the CDI and MRSA models warrant further investigation. This specification check highlights the importance of correctly identifying whether a CDI or MRSA infection in the NIS is in fact hospital-acquired or not. Sutton & Steiner (2016)

suggest that the way to do this in the HCUP database is to use the present on admission indicator. However, this is only available in the HCUP SID, and not in the NIS.

Table 1.13. Difference-in-Difference Coefficients Using More Conservative Definitions of an HAI (Outcome of Interest: CDI)

	Excluded diagnosis		
	Up to 1st listed	Up to 2nd listed	Up to 3rd listed
DD coeff.	-0.46**	0.40*	0.44**
(Std. Err.) *per 100k*	(0.23)	(0.21)	(0.19)
Mean of dep. Var. *per 100k*	729	576	462
Change in probability of infection for every 1 SD decrease in Medicare share	-1.58%	1.74%	2.38%
No. of obs.	44,687,803	44,687,803	44,687,803

Notes: *, **, *** denote significance levels of 10%, 5%, and 1%, respectively. HCUP discharge weights used. Discharge-level characteristics, hospital-level characteristics, stratum fixed effects, and year fixed effects included in the models. Robust standard errors in parentheses.

Table 1.14. Difference-in-Difference Coefficients Using More Conservative Definitions of an HAI (Outcome of Interest: MRSA)

	Excluded diagnosis		
	Up to 1st listed	Up to 2nd listed	Up to 3rd listed
DD coeff.	-2.72***	-1.15***	-0.67***
(Std. Err.) *per 100k*	(0.29)	(0.26)	(0.24)
Mean of dep. Var. *per 100k*	1032	834	707
Change in probability of infection for every 1 SD decrease in Medicare share	-6.59%	-3.45%	-2.37%
No. of obs.	44,687,803	44,687,803	44,687,803

Notes: *, **, *** denote significance levels of 10%, 5%, and 1%, respectively. HCUP discharge weights used. Discharge-level characteristics, hospital-level characteristics, stratum fixed effects, and year fixed effects included in the models. Robust standard errors in parentheses.

The last specification check I perform considers different definitions of foresight as described in Section 1.2 and summarized in Table 1.2. For CAUTI and CLABSI, I argued earlier that hospitals are more likely to have partial foresight, and so the post period should begin in 2013 Q2. Running CAUTI and CLABSI models under zero foresight (post period beginning 2013 Q3) does not change these results, but considering perfect foresight (post period beginning 2012 Q1) yields smaller coefficients (Table 1.15 and Table 1.16). For CDI and MRSA, I initially considered hospitals to have perfect foresight (post period beginning 2014 Q1). Partial and zero foresight scenarios (post periods beginning 2015 Q2 and 2015 Q3, respectively) yield smaller coefficients for CDI and generally similar coefficients for MRSA (Table 1.17 and Table 1.18).

In general, the small differences between the partial and zero foresight scenarios across all HAI types are not surprising, given that they only begin one period apart. The smaller effects seen under the perfect foresight case for CAUTI and CLABSI is consistent with our expectation if we assume that hospitals in 2012 Q1 did not know that this quarter marks the beginning of the relevant performance period for FY2014. They really started to improve their performance in these areas only when they read about the proposed rule in May 2013. On the other hand, if we stick to our assumption that hospitals had perfect foresight when it comes to the evaluation of their performance for CDI and MRSA, then the effects being bigger under perfect foresight scenario becomes consistent with our expectations.

Table 1.15. Difference-in-Difference Coefficients Using Different Foresights (Outcome of Interest: CAUTI)

	Foresights		
	Perfect	Partial	Zero
DD coeff.	-0.060	-0.17**	-0.23***
(Std. Err.) *per 100k*	(0.080)	(0.074)	(0.074)
Mean of dep. Var. *per 100k*	100	103	102
Change in probability of infection for every 1 SD increase in Medicare share	-1.37%	-4.03%	-5.56%
Post period	2012 Q1	2013 Q2	2013 Q3
Years included	2009-2019	2009-2019	2009-2019
No. of obs.	59,362,531	59,362,531	59,362,531

Notes: *, **, *** denote significance levels of 10%, 5%, and 1%, respectively. HCUP discharge weights used. Discharge-level characteristics, hospital-level characteristics, stratum fixed effects, and year fixed effects included in the models. Robust standard errors in parentheses.

Table 1.16. Difference-in-Difference Coefficients Using Different Foresights (Outcome of Interest: CLABSI)

	Foresights		
	Perfect	Partial	Zero
DD coeff.	-0.25***	-0.39***	-0.40***
(Std. Err.) *per 100k*	(0.089)	(0.073)	(0.071)
Mean of dep. Var. *per 100k*	121	113	111
Change in probability of infection for every 1 SD increase in Medicare share	-4.72%	-8.43%	-8.88%
Post period	2012 Q1	2013 Q2	2013 Q3
Years included	2009-2019	2009-2019	2009-2019
No. of obs.	59,362,531	59,362,531	59,362,531

Notes: *, **, *** denote significance levels of 10%, 5%, and 1%, respectively. HCUP discharge weights used. Discharge-level characteristics, hospital-level characteristics, stratum fixed effects, and year fixed effects included in the models. Robust standard errors in parentheses.

Table 1.17. Difference-in-Difference Coefficients Using Different Foresights (Outcome of Interest: CDI)

	Foresights		
	Perfect	Partial	Zero
DD coeff.	-0.46**	-0.12	-0.039
(Std. Err.) *per 100k*	(0.23)	(0.20)	(0.20)
Mean of dep. Var. *per 100k*	729	748	749
Change in probability of infection for every 1 SD increase in Medicare share	-1.58%	-0.45%	-0.14%
Post period	2014 Q1	2015 Q2	2015 Q3
Years included	2012-2019	2012-2019	2012-2019
No. of obs.	44,687,803	44,687,803	44,687,803

Notes:*, *, **, *** denote significance levels of 10%, 5%, and 1%, respectively. HCUP discharge weights used. Discharge-level characteristics, hospital-level characteristics, stratum fixed effects, and year fixed effects included in the models. Robust standard errors in parentheses.

Table 1.18. Difference-in-Difference Coefficients Using Different Foresights (Outcome of Interest: MRSA)

	Foresights		
	Perfect	Partial	Zero
DD coeff.	-2.72***	-2.36***	-2.47***
(Std. Err.) *per 100k*	(0.29)	(0.25)	(0.25)
Mean of dep. Var. *per 100k*	1032	1001	998
Change in probability of infection for every 1 SD increase in Medicare share	6.59%	6.57%	6.85%
Post period	2014 Q1	2015 Q2	2015 Q3
Years included	2012-2019	2012-2019	2012-2019
No. of obs.	44,687,803	44,687,803	44,687,803

Notes: *, **, *** denote significance levels of 10%, 5%, and 1%, respectively. HCUP discharge weights used. Discharge-level characteristics, hospital-level characteristics, stratum fixed effects, and year fixed effects included in the models. Robust standard errors in parentheses.

1.6.3. Heterogeneity Tests

I also compare estimates across different population subgroups, namely, by race, gender, and age. Running Equations 1 and 2 (Table 1.19), we see that whites see better outcomes when it comes to changes in the probability of having CAUTI compared to blacks, Asians, and Pacific Islanders. In terms of coefficient signs, whites, Asians, and Pacific Islanders realize a decrease in probability, while blacks see an increase, albeit insignificant. However, statistical tests indicate that the estimated coefficients for different racial groups were not significantly different from one another (p-value of 0.1011). By age groups, the signs of the estimated coefficients for the elderly and non-elderly differ, with the former pointing to an increase in probability after the

program was implemented while the latter to a decrease. However, tests also show that these coefficients are not statistically significant from each other (p-value of 0.3890). Meanwhile both men and women see a decrease in the probability of having CAUTI, but this observed change is only significant for men and not for women. Again, statistical tests show that the coefficients between men and women are not statistically different (p-value of 0.1746).

The models for CLABSI yields slightly different results. As we see in Table 1.20, whites also see a decrease in probability of having CLABSI, while Asians and Pacific Islanders see an increase in probability, although still insignificant (unlike the comparisons by race for CAUTI, tests show that the coefficients by races are statistically different from each other at the 10% level, with a p-value of 0.0551). Comparing elderly and non-elderly, as well as men and women, we see that all groups have significant negative coefficients, with the effects larger for the elderly and men. Formally comparing the estimates by age group and gender, I find no statistical difference between men and women (p-value of 0.1528) and a statistically significant difference between elderly and non-elderly (p-value of 0.0760).

Models for CDI show that women have better outcomes compared to men, while nonelderly have worse outcomes compared to the elderly (Table 1.21). Doing the same comparisons across race, age group, and gender, I get p-values of 0.0059, 0.0245, and 0.0141, respectively. Lastly, models for MRSA show that all population subgroups (except Asians and Pacific Islanders) had better outcomes after the policy was implemented, but whites had better outcomes compared to blacks, women did better compared to men, and elderly did better than

Table 1.19. Difference-in-Difference Coefficients by Population Sub-Group (Outcome of Interest: CAUTI)

	Population sub-group							
	White	Black	Asian/Pacific Islander	Hispanic	Men	Women	Elderly	Non-elderly
DD coeff. (Std. Err.) *per 100k*	-0.32** (0.15)	0.24 (0.29)	-0.85 (0.57)	0.15 (0.24)	-0.47** (0.21)	-0.14 (0.12)	0.088 (0.25)	-0.15 (0.11)
Mean of dep. Var. *per 100k*	116	112	71	63	145	82	174	60
Change in probability of infection for every 1 SD decrease in Medicare share	-5.28%	4.48%	-24.80%	5.24%	-6.38%	-3.46%	0.94%	-5.22%
No. of obs.	30,498,232	6,653,457	1,158,587	4,785,440	18,580,034	26,107,769	19,128,817	25,558,986

Notes: *, **, *** denote significance levels of 10%, 5%, and 1%, respectively. HCUP discharge weights used. Discharge-level characteristics, hospital-level characteristics, stratum fixed effects, and year fixed effects included in the models. Robust standard errors in parentheses.

Table 1.20. Difference-in-Difference Coefficients by Population Sub-Group (Outcome of Interest: CLABSI)

	Population sub-group							
	White	Black	Asian/Pacific Islander	Hispanic	Men	Women	Elderly	Non-elderly
DD coeff. (Std. Err.) *per 100k*	-0.65*** (0.13)	-0.028 (0.32)	0.26 (0.58)	-0.024 (0.29)	-0.74*** (0.19)	-0.42*** (0.12)	-0.83*** (0.18)	-0.43*** (0.14)
Mean of dep. Var. *per 100k*	84	152	71	91	116	81	87	102
Change in probability of infection for every 1 SD decrease in Medicare share	-14.81%	-0.39%	7.59%	-0.58%	-12.55%	-10.50%	-17.77%	-8.81%
No. of obs.	30,498,232	6,653,457	1,158,587	4,785,440	18,580,034	26,107,769	19,128,817	25,558,986

Notes: *, **, *** denote significance levels of 10%, 5%, and 1%, respectively. HCUP discharge weights used. Discharge-level characteristics, hospital-level characteristics, stratum fixed effects, and year fixed effects included in the models. Robust standard errors in parentheses.

Table 1.21. Difference-in-Difference Coefficients by Population Sub-Group (Outcome of Interest: CDI)

	Population sub-group							
	White	Black	Asian/Pacific Islander	Hispanic	Men	Women	Elderly	Non-elderly
DD coeff. (Std. Err.) *per 100k*	-0.21 (0.31)	-0.64 (0.58)	-4.40*** (1.33)	-1.54*** (0.55)	0.24 (0.40)	-0.86*** (0.28)	-0.33 (0.51)	1.04*** (0.24)
Mean of dep. Var. *per 100k*	771	705	674	535	798	683	1101	461
Change in probability of infection for every 1 SD increase in Medicare share	-0.70%	-2.16%	-14.94%	-6.72%	0.75%	-3.16%	-0.76%	5.55%
No. of obs.	30,498,232	6,653,457	1,158,587	4,785,440	18,580,034	26,107,769	19,128,817	25,558,986

Notes: *, **, *** denote significance levels of 10%, 5%, and 1%, respectively. HCUP discharge weights used. Discharge-level characteristics, hospital-level characteristics, stratum fixed effects, and year fixed effects included in the models. Robust standard errors in parentheses.

Table 1.22. Difference-in-Difference Coefficients by Population Sub-Group (Outcome of Interest: MRSA)

	Population sub-group							
	White	Black	Asian/Pacific Islander	Hispanic	Men	Women	Elderly	Non-elderly
DD coeff. (Std. Err.) *per 100k*	-3.79*** (0.39)	-2.28*** (0.75)	0.65 (1.35)	-0.89 (0.69)	-2.75*** (0.55)	-2.65*** (0.32)	-2.78*** (0.53)	-2.00*** (0.36)
Mean of dep. Var. *per 100k*	1088	1060	706	845	1387	806	1097	1002
Change in probability of infection for every 1 SD increase in Medicare share	-8.90%	-5.12%	2.11%	-2.46%	-4.93%	-8.25%	-6.43%	-4.91%
No. of obs.	30,498,232	6,653,457	1,158,587	4,785,440	18,580,034	26,107,769	19,128,817	25,558,986

Notes: *, **, *** denote significance levels of 10%, 5%, and 1%, respectively. HCUP discharge weights used. Discharge-level characteristics, hospital-level characteristics, stratum fixed effects, and year fixed effects included in the models. Robust standard errors in parentheses.

non-elderly (Table 1.22). These differences are also found to be statistically significant (p-value of 0.0001). On the other hand, comparisons by age group and gender yield p-values of 0.2209 and 0.8770, respectively.

1.6.4. Potential Mechanisms

Hospital guidelines aimed at controlling these HAIs often emphasize strict hand hygiene before and after medical procedures, improved antibiotic stewardship programs, as well as proper device maintenance practices (CDC, 2011, 2015, 2019b, 2021b). Together with specific preventive actions tailored to each infection, these efforts help hospitals minimize the risk and impact of various hospital-acquired infections.[7] Due to the nature of the NIS, I am unable to use this dataset to test if hospitals indeed improved in these areas after the implementation of HACRP. However, I can analyze whether hospitals altered their admission and transfer patterns to reduce the occurrence of HAIs. Specifically, I look at changes in admissions for elective surgeries, patient transfers received from other hospitals and their own emergency department, and transfers made to other hospitals.

It can be argued that hospitals might have reduced elective admissions to minimize the risk of patients contracting HAIs unnecessarily. Additionally, they might be cautious about accepting patients from other hospitals and their own emergency departments, as these individuals could be sicker and more susceptible to HAIs, potentially increasing the overall HAI occurrences within the hospitals. To mitigate/offset this risk, hospitals could be transferring patients to other facilities more frequently (along with the reduction in elective admissions). To

[7] Protocols hospitals take to prevent these infections include:

- CAUTI: using Castile Soap Wipes at the site of insertion to the rest of the urinary catheter
- CLABSI: performing chlorhexidine bathing for patients inserted with central lines, routine dressing changes by dedicated IV teams, and implementing improved line maintenance protocols
- CDI: observing contact precaution practices, wearing gowns inside patient rooms, bleaching all equipment and devices that go inside patient rooms

test these hypotheses, I run models based on Equation 1, with binary outcome variables equal to 1 if: (i) admission is due to an elective surgery, (ii) admission is a transfer from another hospital/healthcare facility, (iii) admission is a transfer from the emergency department, and (iv) admitted patient was transferred to another hospital/healthcare facility.

Table 1.23 presents these results. We can see that after HACRP's implementation, hospitals started reducing admissions due to elective surgeries by -1.91%. Transfers from other hospitals/healthcare facilities and the emergency department increased by 2.69% and 0.37%, respectively, while transfers to other hospitals also increased by 1.98%. Putting these figures together, we can say that there was a "net decrease" (transfer-ins minus transfer-outs and reduced elective admissions) in the number of patients that hospitals admit after the policy's implementation.

Table 1.23. Hospital Admission and Transfer Patterns

	HAI Type			
	Elective?	Transfer in?	Transfer out?	Transfer (ED)?
	(1)	(2)	(3)	(4)
DD coeff.	-23.7***	10.3***	17.9***	10.5***
(Std. Err.) *per 100k*	(1.51)	(0.88)	(1.20)	(1.67)
Pre-policy implementation mean of dep. var. *per 100k*	24903	7670	18126	56536
Change in probability of infection for every 1 SD decrease/increase in Medicare share	-1.91%	2.69%	1.98%	0.37%
No. of obs.	44,559,509	44,687,803	44,687,803	44,687,803

Notes: *, **, *** denote significance levels of 10%, 5%, and 1%, respectively. HCUP discharge weights used. Discharge-level characteristics, hospital-level characteristics, stratum fixed effects, and year fixed effects included in the models. Robust standard errors in parentheses.

1.7. Discussion and Conclusion

Overall, my results suggest that HACRP led to a decrease in the incidence of HAIs after its implementation. My causal findings are generally consistent with the descriptive findings of Arntson et al. (2021) and Alrawashdeh et al. (2021), despite their use of other data sources and no rigorous methodology. I find that for every 1 standard deviation increase in a hospitals' Medicare revenue share, the probability of having CAUTI and CLABSI go down by -5.56% and

-11.17%, respectively. Similarly, for every 1 standard deviation decrease in a hospitals' Medicare revenue share, the probability of having CDI and MRSA go down by -1.58% and -6.59%, respectively. To put these figures in proper perspective, it is important to note HACRP only imposes a 1% reduction in Medicare reimbursements for hospitals with a total HAC score greater than the 75th percentile of all Total HAC Scores. In other words, one might have expected a larger penalty to lead to larger changes in hospital behavior.

Differential effects by race, gender, and age group were observed. Among Whites, there have been significant reductions in CAUTI, CLABSI, and MRSA. Among Asians/Pacific Islanders and Blacks however, this significant effect was only observed for CDI and MRSA, respectively. Men seemed to benefit in all HAI types, except CDI, while women saw significant reductions in all types but CAUTI. The elderly, which is Medicare's main covered population, only saw significant reductions in CLABSI and MRSA, while the non-elderly had significant reductions in all HAI types except CAUTI.

These results contribute to the literature in the following ways. First is that I was able to observe longer post periods and a more general inpatient care setting compared to existing research. Most of the works in this topic used data until June 2018 and considered outcomes limited in the critical care setting (Hsu et al., 2019), only among patients that underwent surgery (Sheetz et al., 2019), and outcomes at the hospital level (Hsu et al., 2020). My work however uses data until December 2019 and includes outcomes from a nationally representative sample of discharges among community hospitals in the United States (excluding rehabilitation and long-term acute care hospitals). Compared to these cited works which found null results, this paper shows that the policy had significant effects in reducing the incidence of HAIs. This could mean

that while the effects may have been insignificant in specific instances, looking at a more general picture tells us that there have been improvements.

Another contribution I make is the use of different post-periods in setting up my identification strategy. Since the penalties were applied to HAI-related Medicare reimbursements beginning in FY 2015 (i.e., October 2014), existing studies mainly used October 2014 as the start of their post-period. However, as I argue in this work, there are other more appropriate post periods, depending on the HAI we are looking at. This may explain why existing studies find null results, since the effects have already been realized even before the post periods they considered began.

Policymakers may then use these results to determine which infections they can shift their attention to. Changes in how the Total HAC Score is computed may be used to further improve CDI and CAUTI outcomes, since these two infections appear to be least affected by the policy. In line with this, the social marginal costs attributed to each infection and social marginal benefits attributed to the policy may be computed to more rigorously determine which infections need to be given more attention to. In addition, my heterogeneity results suggest that policymakers may want put in place measures to protect the population subgroups that do not benefit (or experience worse outcomes) from the policy. Communities with predominantly black or Asian/Pacific Islanders individuals may be given more public health funding in order to help control the levels of infections in these areas.

It is important to understand these findings given the following limitations. First is that present-on-admission indicators are absent in the NIS, meaning the identified outcome variables might be incorrectly classified (i.e., considered as hospital-acquired, when in reality they are not). This means that the estimated coefficients might be biased upwards, and hence can be

interpreted only as an upper-bound of the actual effect. Specification checks however show that results do not significantly change despite using more conservative definitions of a HAI in the NIS.

Second is that the NIS takes a sample from the entire universe of discharges, leaving a possibility that not all discharges within a hospital are included in the dataset. This affects the computation of the within-sample Medicare revenue share that was used as treatment variable in the difference-in-differences model, which then spill over to the classification of hospitals as being treated or controlled. However, given the nature of the dataset, this is the best approach one could take. To address this concern, one may use the HCUP SID which allows for the accurate computation of a hospital's within-sample Medicare revenue share.

Third is that hospitals may potentially adjust their coding behavior strategically, which could lead to underreporting of infections and consequently, improvement in their total HAC scores. However, if hospitals, regardless of type, engage in similar coding practices, the impact on the findings of this paper may not be substantial. Notably, existing literature does not extensively explore differential responses by hospital type in terms of coding behavior. Therefore, investigating hospital miscoding behavior could be a valuable avenue for future research in this paper.

Chapter 2: Medicare Part D and Hospital Admissions Due to Antimicrobial Resistance

2.1. Introduction

The general public consistently shows high interest in antibiotic resistance (Google Trends, n.d.). Antibiotic-resistant infections represent the most common type of a larger class of infections known as antimicrobial-resistant infections.[8] Each year, 2.8 million cases of antimicrobial-resistant infections are recorded in the United States (CDC, 2021a). This larger class of infections are associated with more than 35,000 deaths as well as increasing treatment costs. Estimates show that 6-month unadjusted costs associated with one particular antibiotic resistant infection, methicillin-resistant *Staphylococcus aureus* (MRSA), alone could amount to as much as $34,657 per hospitalization (Filice et al., 2015).

One cause of antimicrobial resistance (AMR) is drug non-compliance (Laxminarayan & Brown, 2001). In the case of antimicrobials, an example of one type of non-compliance would be when patients stop taking their medications "early" due to a variety of reasons. For example, patients may already feel better (and hence think that there is no need to take the rest of their prescribed medicines) or they may face barriers (e.g., financial, cultural) that prevent them from taking all of their necessary medicines (Kardas, 2006). Lee et al. (2018) points out that cost-related medication under-utilization is observed among 10-40% of the elderly in the US.

Another example of non-compliance linked to increases in AMR is the overuse of antimicrobial drugs (World Health Organization, 2023). While antibiotics are proven to treat bacterial infections, prevent the spread of diseases, and reduce serious disease complications, around one-third of their use is estimated to be unnecessary or inappropriate (Mayo Clinic, 2023a). As a result, surviving microbes such as parasites, viruses, fungi, and bacteria develop

[8] Antibiotic resistance comprises around 87% of antimicrobial resistance-related diagnoses in the NIS from 2004 to 2011

resistance that make the future use of antimicrobial drugs ineffective. However, it should be noted that the use of antimicrobials, whether appropriate, too little or too much, naturally leads to the emergence of drug-resistant organisms (National Institutes of Health, 2011; CDC, 2022).

In January 2006, Medicare Part D went into effect, requiring Medicare plans to cover a wide range of prescription medicines, including antibiotics and other antimicrobial drugs. This program reduced user cost among the elderly by 18.4%, increased their use of prescription drugs by about 12.8%, and increased total U.S. usage by 4.5% in 2006 (Lichtenberg & Sun, 2007). If cost barriers had led to under-utilization of prescriptions among those without previous prescription coverage, then Medicare Part D may reduce AMR. Descriptive evidence suggests that Medicare Part D is associated with a reduction in medication under-utilization among some sub-sets of the elderly (Madden et al., 2008). Zhang et al. (2010) find that improved drug coverage after Medicare Part D implementation was associated with increased antibiotic usage, particularly for broad-spectrum, newer, and more expensive antibiotics among the elderly. On the other hand, if Medicare Part D encourages over-utilization of prescriptions then an unintended consequence may be an increase in AMR. The findings of these previous studies do not rule out such a phenomenon.

This paper aims to estimate the causal impact of Medicare Part D on AMR-related hospital discharges, focusing on adults aged 60 to 69. To the best of my knowledge, this paper is the first study to examine Medicaid Part D's net effect on the likelihood of such discharges among elderly patients. Thus, I allow for the possibility of an unintended negative impact of the policy. I use data from the Nationwide Inpatient Sample (NIS), Healthcare Cost and Utilization Project (HCUP), Agency for Healthcare Research and Quality for years 2004 to 2011. The NIS is

the largest publicly available all-payer inpatient care dataset in the United States. I also look at the results separately by gender and race.

To identify the causal impact Medicare Part D had on the incidence of AMR-related discharges, I compare the outcomes of "treated" individuals aged 65 to 69 to a control group aged 60 to 64 using a difference-in-differences approach. This identification strategy relies on the assumption that in the absence of the policy, changes in the likelihood of AMR-related discharges would not vary by age group. My results suggest a 22.17% increase in antibiotic utilization among the elderly and a decrease in AMR-related discharges, with a reduction of 87.7 discharges per 100,000 among the Medicare-eligible population. This represents a 7.95% decrease from the average of 1,103 AMR-related discharges per 100,000 before January 2006. These findings suggest that the benefits gained from making antimicrobials more accessible outweigh the risks of over-prescription stemming from the introduction of Medicare Part D. However, there are notable heterogeneity by race and gender, with whites and men experiencing greater reductions compared to non-whites and women.

The rest of this paper is organized as follows: section 2.2 discusses the institutional background of this paper. Section 2.3 discussed my dataset. Section 2.4 conducts a first stage analysis to supplement my identification strategy. Section 2.5 explains the methodology used in my analysis. Section 2.6 presents my results, while section 2.7 concludes the paper.

2.2. Institutional Background

2.2.1. Medicare Part D

Medicare Part D was introduced in January 2006 to address the growing need for prescription drug coverage among elderly and disabled individuals in the United States. Its introduction marked a substantial shift in healthcare policy, providing beneficiaries with access

to a wide range of prescription medications that were previously unaffordable. Unlike other parts of Medicare that primarily cover hospital or medical services, Medicare Part D focuses exclusively on prescription drugs and is offered through private insurance plans approved by Medicare (Medicare.gov, n.d.-b; MedicareInteractive.org, n.d.-b).

Eligibility for Medicare Part D depends on several factors that determine an individual's eligibility status. To qualify for the program, individuals must be eligible for Original Medcare, which includes Medicare Part A and/or Part B (Medicare.gov, n.d.-a). Part A covers hospital services, while Part B provides coverage for outpatient medical services. Once a person is enrolled in either Part A or Part B, they automatically become eligible to enroll in Medicare Part D. Additionally, the program extends its benefits to various categories of individuals, including those aged 65 and older who are eligible for Medicare due to their age. Moreover, younger beneficiaries, specifically individuals under 65, may also qualify for Medicare Part D if they have received Social Security Disability Insurance (SSDI) benefits for more than 24 months or if they have been diagnosed with end-stage renal disease (Social Security Administration, n.d.).

Medicare Part D provides coverage for a wide range of prescription drugs, offering beneficiaries access to an extensive formulary of medications (Medicare.gov, n.d.-c). The formularies under Medicare Part D are compiled by private insurance companies that partner with Medicare. These formularies are subject to regular updates and revisions, ensuring that beneficiaries have access to the most effective and cost-efficient drugs available (MedicareInteractive.org, n.d.-a). It is important to note that the specific drugs covered and the associated costs can vary significantly among different Medicare Part D plans.

The covered drugs under Medicare Part D encompass a wide spectrum of therapeutic categories, including but not limited to: chronic disease management, pain management, mental

health, and respiratory medications. Considering the importance of antibiotic access in promoting public health, Medicare Part D formularies also typically cover a variety of antibiotics and antimicrobial drugs. These medications help combat bacterial infections and reduce the risk of severe complications.

2.2.2. Direct Effects of Medicare Part D

The implementation of Medicare Part D had significant impacts on prescription drug coverage, prices, out-of-pocket costs, and utilization among eligible individuals. Levy & Weir (2010) find that the implementation of Medicare Part D significantly enhanced prescription drug coverage rates among seniors. In Engelhardt & Gruber (2011), they estimate that Medicare Part D resulted in a 10 percentage point increase in coverage among the elderly. This rise was deemed substantial, yet it is important to note that this figure only accounts for a quarter of seniors who received public coverage. This suggests that Medicare Part D's introduction might have led to the displacement of other forms of prescription drug coverage to a considerable extent.

Meanwhile, Ketcham & Simon (2008) found that in the first year of the program, seniors experienced considerable reductions in out-of-pocket costs. However, Engelhardt & Gruber (2011) highlighted heterogeneous effects, where reductions in out-of-pocket costs were concentrated among a small proportion of elderly individuals with the highest spending risk. Despite the overall decline in out-of-pocket drug spending, their estimates showed an increase in total drug expenditure due to Medicare Part D.

In terms of utilization, Lichtenberg & Sun (2007) observed an 18.4% reduction in user costs among the elderly, resulting in a 12.8% increase in their prescription drug usage, while also contributing to a 4.5% rise in total U.S. drug usage in 2006. Additionally, Khan & Kaestner (2009) estimated a 4-10% increase in prescription drug utilization after the introduction of

Medicare Part D. Studies by Yin et al. (2008) and Schneeweiss et al. (2009) also noted a noticeable increase in prescription drug use following the implementation of Medicare Part D. Duggan & Morton (2010) reported a substantial increase in prescription drug use, especially among the elderly, attributed to lower prices facilitated by the program. This was evident in the significant reduction in prices for brand-name drugs with close substitutes due to Medicare Part D, leading to increased bargaining power for plans with pharmaceutical companies.

Existing evidence also indicates that Medicare Part D has been linked to a decrease in medication under-utilization among certain subsets of the elderly (Madden et al., 2008). Additionally, after the implementation of Medicare Part D in 2006, there was a noticeable reduction in cost-related non-adherence to medications (Blanchard et al., 2013).

2.2.2.1. Medicare Part D and Use of Antimicrobial Drugs. The introduction of Medicare Part D also had significant implications for the utilization of antimicrobial drugs in the United States. As a prescription drug benefit program aimed at providing coverage to elderly and disabled individuals, Medicare Part D played an important role in influencing the accessibility and utilization patterns of antimicrobial medications.

For example, a study by Zhang et al. (2010) found that after the introduction of Medicare Part D, there was a significant increase antimicrobial drug use. Using insurance claims data from a large Pennsylvania-based Medicare Advantage plan, they compared antibiotic use changes across multiple groups. Their treatment groups (total of 3) included individuals with no or limited drug coverage ($8/$20 copay) prior to Medicare Part D's introduction, and whose coverage improved in January 2006. Their control group consisted of enrollees who had stable drug coverage through their former employers. They estimated propensity scores and used them in logistic models to estimate the effects on the likelihood of using any antibiotics as well as each

major subclass. They explain that the increase in antibiotic prescription rates could be attributed to changes in patient and physician behavior, likely influenced by patients' drug coverage and physicians' perceptions of their ability to pay for drugs.

Medicare Part D's expansion of drug coverage also emphasized the need to focus on antimicrobial stewardship efforts. Gouin et al. (2022) find that a mere 10% of antibiotic prescribers accounted for approximately 40% of all Medicare Part D antibiotic prescriptions in 2019. This significant concentration in prescribing practices highlights a potential for enhanced antibiotic stewardship through targeted interventions directed at these high-volume prescribers. Arizpe et al. (2013) find that in 2013, fluoroquinolone antibiotics were the most frequently prescribed among Medicare Part D beneficiaries, comprising 22% of all claims. Notably, fluoroquinolone is associated with infrequent but severe adverse effects, more likely to affect elderly patients (Owens & Ambrose, 2005; Stahlmann & Lode, 2010). This antibiotic class is also linked to the emergence of antibiotic-resistant bacteria (MacDougall et al., 2005). These studies highlight the need for surveillance to track antibiotic usage changes and identify areas for targeted interventions to encourage appropriate antimicrobial prescribing practices.

Overall, the literature on the impact of Medicare Part D on antimicrobial drugs/antibiotics is somewhat limited, with no study using nationally representative data to look for causal effects. This is an important gap in the literature for the purposes of this study, as I am interested in the impact of Medicare Part D on AMR-related hospital discharges. One would not expect that outcome to change if Medicare Part D had no impact on antibiotic utilization. Given the lack of evidence on this "first stage" relationship, I conduct my own analysis, which is discussed further below.

2.2.3. Some Broader Impacts of Medicare Part D

Ayyagari & Shane (2015) used a difference-in-difference (DD) approach to investigate the impact of Medicare Part D on mental health. Their research focused on individuals aged between 60 and 70 years, with adults aged 60-64 forming the control group, and adults aged 65-70 comprising the treatment group. To ensure accuracy, individuals between 60-64 years who already had Medicare coverage were excluded from the study. The findings of their study revealed that the Medicare Part D program had a significant and positive effect in reducing depressive symptoms among older adults.

Ayyagari et al. (2016) looked at the causal impacts of Medicare Part D on emergency department (ED) visits. They emphasized the vital role of prescription drugs in effectively managing chronic ailments, such as heart disease and diabetes, and argued that enhanced access to prescription drug coverage through Medicare Part D could lead to a reduction in ED visits by facilitating better health condition management and overall health improvement. Using a similar research design as in Ayyagari & Shane (2015), the estimated a decline in the number of ED visits related to non-emergency care, indicating that Medicare Part D's implementation may have resulted in improved health management and reduced unnecessary utilization of ED services. Other papers examined the impact of Medicare Part D on various health-related outcomes. Works such as Kaestner & Khan (2012) and Kaestner et al. (2019) found that the program had no noticeable effect on self-rated health or functional disability, nor did it affect mortality rates. Medicare Part D, however, may have led to a reduction in inpatient admissions, implying potential overall health improvement (Afendulis et al., 2011; Kaestner et al., 2019). Specifically, Afendulis et al. (2011), using a difference-in-difference (DD) approach, estimated that Medicare

Part D resulted in a 4.1% decrease in the overall rate of hospitalization (equivalent to 20.5 per 10,000 individuals) among adults aged 65 to 70.

The primary contribution of this paper is the analysis of a potential unintended consequence of Medicare Part D (in the form of AMR-related hospital discharges) not previously considered in the literature. If Medicare Part D implementation leads to changes in AMR-related discharges then this must be included in any full accounting of the impact of the policy.

2.3. Data

The main data source that I use is the Nationwide Inpatient Sample (NIS), Healthcare Cost and Utilization Project (HCUP), Agency for Healthcare Research and Quality. The NIS is "*the largest publicly available all-payer inpatient healthcare database designed to produce U.S. regional and national estimates of inpatient utilization, access, cost, quality, and outcomes. Unweighted, it contains data from more than 7 million hospital stays each year. Weighted, it estimates more than 35 million hospitalizations nationally*" (AHRQ, 2024b).

Beginning in 2013, several efforts to combat antibiotic resistance have been started (CDC, 2021d). To avoid confounding the effects of Medicare Part D with the effects of these efforts, I limit my sample period from the first quarter of 2004 to the fourth quarter of 2011. Furthermore, discharges in 2012 were also excluded since HCUP changed its sampling methodology beginning this year. The sample I use in this work still covers a sufficiently long period before and after the policy's implementation in 2006.

Following the works of Ayyagari & Shane (2015), Ayyagari et al. (2016), and Engelhardt & Gruber (2011) in the Medicare Part D literature focused on other outcomes, I restrict my sample to individuals from 60 to 69 years of age in each survey year.[9] Furthermore, I also

[9] I also examine the sensitivity of my analysis to the use of other ranges such as 61 to 68, 62 to 67, 63 to 66, and 64 to 65.

exclude individuals younger than 65 years old who have Medicare coverage as they do not fall in either treatment or control groups.

My main dependent variable of interest, denoted by AMR, is a binary variable equal to 1 if a given discharge records infections with drug-resistant micro-organisms, and 0 otherwise. A discharge is defined as associated with this infection when the ICD-9 code of any recorded diagnosis begins with V09. Beginning October 1, 2008, methicillin-resistant *Staphylococcus aureus* (MRSA), a specific type of drug-resistant organism, does not fall under the ICD-9 code V09 anymore. Instead, it is identified using the ICD-9 codes 038.12, 482.42, and 041.12 (Burnham et al., 2017). My coding of AMR discharges accounts for this change. All other drug-resistant organisms still fall under V09 after October 1, 2008.

Table 2.1 reports mean values for my outcomes of interest split by adults aged 65 to 69 (my treatment group) vs. adults aged 60 to 64 (my control group) as well as by before vs. after Medicare Part D implementation. Before Medicare Part D's introduction, there is no statistically (or economically) significant difference in the average rate of AMR-related discharges between the treatment and control group (Column 7). Table 2.1 also suggests that Medicare Part D implementation was associated with statistically significant increases in the incidence of AMR-related hospital discharges for both groups (Columns 3 and 6). For Medicare-eligible individuals, the incidence increased from 1,101 to 1,591 (per 100,000 discharges) after January 2006, and for Medicare non-eligible individuals, it went up from 1,105 to 1,678 (per 100,000 discharges). The post-reform difference is statistically significant as well (Column 8). Overall, these descriptive statistics suggest that Medicare Part D implementation is associated with a net reduction in the incidence of AMR-related discharges, motivating my causal analysis.

Table 2.1. Summary Statistics of the Outcome Variable

Outcome variable	Treatment (adults age 65 to 69)			Control (adults age 60 to 64)			Differences [p-value]	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Pre-Jan 2006	Post-Jan 2006	Δ [p-value]	Pre-Jan 2006	Post-Jan 2006	Δ [p-value]	(1)-(4)	(2)-(5)
AMR (per 100k discharges)	1101 (10435)	1591 (12513)	490*** [0.0000]	1105 (10452)	1678 (12846)	574*** [0.0000]	-4 [0.6669]	-87*** [0.0000]

Notes: HCUP discharge weights used. Standard deviations in parenthesis. p-values in square brackets. *, **, *** = statistically significant difference at the 10%, 5%, and 1%, respectively.

Figure 2.1 graphically presents the trend of AMR-related discharges (per 100 thousand) from the first quarter of 2004 to the fourth quarter of 2011. We see that until early 2008, the incidence of AMR-related discharges between the treatment and control groups seems to be increasing at the same rate. However, from early 2008 onwards, the treatment group consistently showed lower incidence compared to the control group. This further motivates my causal analysis.

Figure 2.1. AMR-Related Discharges from 2004 Q1 to 2011 Q4

Notes: Red vertical lines indicate the beginning of the post period. HCUP discharge weights used.

Table 2.2. Summary Statistics of the Covariates

	Full sample mean	Treatment (age 65 to 69)	Control (age 60 to 64)	Difference [p-value]
Age	64.56	67.01	61.99	5.02
	(2.84)	(1.34)	(1.34)	[0.0000]
Female	0.5062	0.5096	0.5026	0.0070
	(0.5000)	(0.4999)	(0.5000)	[0.0000]
Race/Ethnicity				
White	0.7433	0.7530	0.7332	0.0198
	(0.4368)	(0.4313)	(0.4423)	[0.0000]
Black	0.1309	0.1226	0.1396	-0.0170
	(0.3373)	(0.3279)	(0.3465)	[0.0000]
Asian/Pacific Islander	0.0205	0.0211	0.0198	0.0012
	(0.1416)	(0.1436)	(0.1395)	[0.0000]
Native American	0.0062	0.0060	0.0063	-0.0003
	(0.0783)	(0.0772)	(0.0794)	[0.0000]
Hispanic	0.0739	0.0722	0.0757	-0.0035
	(0.2616)	(0.2588)	(0.2645)	[0.0000]
Income Quartile				
First	0.2898	0.2911	0.2885	0.0026
	(0.4537)	(0.4543)	(0.4530)	[0.0000]
Second	0.2453	0.2473	0.2433	0.0041
	(0.4303)	(0.4315)	(0.4291)	[0.0000]
Third	0.2310	0.2308	0.2312	-0.0004
	(0.4215)	(0.4214)	(0.4216)	[0.0076]
Fourth	0.2338	0.2308	0.2370	-0.0062
	(0.4233)	(0.4213)	(0.4253)	[0.0000]
Bed size				
Small	0.1330	0.1368	0.1290	0.0078
	(0.3396)	(0.3437)	(0.3352)	[0.0000]
Medium	0.2459	0.2461	0.2457	0.0004
	(0.4306)	(0.4307)	(0.4305)	[0.0237]
Large	0.6211	0.6171	0.6253	-0.0082
	(0.4851)	(0.4861)	(0.4840)	[0.0000]
Location				
Urban	0.8761	0.8700	0.8826	-0.0126
	(0.3294)	(0.3363)	(0.3220)	[0.0000]
Rural	0.1239	0.1300	0.1174	0.0126
	(0.3294)	(0.3363)	(0.3220)	[0.0000]
Teaching status				
Teaching	0.4646	0.4508	0.4790	-0.0282
	(0.4987)	(0.4976)	(0.4996)	[0.0000]
Non-teaching	0.5354	0.5492	0.5210	0.0282
	(0.4987)	(0.4976)	(0.4996)	[0.0000]
No. of observations	5,604,448	2,861,738	2,742,710	

Notes: HCUP discharge weights used. Standard deviations in parenthesis. p-values in square brackets.

I use the following discharge characteristics from the NIS as controls: age, race, sex, and median household income for patient's ZIP code. I also use the following hospital characteristics from the NIS: bed size, urban vs. rural setting, state, and teaching status. I also control for

quarterly state unemployment rates to capture the possible time-varying economic characteristics that may affect an individual's likelihood of getting admitted to due AMR.

Table 2.2 presents summary statistics using the full sample, the treatment group, the control group, and the mean differences between the two. We see that the treatment group has a higher composition of females than the control group (50.96% versus 50.25%). Similarly, the treatment group has a higher composition of whites and Asians/Pacific Islanders and lower composition of blacks and Hispanics. In terms of income quartiles, individuals in the treatment group are more likely to live in ZIP codes where the median incomes are in the first and second quartiles. In terms of the types of hospitals they go to, individuals in the treatment group are more likely to go to small and medium ones, and those in rural areas.

2.4. "First-Stage" Analysis

If the introduction of Medicare Part D is to have an impact on AMR-related discharges, then we would expect to see a "first stage" relationship between Part D and antibiotic utilization. This subsection estimates this relationship empirically. In order to estimate the effect of Medicare Part D on antibiotics utilization, I compare changes in the number of antibiotics prescriptions filled by adults aged 65 to 68 to adults aged 60 to 64 before versus after Part D implementation.

The Agency for Health Care Research and Quality (AHRQ) Medical Expenditure Panel Survey (MEPS) is an ideal dataset for this purpose because it is a nationally representative dataset that includes individual level information on prescription utilization and age over the time period I am interested in. To construct the analytic dataset I use for this analysis I merge data from the Medical Expenditure Panel Survey (MEPS) Full-Year Consolidated Data files and the MEPS Prescribed Medicines files for years 2002 to 2009. The MEPS attaches the appropriate

national drug code (NDC) to each self-reported prescription for each individual in the sample. I flagged any prescriptions with NDC codes indicating that they were "antibacterial" and orally administered as being antibiotics (US FDA, 2022).

I adapt the approach of Powell et al. (2020)[10] and use the following specification to estimate the effect of Medicare Part D on antibiotic utilization:

$$y_{iat} = \theta_a + \gamma_t + \rho[Post_{2006} \times AGE65 - 68] + \epsilon_{iat}, \quad (4)$$

where y_{iat} is the number of antibiotic prescriptions filled by individual i at age a in year t, $Post_{2006}$ is an indicator for observations in 2006 or later, $AGE65 - 68$ is a binary indicator for being 65 to 68 years old, θ_a, γ_t are age and year fixed effects, respectively, and ϵ_{iat} is an error term. The coefficient of interest is ρ, and a positive ρ implies that Medicare Part D led to an overall increase in antibiotics utilization among eligible adults.

Table 2.3 column 1 presents the results using the full sample of individuals aged 60 to 68. The estimated effect (significant at the 10% level) implies that individuals aged 65 to 68 increased their antibiotic utilization by 0.0149 prescriptions more than individuals age 60 to 64. This represents a 22.17% increase from the pre-2006 mean antibiotic utilization of 0.0672. Table 2.3 also reports the results of a set of specification checks. Column 2 excludes adults aged 65 who, as Powell et al. (2020) describe, are partially-treated by Medicare Part D implementation. One would expect that removing them from the sample would increase the estimated effect of the policy, which is what I find. However, statistical tests fail to reject the null hypothesis that the estimated effect in column 2 is significantly different from that in column 1.

[10] Powell et al. (2020) estimated the causal impact of Medicare Part D on opioid outcomes such as abuse and mortality. As an intermediate step to support their analysis, they also estimated the causal impact of Medicare Part D on opioid utilization. Using a model where Equation 4 is based on, they find that "individuals ages 65+ increased the number of annual prescriptions by 0.174 more prescriptions than individuals ages 59–64".

Table 2.3. Difference-in-Difference Results (Outcome: Number of Antibiotic Prescriptions)

	(1)	(2)	(3)	(4)	(5)
Marginal effect	0.0149*	0.0180*	0.0229**	0.0202**	0.0326*
(Std. Err.)	(0.0084)	(0.0094)	(0.0101)	(0.0102)	(0.0123)
Pre-policy mean of dep. var. for treatment group	0.0672	0.0676	0.0676	0.0665	0.0689
Marginal effect as % of mean	22.17%	26.63%	33.88%	30.38%	47.31%
Age FE?	Y	Y	Y	Y	Y
Year FE?	Y	Y	Y	Y	Y
Years 2002-2009?	Y	Y	Y	Except 2004-2005	Except 2004-2005
Ages 60 to 68?	Y	Except 65	Except 63-65	Y	Except 63-65
No. of obs.	18,195	16,272	12,287	13,991	9,433

Notes: *, **, *** denote significance levels of 10%, 5%, and 1%, respectively. MEPS weights used. Individual-clustered standard errors in parentheses.

Some raise concerns that adults whose age are close to 65 are "also 'treated' by Part D because they defer some treatments until they are eligible for Medicare", so following Powell et al. (2020), I also run models where those adults aged 63 and 64 are excluded from the analysis (column 3). If indeed there is this "anticipation" effect arising from these individuals, then excluding them from the analysis should yield larger results.

Alpert (2016) finds that there are also anticipation effects with respect to Medicare Part D in the years 2004 to 2005, so I also run additional specification checks excluding these two years (column 4). In column 5, I apply the exclusion criteria used in columns 3 and 4. Similarly, if this "anticipation" effect is significant, excluding the affected years from the analysis should yield larger results. Table 2.3 columns 3 to 5 confirm these expectations. However, the result in column 5 being significantly different from the results in other columns (except column 4) is only significant at the 10% level. Regardless, these findings generally show that after Medicare Part D was implemented, utilization of antibiotics increased. This is evidence of a "first stage" relationship that is necessary (though not sufficient) for Part D to have an impact on AMR-related hospital discharges.[11]

[11] I also conduct an event study to support this finding as presented in Appendix D.

2.5. Methodology

To estimate the causal impact of Medicare Part D on the incidence of AMR-related discharges, I run the following difference-in-differences equation:

$$AMR_{iht} = \alpha_0 + \alpha_1 AGE65-69_{iht} \times \mathbf{1}(Post2006) + \alpha_2 AGE65-69_{iht} + \alpha_3 \mathbf{1}(Post2006) + \mathbf{X}'_{iht}\boldsymbol{\beta}_3 + \delta'_h + \gamma'_s + \eta'_t + \varepsilon_{iht}, \quad (5)$$

where $AMR_{iht}$is a binary variable equal to 0 if discharge i in year-quarter t indicates that the discharge is associated with an infection due to drug-resistant microorganisms, $AGE65-69_{iht}$is a binary indicator for being 65 to 69 years old, $\mathbf{1}(Post2006)$ is an indicator for observations in 2006 Q1 or later, $\mathbf{X}_{iht}$ is a vector of controls, $\delta_h, \gamma_s, \eta_t$ are hospital, state, and year-quarter fixed effects, respectively, and ε_{iht} is an error term. Here, the treatment group consists of individuals who are 65 to 69 years old, while the control group are those who are 60 to 64 years old. The main coefficient of interest is α_1 which gives us the effect of the policy on the likelihood of having an AMR-related discharge. A negative α_1 implies that Medicare Part D led to an overall reduced incidence of discharges associated with AMR.

2.5.1. Event Study

To provide support to the parallel trends assumption, allowing for causal interpretation of the difference-in-difference results, I run an event study of the form

$$AMR_{iht} = \beta_0 + \sum_{\substack{YQ=2004Q1 \\ YQ\neq 2005Q4}}^{2011Q4} \beta_{YQ}\mathbf{1}(YQ)_t \times AGE65-69_{iht} + \mathbf{X}'_{iht}\boldsymbol{\beta}_3 + \delta'_h + \gamma'_s + \eta'_t + \varepsilon_{iht}, \quad (6)$$

where β are coefficients, YQ are year-quarters from 2004 Q1 to 2011 Q4, $\mathbf{1}(YQ)_t$ are yearquarter dummies for each YQ, and other variables as previously defined. In this specification, I want the $AGE65-69_{iht}$ interactions with each of the pre-2006 dummies to be insignificant.

2.6. Results

In this section, I present my baseline results based on Equation 5. I also look at the heterogeneous effects of the policy by race, ethnicity, and sex, as well as consider alternative specifications to test the robustness of my results.

2.6.1. Baseline Results and Event Study

Table 2.4 Column 1 presents the results based on Equation 5. We see that AMR-related discharges decreased by 87.7 per 100,000 after Medicare Part D's introduction, equivalent to a 7.97% decrease from the pre-January 2006 mean of 1,101 AMR-related discharges per 100,000 (Table 2.1, column 1). Together with Figure 2.1, this result implies that the incidence of AMR-related discharges among individuals in the treatment group increased at a slower rate compared to the incidence of AMR-related discharges in the control group.

Table 2.4. Difference-in-Difference Results (by Population Subgroup)

	Population subgroup						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	All	White	Black	Asian/Pacific Islander	Hispanic	Men	Women
DD coeff.	-87.7***	-86.6***	-6.39	-96.4	-168.3	-129.5***	-45.6
(Std. Err.) *per 100k*	(26.9)	(31.1)	(74.1)	(181.6)	(103.1)	(38.5)	(36.3)
Pre-2006 mean of dep. var. *per 100k*	1100.98	1081.032	1184.393	1124.371	1213.616	1161.492	1046.109
Coeff as % of mean	-7.97%	-8.01%	-0.54%	-8.57%	-13.87%	-11.15%	-4.36%
Age range	60-69	60-69	60-69	60-69	60-69	60-69	60-69
No. of obs.	5,604,448	4,163,687	733,330	116,085	416,027	2,765,807	2,838,641

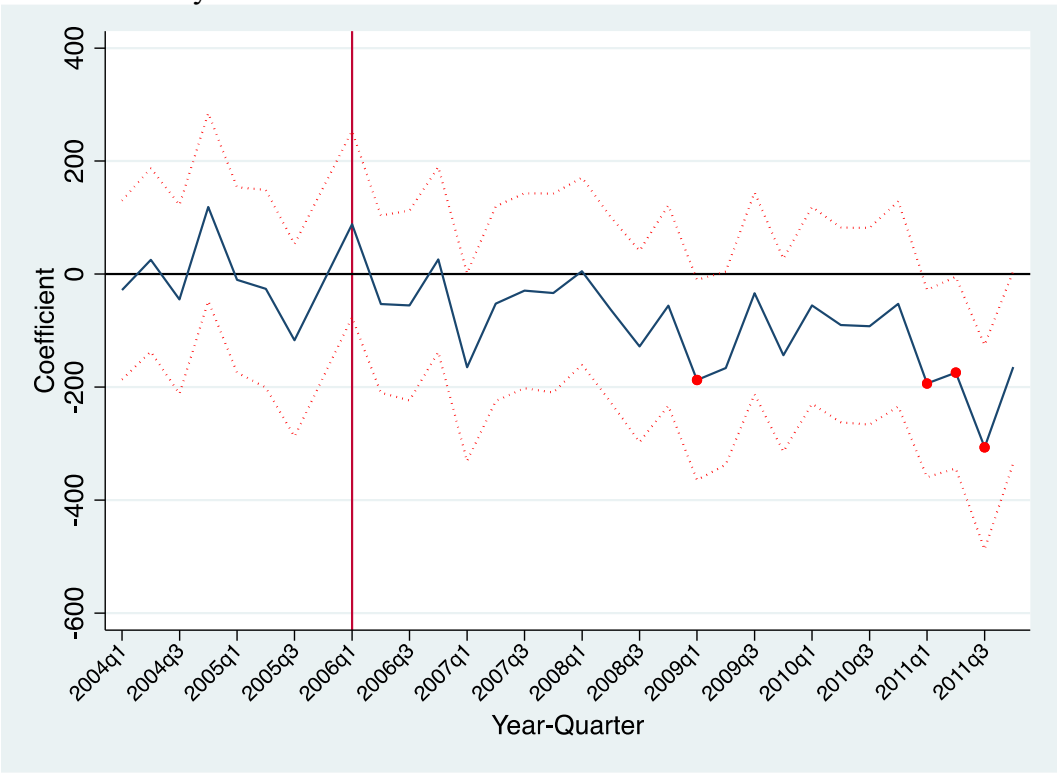
Notes: *, **, *** denote significance levels of 10%, 5%, and 1%, respectively. HCUP discharge weights used. Discharge-level characteristics, hospital characteristics, state characteristic, hospital fixed effects, state fixed effects, and year-quarter fixed effects included in the models. Hospital-clustered standard errors in parentheses.

Figure 2.2 graphically presents the event study results based on Equation 6. This figure allows us to see two things: first the pre-reform coefficients indirectly test the identifying assumption that outcomes in the treatment group would have trended in the same way as the control group in the absence of the policy (i.e. the "parallel trend test") and second if the effects

of the policy are immediate, delayed, or spread over time. The figure shows that no pre-reform interactions are significantly different from 0, and that they do not seem to exhibit any consistent pre-trend. This gives me more confidence in a causal interpretation of my baseline results.

Additionally, Figure 2.2 suggests that the reduction in AMR-related discharges seems to be driven more by the later part of the post-period in terms of statistical significance, and that we see a gradual downward trend over the post-period. This is supported by Figure 2.1, where the treatment group exhibits lower incidence of AMR-related discharges in the latter part of the post-period. The event study coefficient estimates themselves are presented in Table C.4.

Figure 2.2. Event Study Results



Notes: Significant coefficients are marked with solid red dots for emphasis. Dotted lines indicate 95% confidence interval.

2.6.2. Heterogeneity and Specification Tests

Disaggregating by race/ethnicity (Table 2.4, columns 2 to 5), we see that AMR-related discharges went down across all groups, with the effect only statistically significant for whites

(statistically significant decline of 86.6 AMR-related discharges per 100,000) and not for blacks and Asians and Pacific Islanders. While the point estimates for Asian/Pacific Islands as well as Hispanics are larger in magnitude than the point estimate for the white-only subgroup, I cannot reject the null hypothesis that the coefficients are equal. The "noisy" results for these other subgroups may be explained by their much smaller sample sizes (115,085 and 416,027 observations for Asian/Pacific Islands and Hispanics, respectively, compared to 4,163,687 for whites). Disaggregating by gender (Table 2.4, columns 6 to 7) reveals a decline in AMR-related discharges for both men and women. However, only men showed a significant decline of 129.5 AMR-related discharges per 100,000 after the policy change, while women did not show a statistically significant decrease. Statistical tests show that these two coefficients are significantly different from each other.

I also conduct two specification tests in consideration of the following arguments. First is that since the hospital characteristics I use in my analysis such as bed size, location, and teaching status tend to be constant/barely change for each hospital over time, there might be no need for these variables anymore when hospital fixed effects are included. Thus when hospital characteristics are dropped, but hospital fixed effects are still included, the results should generally by the same with my initial results. Conversely, if hospital fixed effects are dropped while hospital characteristics are still included, we should see slightly different results, if these hospital characteristics are important and several of them are unobserved. The other specification check considers progressively shorter age ranges. If the development of antimicrobial resistance is a gradual process, using shorter age ranges for comparison would likely yield more modest results. This makes intuitive sense if we assume that individuals need extended exposure to the treatment before we can observe any potential benefits. The event study graph in Figure 2.2

supports this assumption, where we see the decrease in incidence happening several quarters after Medicare Part D was implemented.

Table 2.5. Difference-in-Difference Results (Inclusion and Exclusion of Hospital Controls)

	Full	No hosp control, With hosp FE	With hosp control, No hosp FE	No hosp control, No hosp FE
	(1)	(2)	(3)	(4)
DD coeff.	-87.7***	-87.3***	-76.8***	-76.3**
(Std. Err.) *per 100k*	(26.9)	(26.9)	(27.3)	(31.9)
Pre-2006 mean of dep. var. *per 100k*	1100.98	1100.98	1100.98	1100.98
Coeff as % of mean	-7.97%	-7.93%	-6.98%	-6.93%
Age range	60 to 69	60 to 69	60 to 69	60 to 69
No. of obs.	5,604,448	5,604,448	5,604,448	5,604,448

Notes: *, **, *** denote significance levels of 10%, 5%, and 1%, respectively. HCUP discharge weights used. Discharge-level characteristics, hospital characteristics, state characteristic, hospital fixed effects, state fixed effects, and year-quarter fixed effects included in the models. Hospital-clustered standard errors in parentheses.

In Table 2.5, we see that indeed, when hospital bed size, location, and teaching status are dropped (but hospital fixed effects remain included), results do not meaningfully change (Table 2.5, column 2). The estimated effect of the policy went down from -7.97% to -7.93%, but this difference is not statistically significant. However, specifications removing hospital fixed effects (Table 2.5, column 3), and both hospital controls and fixed effects together (Table 2.5, column 4), produce slightly different results (-6.98% and -6.93%, respectively). This suggests that including hospital fixed effects is important to produce more accurate results.

Table 2.6. Difference-in-Difference Results (Different Age Ranges)

	Age range				
	60 to 69	61 to 68	62 to 67	63 to 66	64 to 65
	(1)	(2)	(3)	(4)	(5)
DD coeff.	-87.7***	-80.3***	-73.7**	-95.8**	-69.3
(Std. Err.) *per 100k*	(26.9)	(28.9)	(33.1)	(42.9)	(58.8)
Pre-2006 mean of dep. var. *per 100k*	1102.788	1102.965	1110.82	1067.996	1048.125
Coeff as % of mean	-7.95%	-7.28%	-6.63%	-8.97%	-6.61%
No. of obs.	5,604,448	4,589,108	3,580,736	1,995,679	991,801

Notes: *, **, *** denote significance levels of 10%, 5%, and 1%, respectively. HCUP discharge weights used. Discharge-level characteristics, hospital characteristics, state characteristic, hospital fixed effects, state fixed effects, and year-quarter fixed effects included in the models. Hospital-clustered standard errors in parentheses.

Table 2.6 shows the results when I consider other age ranges for my analysis, namely 61 to 68, 62 to 67 years old, 63 to 66, and 64 to 65. We see that the estimated effects indeed get smaller in magnitude as the age range gets narrower (except for column 4). However, statistical tests show that I cannot reject the null hypothesis that these effects are equal.

2.7. Discussion and Conclusion

Overall, my results suggest that Medicare Part D led to a decrease in the incidence of AMR-related discharges after its implementation. I find that compared to the control group comprised of adults age 60 to 64, the probability of having AMR-related hospital discharges go down by 7.97%. Differential effects by race and gender were observed. Only Whites saw significant declines in the outcome of interest; however, I am unable to reject the null hypothesis that the coefficients across race/ethnicity are equal. Men also seemed to significantly benefit more than women. My event study analysis shows that these general improvements seem to be delayed, with event study coefficients being statistically significant in the latter part of the post-period.

In an intermediate analysis using data from the MEPS, I also find that after Medicare Part D was implemented, the utilization of antibiotics increased among adults age 65 to 68 compared to adults age 60 to 64. These results are robust under several alternative specifications. To the best of my knowledge, this is the first attempt to estimate the causal impact Medicare Part D had on the utilization of antibiotics.

These results contribute to the literature by estimating the currently unknown impacts of the Medicare Part D on AMR using an all-payer, nationally representative dataset of hospital discharges in the country. These findings may aid policymakers in crafting laws that make antimicrobials more accessible, as well as improve guidelines in terms of prescription

monitoring. In addition, my heterogeneity results suggest that policymakers may want put in place measures to protect the population subgroups that do not benefit from the policy. Communities with predominantly black, Asian/Pacific Islander, or Hispanic individuals may be given more attention in order to improve AMR-related discharges in these areas.

It is important to understand these findings given the following limitations. First is that the NIS only contains discharge records, and not the universe of all diseases. Hence the results here should not be interpreted as a comprehensive estimate of the effect of Medicare Part D on total AMR in the United States. Second is that I was not able to link actual prescription use data from the MEPS to the discharge data from the NIS. I only used the MEPS in an independent analysis to establish that prescription use among the elderly increased after Medicare Part D's introduction. Finding the actual link between these two could potentially be explored in a future work.

There are also other federal initiatives aimed at addressing AMR (CDC, 2021d). Since 2013, the CDC has been conducting more focused surveillance on the burden and threats posed by AMR and published its first Antibiotic Resistance Threats Report. In 2018, they established the Antimicrobial Resistance Laboratory Network, providing support for improved laboratory capacities and increased funding to aid experts in developing ways to combat AMR. Meanwhile, the White House released the U.S. National Strategy for Combating Antibiotic-Resistant Bacteria in 2014 and established The Interagency Task Force for Combating Antibiotic-Resistant Bacteria and Presidential Advisory Council on Combating Antibiotic-Resistant Bacteria, as recommended by the President's Council of Advisors on Science and Technology. Several years later, the White House released a follow-up to the U.S. National Action Plan for Combating Antibiotic-Resistant

Bacteria. Studies looking into the effects of these policies can also be considered in future papers.

Chapter 3: Prescription Coverage and Opioid Use Disorders: Evidence from Medicare Part D

3.1. Introduction

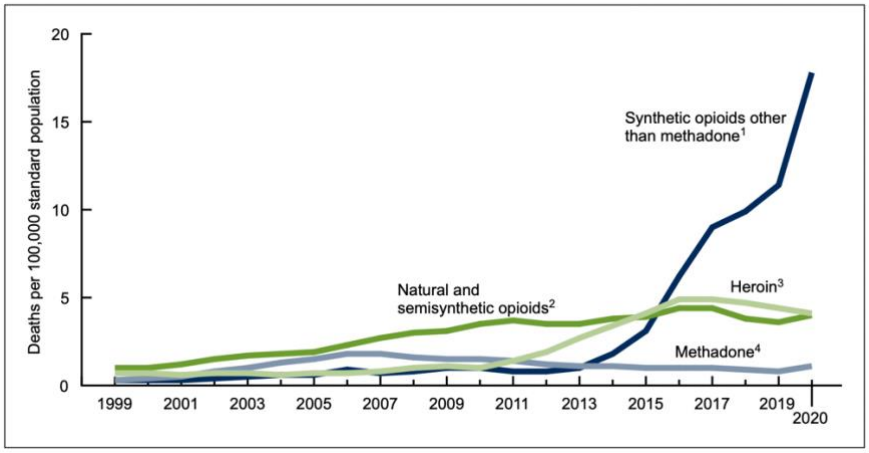
There is an ongoing opioid epidemic in the United States. Data shows that in 2020, around 2.7 million people are diagnosed with an opioid use disorder (OUD) (National Institute on Drug Abuse, 2021). Its associated costs are estimated to reach 471 billion US dollars, 14.8 billion of which are attributed to criminal justice costs and 92 billion to lost productivity (Florence et al., 2020). On top of this, the same study finds that fatal opioid overdose costs are at around 550 billion US dollars, making the combined expenditures go up to around 1 trillion US dollars, or around 4% of the US GDP in 2020.

In terms of lives lost, more people are dying from opioid overdose each year, with an estimated 40% of deaths associated with prescription opioid (US DHHS, 2021b). In 2016, there was an estimated 42,000 opioid overdose-related deaths, going up to 47,000 in 2018 and 71,000 in 2019 (Luo et al., 2021, US DHHS, 2021b). In fact, historical data shows that opioid overdose-related death rates have been increasing from as early as 1999 (Figure 3.1). In the 2000s, these deaths were mostly attributed to natural and semisynthetic opioids, followed by methadone, heroin, and synthetic opioids other than methadone (includes fentanyl and tramadol, among others).

This increase in the incidence of OUD and related deaths are influenced by a variety of factors, including (but are not limited to) poverty, unemployment, age, personal history of substance abuse, and history of severe depression or anxiety (Mayo Clinic, 2023c). In fact, the mere use of opioids, whether properly or otherwise, puts the user at risk of developing addiction,

and often overdose. This makes it more crucial for patients and providers to properly monitor their opioid intake, and only take it when deemed medically necessary.

Figure 3.1. Opioid Overdose Deaths per 100,000 Population, 1999 to 2020



Source: Hedegaard et al. (2021).

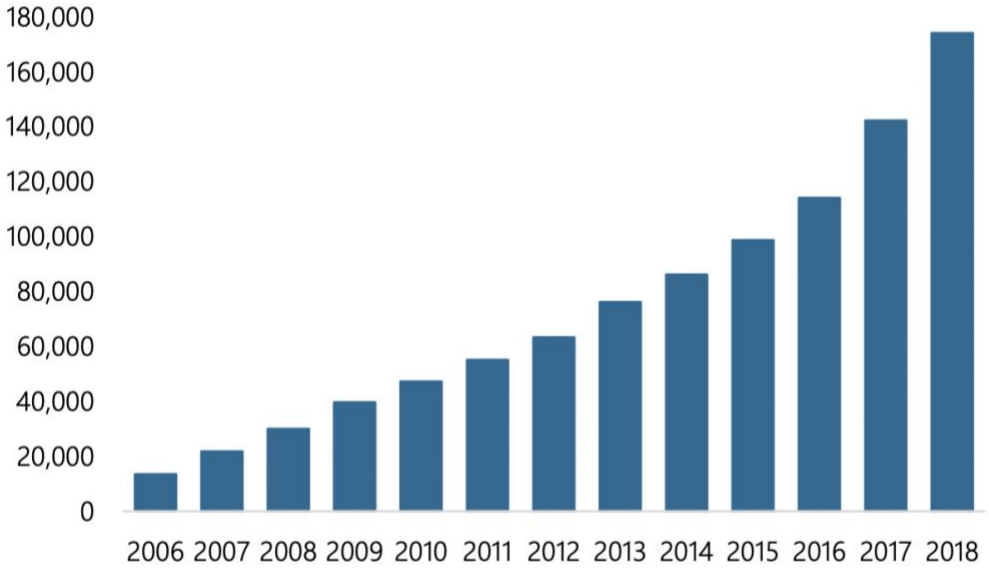
To aid those who are suffering from OUD, there are medications available for them to take, namely, methadone, buprenorphine, and naltrexone. However, utilization of these drugs are still found to be low (National Institute on Drug Abuse, 2021), with costs potentially being a major factor. Methadone, for example, could cost an individual $6,500 annually, assuming they visit their Opioid Treatment Program (OTP) providers daily. Similarly, buprenorphine and naltrexone could cost as much as $6,000 and $14,100 yearly, respectively. Most insurance plans, including Medicare plans, cover these prescriptions drugs[12] for purposes of medication-assisted treatment (MAT) of OUD, making it more accessible for plan-eligible individuals to get proper treatments.

If cost barriers hindered the use of MAT drugs among those without previous prescription coverage, then Medicare Part D may contribute to the improvements in OUD outcomes. Medicare data shows that in recent years, there was a decrease in the use of opioids, and an

[12] By 2019, Medicare Part D only covered methadone for purposes of pain management and not OUD treatment (Binder & Duff, 2020).

increase in use of drugs for treatment of OUD among Part D beneficiaries (US DHHS, 2021a). Utilization of MAT drugs (buprenorphine and naltrexone) for OUD among Part D beneficiaries have been increasing since the policy went into effect (Figure 3.2), pointing to a possible increase in treated individuals. Furthermore, US DHHS (2019) also finds that the number of beneficiaries at serious risk of opioid misuse and overdose, as well as the number of prescribers with questionable opioid prescribing for beneficiaries at serious risk decreased since Medicare Part D went into effect.

Figure 3.2. Number of Medicare Part D Beneficiaries Receiving MAT Drugs for OUD



Source: US DHHS (2019).

Thus, in this paper I aim to investigate if Medicare Part D led to improvements in OUD outcomes in the form of associated hospital discharges. To date there is no paper in the economics literature that attempts to answer this question. Most of the literature focuses on the correlation between opioid prescription and overdose, and find that there is a positive relationship between them (Dart et al., 2015; Bohnert et al., 2011). A somewhat-related work conducting causal analysis in this area is Powell et al. (2020), where they used state level data to look at the negative spillovers of Medicare Part D on the incidence of opioid misuse among the

Medicare-ineligible population. They find that increased opioid supply (driven by increased access of the elderly through Medicare Part D) is an important driver of the opioid crisis, and that after Part D's implementation, opioid abuse-related treatment admissions among individuals age 12-54 went up by 11.54 per 100k, a 13% increase relative to a pre-treatment mean of 86.69 per 100k opioid abuse-related admissions.

I attempt to fill this gap by estimating the causal relationship between Medicare Part D and the incidence of OUD-related hospital discharges among the elderly using data from the Nationwide Inpatient Sample (NIS), Healthcare Cost and Utilization Project (HCUP), Agency for Healthcare Research and Quality for years 2004 to 2011 and a difference-in-differences identification strategy. In this approach, I compare the outcomes of Medicare-eligible individuals (65 years old and above) and Medicare-ineligible individuals (64 years old and below), and find that OUD-related discharges among the Medicare-eligible sample decreased by 213.9 per 100,000 after Part D's introduction, equivalent to a 56.74% decrease from the pre-January 2006 mean of 377 OUD-related discharges per 100,000.

Other works in the literature estimate more modest impacts of Medicare Part D on *other* types of hospitalizations. For example, Afendulis et al. (2011) find that Part D reduced the overall hospitalization rate by 4.1% while Kaestner et al. (2019) estimate that Part D led to a 13% and 19% decrease in congestive heart failure (CHF) and chronic obstructive pulmonary disease (COPD)-related admissions, respectively. Comparisons with these works warrant further investigation regarding the seemingly large effect (56.74%) that this paper finds.

Subsample analyses show that the estimated effects are statistically significant regardless of patient race and sex. I also look at specific OUD outcomes, namely, opioid dependence, opioid abuse, and opioid poisoning, and find that the after Part D's implementation, the incidence

of these outcomes decreased, with the effects largest for opioid abuse, followed by opioid dependence, and opioid poisoning, respectively. This difference in effects can be attributed to the differing severity levels associated with each type–opioid abuse is a less severe form of addiction compared to dependence, and poisoning represents the most severe outcome.

The rest of this paper is organized as follows: section 3.2 discusses the institutional background of this paper. Section 3.3 discusses my dataset. Section 3.4 explains the methodology used in my analysis. Section 3.5 presents my results, while section 3.6 summarizes and concludes the paper.

3.2. Institutional Background

3.2.1. Medicare Part D

Medicare Part D was introduced in January 2006 to address the elderly and disabled individuals' needs for prescription drug coverage in the United States, with its implementation leading to improvements in drug coverage (Levy & Weir, 2010; Engelhardt & Gruber, 2011), out-of-pocket costs (Ketcham & Simon, 2008; Engelhardt & Gruber, 2011), and utilization (Lichtenberg & Sun, 2007; Khan & Kaestner, 2009; Yin et al., 2008; Schneeweiss et al., 2009; Duggan & Morton, 2010) among eligible individuals. Compared to Medicare Parts A and B that are primarily focused on hospital or medical services, Medicare Part D covers prescription drugs and is administered through private insurance plans approved by Medicare (Medicare.gov, n.d.-b; MedicareInteractive.org, n.d.-b).

Enrollment in either Medicare Part A or Part B automatically qualifies individuals to enroll in Medicare Part D. Additionally, the program extends its benefits to diverse categories of individuals, including those aged 65 and older eligible for Medicare due to their age. Younger beneficiaries, specifically individuals under 65, may also meet the criteria for Medicare Part D if

they have received Social Security Disability Insurance (SSDI) benefits for more than 24 months or have been diagnosed with end-stage renal disease (Social Security Administration, n.d.).

Medicare Part D offers coverage for an extensive formulary of prescription drugs, providing beneficiaries with access to a comprehensive range of medications (Medicare.gov, n.d.-c). The formularies under Medicare Part D are determined by private insurance companies collaborating with Medicare, subject to regular updates and revisions. This ensures that beneficiaries have access to the most effective and cost-efficient drugs available (MedicareInteractive.org, n.d.-a). While covered drugs and associated costs can vary significantly among different Medicare Part D plans, the medications covered include those specific to addressing opioid-related issues, such as buprenorphine, methadone, and naltrexone. These drugs play an important role in managing opioid use disorder, aiming to mitigate the associated risks and complications.

3.2.2. Opioid Use Disorders

Opioid use disorder (OUD) is a chronic condition characterized by a problematic pattern of opioid use leading to significant distress or impairment in various aspects of an individual's life (American Psychiatric Association, 2022). The Diagnostic and Statistical Manual of Mental Disorders, 5th Edition (DSM-5), published by the APA, outlines specific criteria for diagnosing OUD. These criteria generally include the following: taking larger amounts or using opioids over a longer period than intended, unsuccessful efforts to cut down or control use, spending excessive time obtaining or using opioids, experiencing cravings, and facing challenges in fulfilling obligations at work, school, or home.

OUD can take different forms, such as abuse and dependence. In the DSM-4, these two were distinct disorders. However, with the release of DSM-5, the manual no longer maintains

this differentiation (Addiction Center, 2023). Instead, both abuse and dependence are now collectively categorized under the umbrella term of OUD. Nonetheless, Addiction Center (2023) notes that abuse is a mild form of addiction, and dependence a moderate or severe form of addiction. This distinction can be useful later on in explaining how Medicare Part D could differentially affect the incidence of these two types of OUD.

3.2.3. Medication-Assisted Treatment for OUD

Medication-assisted treatment (MAT) emerges as a critical strategy in addressing opioid use disorders (OUD). According to the U.S. Food and Drug Administration (FDA), MAT involves the use of medications alongside counseling and behavioral therapies, proving to be an effective approach in helping individuals sustain recovery (FDA, 2023, NCSACW, n.d., SAMHSA, 2024)

Three drugs, namely buprenorphine, methadone, and naltrexone, are FDA-approved for the treatment of opioid dependence. These drugs operate to normalize brain chemistry, block the euphoric effects of opioids, relieve physiological cravings, and improve overall quality of life for individuals in recovery (FDA, 2023, SAMHSA, 2024). When used in combination with therapy, these drugs have been shown to successfully treat substance use disorders, improving patient survival, increasing retention in treatment, reducing illicit opiate use, decreasing criminal activity, enhancing employment prospects, and improving birth outcomes among pregnant women with substance use disorders (SAMHSA, 2024).

These MAT drugs (i.e., buprenorphine, methadone, naltrexone) are used to treat short-acting opioids such as heroin, morphine, and codeine, as well as semi-synthetic opioids like oxycodone and hydrocodone. They are considered safe for use over the long term, with the FDA emphasizing that there is no maximum recommended duration for maintenance treatment (FDA,

2023, SAMHSA, 2024). Moreover, MAT extends its reach beyond treatment, incorporating opioid overdose prevention medications such as naloxone. Naloxone plays a critical role in preventing opioid overdose by reversing its toxic effects (SAMHSA, 2024). Medicare data shows that in recent years, there was an increase in use of drugs for treatment of OUD among Medicare beneficiaries (US DHHS, 2021a).

3.2.4. Existing Literature

Works that look into the effect of Medicare Part D on hospitalizations (not necessarily OUD-related) include Afendulis et al. (2011) and Kaestner et al. (2019). In Afendulis et al. (2011), they used hospital discharge data from years 2005 to 2007 across 23 states and a subsample of adults age 60 and above, and find that Part D reduced the *overall* hospitalization rate by 4.1%. Kaestner et al. (2019), focuses on more specific types of hospitalizations, namely, congestive heart failure (CHF) and chronic obstructive pulmonary disease (COPD)-related admissions. Using Medicare claims data, they find that Part D led to a 13% and 19% decrease in CHF- and COPD-related admissions, respectively.

Papers evaluating another policy (i.e., ACA's Medicaid expansion) that could potentially increase access to MAT drugs and its effects on opioid-related hospitalizations include Wen et al. (2020) and Decker et al. (2023). These works estimate that the ACA's Medicaid expansion led to more modest effects on opioid-related inpatient hospitalizations, ranging from a 9.7% (Wen et al., 2020) to 12% (Decker et al., 2023) decrease in admissions within expansion states relative to non-expansion states. These works however use aggregated data at the state level and do not directly compare hospitalizations among low-income individuals. Looking at opioid mortality as an outcome, Kravitz-Wirtz et al., (2020) find that the adoption of the ACA's Medicaid expansion was associated with a 6% lower rate of total opioid overdose deaths in expansion states

compared to non-expansion states. Meanwhile, Wettstein (2019) finds that a 1 percentage point increase in insurance coverage as a result of the ACA's dependent coverage mandate reduced opioid mortality among young adults by 19.8%. Another policy that potentially increased access to MAT drugs is the 2006 Massachusetts health care reform. Lasser et al. (2018) finds that this policy is not associated with any changes in substance use disorder-related hospitalizations.

3.3. Data

In this paper, I use the Nationwide Inpatient Sample (NIS), Healthcare Cost and Utilization Project (HCUP), Agency for Healthcare Research and Quality as my main data source. The NIS is the "*largest publicly available all-payer inpatient care database in the United States, containing data on more than seven million hospital stays*" (AHRQ, 2024a). I restrict my sample to years 2004 to 2011 due to the change in survey methodology beginning in 2012. This still gives me enough data to use before and after Medicare Part D's implementation in January 2006.

I follow the approach taken by existing works in the Medicare Part D literature (Ayyagari & Shane, 2015; Ayyagari et al., 2016; Engelhardt & Gruber, 2011). I restrict my sample to individuals age 60 to 69 in each survey year, and exclude individuals younger than 65 years old who have Medicare coverage as they are considered to be already-treated.[13] Here, individuals age 65 to 69 are considered as part of my treatment group (i.e., Medicare Part D-eligible), and individuals age 60 to 64 as part of my control group (i.e., Medicare Part D-ineligible).

The NIS uses International Classification of Diseases, Ninth Revision, Clinical Modification (ICD-9-CM) codes to identify the diagnoses observed for each discharge during my entire sample period. From 2004 to 2008, there are as many as 15 diagnoses recorded for each

[13] I also examine the sensitivity of my analysis to the use of other ranges such as 61 to 68, 62 to 67, 63 to 66, and 64 to 65.

discharge, while for years 2009 to 2011, there are as many as 25. Table 3.1 as a whole presents the different ICD-9 codes associated with different types of OUD as listed in Column 1. All models in this paper consider dummy outcome variables at the discharge level. In my baseline analysis, the main outcome variable of interest is equal to 1 if it lists any of the ICD-9 codes on Table 3.1, and 0 otherwise. Subsequent models will consider each specific OUD type (i.e., opioid dependence, opioid abuse, opioid poisoning) as independent outcomes.

Table 3.1. ICD-9 Codes for Each Type of Opioid Use Disorder (OUD)

OUD Type	ICD-9 codes
Opioid dependence	304.00, 304.01, 304.02, 304.03, 304.71, 304.72, 304.73
Opioid abuse	305.50, 305.51, 305.52, 305.53
Opioid poisoning	965.00, 965.01, 965.02, 965.09

Source: Weiss et al. (2020).

Table 3.2 reports mean values for my main outcome of interest (discharge being associated with any OUD type) split by adults aged 65 to 69 (treatment) vs. adults aged 60 to 64 (control) as well as by before and after Medicare Part D's implementation. Table 3.2 suggests that Medicare Part D's implementation was associated with statistically significant increase in the incidence of OUD-related hospital discharges for both groups (Columns 3 and 6). For the treatment group, the incidence increased from 283 to 493 (per 100,000 discharges) after January 2006, while for the control group, it went up from 478 to 919 (per 100,000 discharges). Here, we can see that the increase is larger in the control group (92.26% increase) compared to the treatment group (74.20% increase). Overall, these descriptive statistics suggest that Medicare Part D implementation is associated with a slower increase in the incidence of OUD-related discharges among the elderly aged 65 to 69, motivating my causal analysis.

By specific OUD type, we observe the same trend where increases in OUD-related discharged happen at a faster rate in the control group versus the treatment group. For opioid dependence, Table 3.2 shows that related discharges increased by 88.35% in the control group

and only by 83.13% in the treatment group. For opioid abuse, related discharges increased by 110.75% in the control group and only by 53.45% in the treatment group. For opioid poisoning, related discharges increased by 92.31% in the control group and only by 70.00% in the treatment group. Once again, these descriptive statistics provide motivation for my causal analysis.

Table 3.2. Summary Statistics of the Outcome Variables (per 100 Thousand Discharges)

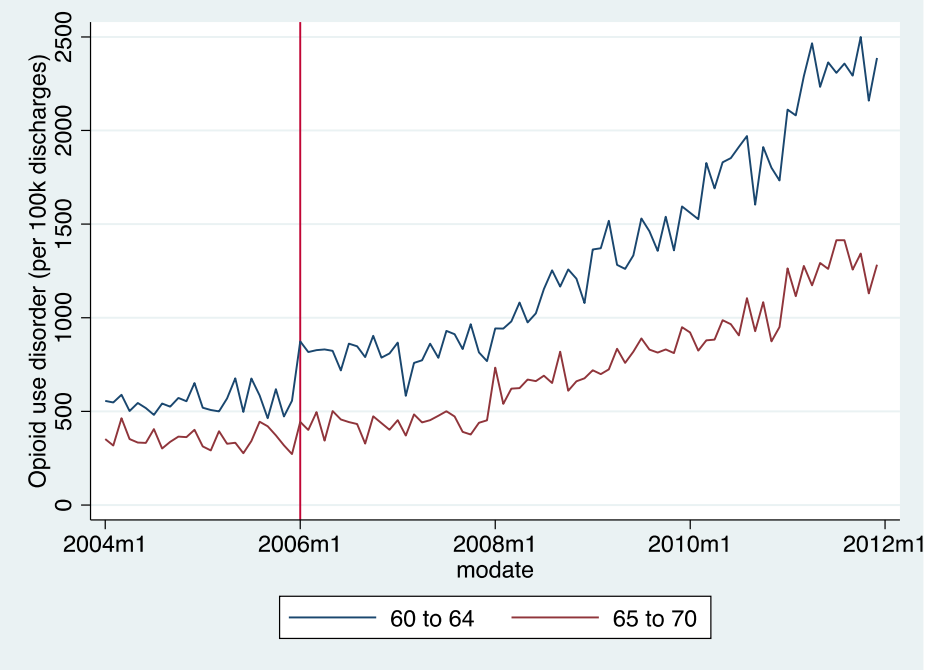
Outcome variable (per 100k discharges)	Adults age 65 to 69 (treatment)			Adults age 60 to 64 (control)		
	(1)	(2)	(3)	(4)	(5)	(6)
	Pre-Jan 2006	Post-Jan 2006	%Δ [p-value]	Pre-Jan 2006	Post-Jan 2006	%Δ [p-value]
Any OUD type	283 (5316)	493 (7003)	+74.20% [0.0000]	478 (6900)	919 (9541)	+92.26% [0.0000]
Opioid dependence	166 (4070)	304 (5502)	+83.13% [0.0000]	309 (5553)	582 (7606)	+88.35% [0.0000]
Opioid abuse	58 (2404)	89 (2983)	+53.45% [0.0000]	93 (3052)	196 (4428)	+110.75% [0.0000]
Opioid poisoning	70 (2636)	119 (3446)	+70.00% [0.0000]	91 (3012)	175 (4176)	+92.31% [0.0000]
No. of obs	613,013	2,248,725		569,555	2,173,155	

Notes: HCUP discharge weights used. Standard deviations in parentheses. p-values in square brackets. *, **, *** = statistically significant difference at the 10%, 5%, and 1%, respectively.

Figure 3.3 graphically presents the trend of OUD-related discharges (per 100 thousand discharges) from the first quarter of 2004 to the fourth quarter of 2011. We see that until around 2009, the incidence of OUD-related discharges between the treatment and control groups seems to be increasing at the same rate. However, from 2009 onwards, the treatment group consistently showed lower incidence compared to the control group. Graphical representations by specific OUD type also exhibit the same trend (Figures 3.4 to 3.6). These graphical representations further motivate my causal analysis.

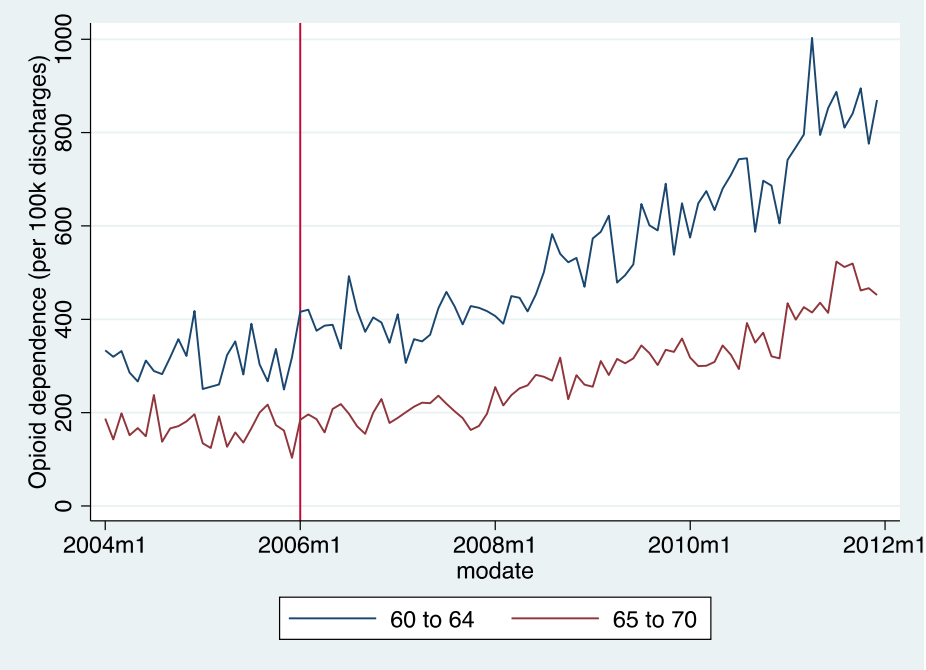
I use the following patient-level characteristics as my controls: patient age, race, sex, and median household income for the patient's zip code. I also use the following hospital-level characteristics: bed size, location, and teaching status. Quarterly state-level unemployment rates are also used to account for possible time-varying economic conditions which may affect an individual's likelihood to get admitted due to OUD. Table 3.3 presents some summary statistics.

Figure 3.3. Trends of OUD-Related Admissions by Age Group



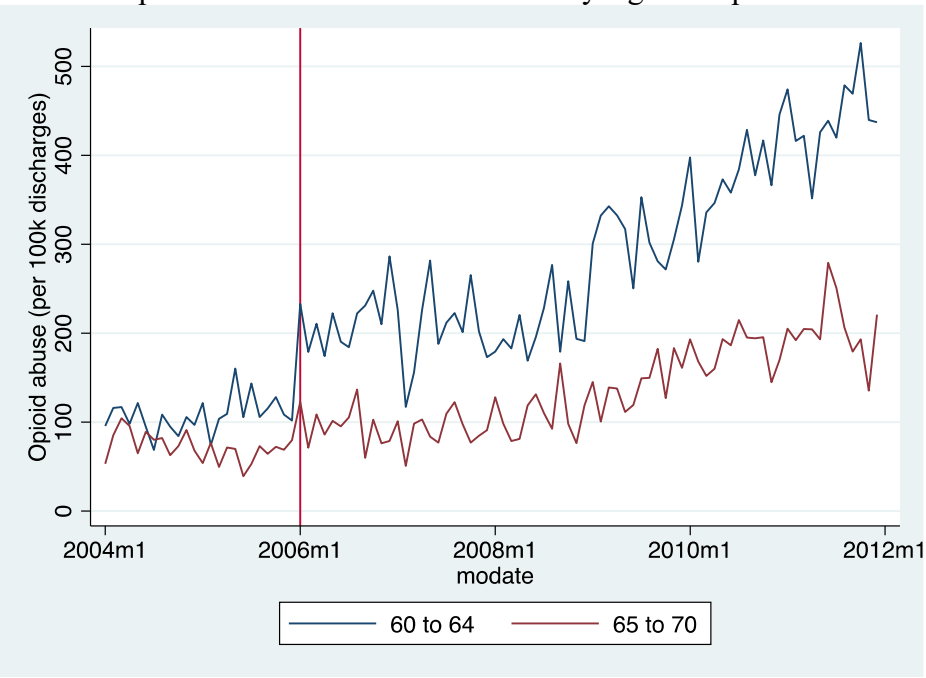
Notes: This figure includes admissions related to opioid dependence, abuse, and poisoning. HCUP discharge weights applied.

Figure 3.4. Trends of Opioid Dependence-Related Admissions by Age Group



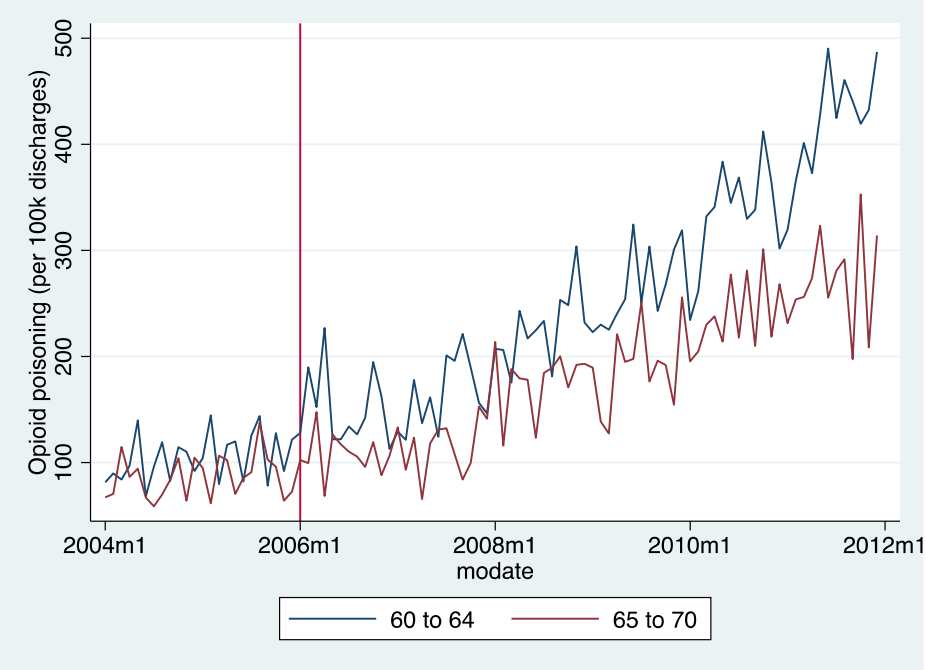
Notes: HCUP discharge weights applied.

Figure 3.5. Trends of Opioid Abuse-Related Admissions by Age Group



Notes: HCUP discharge weights applied.

Figure 3.6. Trends of Opioid Poisoning-Related Admissions by Age Group



Notes: HCUP discharge weights applied.

Table 3.3. Summary Statistics of the Covariates

Covariate	Full	Adults age 65 to 69 (Treatment)	Adults age 60 to 64 (Control)	Difference [p-value]
Age	64.56	67.01	61.99	5.018
	(2.84)	(1.34)	(1.34)	[0.0000]
Female	0.51	0.51	0.50	0.007
	(0.50)	(0.50)	(0.50)	[0.0000]
Race/Ethnicity				
White	0.74	0.75	0.73	0.020
	(0.44)	(0.43)	(0.44)	[0.0000]
Black	0.13	0.12	0.14	-0.017
	(0.34)	(0.33)	(0.35)	[0.0000]
Asian/Pacific Islander	0.02	0.02	0.02	0.001
	(0.14)	(0.14)	(0.14)	[0.0000]
Native American	0.01	0.01	0.01	0.000
	(0.08)	(0.08)	(0.08)	[0.0000]
Hispanic	0.07	0.07	0.08	-0.004
	(0.26)	(0.26)	(0.26)	[0.0000]
Income Quartile				
First	0.29	0.29	0.29	0.003
	(0.45)	(0.45)	(0.45)	[0.0000]
Second	0.25	0.25	0.24	0.004
	(0.43)	(0.43)	(0.43)	[0.0000]
Third	0.23	0.23	0.23	0.000
	(0.42)	(0.42)	(0.42)	[0.0076]
Fourth	0.23	0.23	0.24	-0.006
	(0.42)	(0.42)	(0.43)	[0.0000]
Bed size				
Small	0.13	0.14	0.13	0.008
	(0.34)	(0.34)	(0.34)	[0.0000]
Medium	0.25	0.25	0.25	0.000
	(0.43)	(0.43)	(0.43)	[0.0237]
Large	0.62	0.62	0.63	-0.008
	(0.49)	(0.49)	(0.48)	[0.0000]
Location				
Urban	0.88	0.87	0.88	-0.013
	(0.33)	(0.34)	(0.32)	[0.0000]
Rural	0.12	0.13	0.12	0.013
	(0.33)	(0.34)	(0.32)	[0.0000]
Teaching status				
Teaching	0.46	0.45	0.48	-0.028
	(0.50)	(0.50)	(0.50)	[0.0000]
Non-teaching	0.54	0.55	0.52	0.028
	(0.50)	(0.50)	(0.50)	[0.0000]
No. of observations	5,604,448	2,861,738	2,742,710	

Notes: HCUP discharge weights used. Standard deviations in parentheses. p-values in square brackets.

3.4. Methodology

In this paper, I use a standard difference-in-differences (DD) approach with Medicare-eligible individuals (65 to 69 years old) considered as part of the treatment group, and Medicare-

ineligible individuals (60 to 64 years old) as part of the control group. My estimating equation is as follows:

$$OUD_{iht} = \alpha_0 + \alpha_1 AGE65-69_{iht} \times Post_{Jan2006} + \alpha_2 AGE65-69_{iht} + \alpha_3 Post_{Jan2006} + \mathbf{X}_{iht}\boldsymbol{\alpha}_4 + \gamma_h + \eta_s + \tau_t + \varepsilon_{iht}, \quad (7)$$

where α are coefficients, OUD_{iht} is a binary variable equal to 1 if discharge i hospital h in year-quarter t is associated with an opioid use disorder diagnosis (i.e., the discharge record lists any of the ICD-9 codes given in Table 3.1), $AGE65-69_{iht}$ is a binary variable equal to 1 if the age of the individual is between 65 to 69 years, $Post_{Jan2006}$ is a binary variable equal to 1 for periods after January 2006, $\mathbf{X}_{iht}$ is a vector of discharge and hospital-level controls as mentioned in Section 3.3, as well as state-level unemployment rate, γ_h, η_s, τ_t are hospital, state, and year-quarter fixed effects, and ε_{iht} is an error term.

The main coefficient of interest α_1 estimates the causal impact Medicare Part D had on OUD-related discharges among the elderly population. I expect its sign to be negative, given that Medicare-eligible individuals gained prescription drug coverage, and as a result had increased access to MAT drugs for OUD. The increased access to MAT drugs for OUD then leads to better outcomes (i.e., lower incidence of complications, and hence less admissions) among their age group. Another way of looking at it is that due to Medicare Part D's prescription coverage, the elderly now legally acquire opioids which are much safer than those bought in the illegal markets. In the sense that they now use opioids that are generally safer, and get proper instructions from their doctors prior to buying these opioids, the policy may lead to less complications and lower rates of admissions due to OUD.

3.4.1. Event Study

In this identification strategy, the main assumptions are that (i) the policy does not have spillover effects on the Medicare ineligible population, (ii) the trends prior to the policy's implementation grow in the same levels for the two groups, and (iii) there are no other factors affecting the outcome for the treatment group conditional on the control variables. To give support to assumption (ii), I run an event study of the form

$$OUD_{iht} = \beta_0 + \sum_{\substack{YQ=2004q1 \\ YQ\neq 2005q4}}^{2011q4} \beta_{YQ}\, AGE65-69_{it} \times \mathbf{1}(YQ) + \mathbf{X}_{iht}\boldsymbol{\beta}_3 + \gamma'_h + \eta'_s + \tau'_t + \varepsilon'_{iht}, \quad (8)$$

where β are coefficients, YQ consist of the year-quarters from 2004 Q1 until 2011 Q4, except 2005 Q4 (the quarter prior to the program implementation), $\mathbf{1}(YQ)$ are year-quarter dummies for each YQ, and other variables as previously defined. In this specification, I want the $AGE65-69_{it}$ interactions with each of the pre-January 2006 dummies to be insignificant. This provides support to the parallel trends assumption, allowing for causal interpretation of the difference-in-difference results.

3.5. Results

In this section, I present my baseline results based on Equation 7. I also look at the heterogeneous effects of the policy by specific OUD type, race, ethnicity, and sex, as well as perform specification tests to ascertain the robustness of my results.

3.5.1. Baseline Results and Event Study

Table 3.4 Column 1 presents the preliminary results based on Equation 7. Here, we see that OUD-related discharges went down by 213.9 per 100,000 after Medicare Part D's introduction. This is equivalent to a 56.74% decrease from the pre-January 2006 mean of 377 OUD-related discharges per 100,000, an effect relatively large compared to what other works in

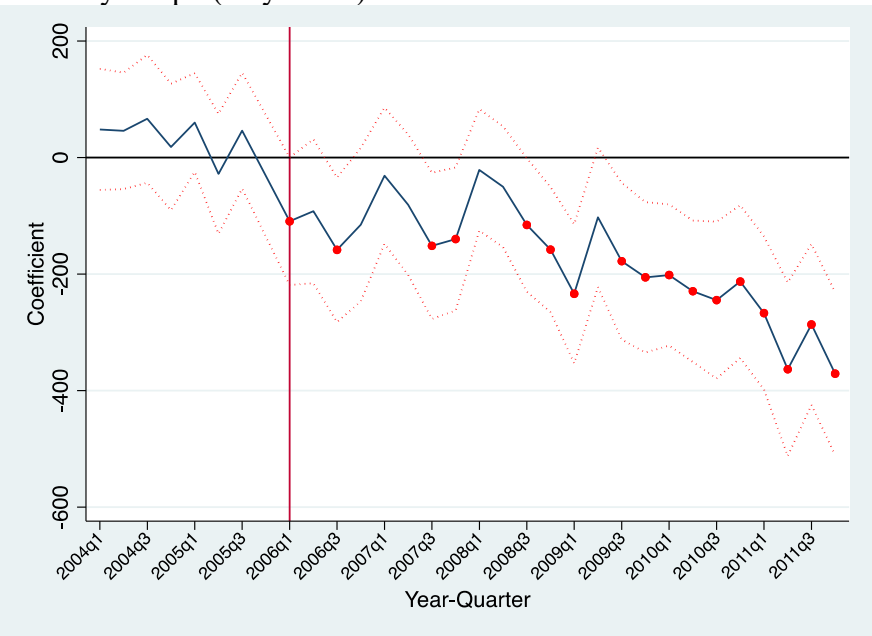
the literature find. This somewhat-inflated effect is observed throughout this paper, suggesting a need for cautious interpretation of these results. It is highly likely that there could be potential confounders unaccounted for in the current model, and so more work is necessary to refine the results. Focusing on the sign and significance of my estimates rather than their magnitude, I find that Part D led to significant declines in OUD-related discharges. Together with Figure 3.3, this implies that such discharges among individuals in the treatment group increased at a slower rate compared to the incidence of OUD-related discharges in the control group.

Table 3.4. Difference-in-Difference Results by OUD Type

	OUD Type			
	(1)	(2)	(3)	(4)
	Any OUD type	Opioid dependence	Opioid abuse	Opioid Poisoning
DD coef.	-213.9***	-123.5***	-65.6***	-34.9***
(Std. Err.)	(23.5)	(19.6)	(8.91)	(6.43)
Pre-Jan 2006 mean of dep. var. per 100k	377	235	75	80
Coeff as % of mean	-56.74%	-52.55%	-87.47%	-43.63%
No. of obs.	5,604,448	5,604,448	5,604,448	5,604,448

Notes: *, **, *** denote significance levels of 10%, 5%, and 1%, respectively. HCUP discharge weights used. Discharge-level characteristics, hospital characteristics, state characteristic, hospital fixed effects, state fixed effects, and year-quarter fixed effects included in the models. Hospital-clustered standard errors in parentheses.

Figure 3.7. Event Study Graph (Any OUD)



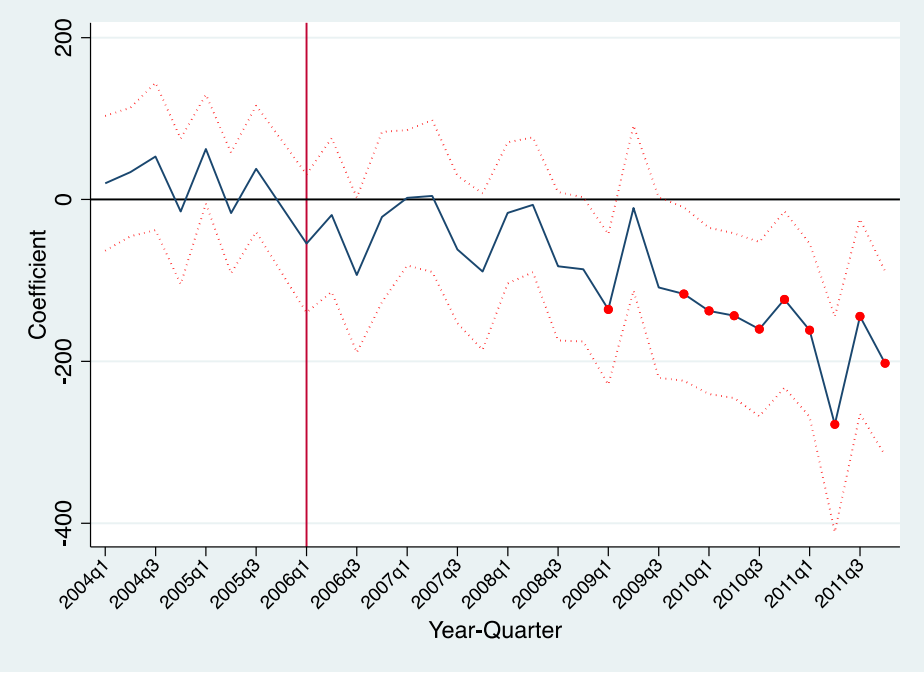
Notes: HCUP discharge weights applied.

The event study results based on Equation 8 is graphically presented in Figure 3.7. This figure shows us that there are no pre-reform interactions are significantly different from 0, and that they do not seem to exhibit any pre-trend. This gives me more confidence in a causal interpretation of my baseline results. Additionally, Figure 3.7 suggests that the reduction in OUD-related discharges has been consistent in the post period in terms of statistical significance. The event study coefficient estimates themselves are presented in Table C.5 Column 1.

3.5.2. Effects by Specific OUD Type

I also consider models where the respective outcome variable is set to 1 if the discharge records a specific OUD type (i.e., opioid dependence, opioid abuse, opioid poisoning), and 0 otherwise. The corresponding ICD-9 codes for each type are in Table 3.1. The difference-in-differences result for each type are given in Table 3.4 Columns 2 to 4. The corresponding event study graphs are given in Figures 3.8 to 3.10, while the coefficients are given in Table C.5 Columns 2 to 4.

Figure 3.8. Event Study Graph (Opioid Dependence)



Notes: HCUP discharge weights applied.

Just like in the previous subsection, the large effects I find by OUD type must be interpreted with caution. Here, we see that hospital discharges related to opioid dependence decreased by 123.5 per 100,000 after Medicare Part D's introduction, equivalent to a 52.55% decrease from the pre-January 2006 mean of 235 opioid dependence-related discharges per 100,000. Similarly, hospital discharges related to opioid abuse and opioid poisoning decreased by 65.6 and 34.9 per 100,000 after Medicare Part D's introduction, equivalent to 87.47% and 43.63% declines from their pre-January 2006 means, respectively.

Comparing these estimates with Figures 3.4 to 3.6 give us the same insights as earlier, that is, the results imply that the incidence of opioid dependence, abuse, and poisoning-related discharges among individuals in the treatment group increased at a slower rate compared to the incidence of OUD-related discharges in the control group as a result of the policy.

Figure 3.9. Event Study Graph (Opioid Abuse)

Notes: HCUP discharge weights applied.

As noted in Section 2.3, opioid abuse is often regarded as a less severe form of addiction, while dependence represents a moderate to severe form. In contrast, opioid poisoning stands out

as the most severe outcome. It is then reasonable to argue that improving the accessibility of MAT drugs through Medicare Part D could yield more substantial marginal effects in reducing hospitalizations associated with opioid abuse when compared to cases of opioid dependence and poisoning. This is what we see in Table 3.4.

Figure 3.10. Event Study Graph (Opioid Poisoning)

Notes: HCUP discharge weights applied.

3.5.3. Heterogeneity and Specification Tests

Documented disparities in opioid prescription patterns by patient race/ethnicity motivate the need for a similar investigation when looking at the impacts of Medicare Part D on OUD-related hospital discharges. Flores et al. (2023) find that racial/ethnic minorities are less likely to receive follow-up pain medications after their initial opioid prescriptions, signaling low care quality for these groups. Scholl et al. (2019) note that compared to whites, black and Hispanic patients experience disproportionate increase in opioid-related mortality rates. In fact, data from 2015 to 2020 shows that opioid-related mortality in the United States increased by 322%, 218% and 86% for blacks, Hispanics, and whites, respectively (Flores et al., 2023). While these are

relatively recent evidence of disparities by race/ethnicity, an earlier work by Pletcher et al. (2008) already note that differences in opioid prescribing by race/ethnicity have not really changed since the 1990s. Hence, it is possible that within the context of Medicare Part D, either (i) the benefits may have continued to disproportionately benefit whites over non-whites, or (ii) while the policy might have provided equal benefits in magnitude across all race/ethnic groups, the relative marginal benefit for non-white individuals could be higher due to their starting point being significantly worse off compared to white individuals.

In Table 3.5 columns 2 to 5, we see that OUD-related discharges went down across all racial/ethnic groups, with all effects statistically significant. However, running statistical tests to check the differences in the estimated coefficients by race show that the coefficients are indeed statistically different from each other. These differences in effects are more in line with hypothesis (ii) above, that is, the relative marginal benefit for non-white individuals being higher due to their starting point being significantly worse off compared to white individuals.

Disaggregating by gender (Table 3.5, columns 6 to 7) reveals a statistically significant decline in OUD-related discharges for both men and women. I also find that the coefficients between men and women are significantly different, with effects for men larger compared to women. While limited studies in the literature find that women are more likely to use prescription opioids compared to men (Serdarevic et al., 2017), there is evidence that men have higher odds of opioid analgesics misuse (McHugh et al., 2021). Thus if Part D makes it easier for the elderly to acquire opioids from licit sources as well as acquire it from providers that could give them proper guidance on how to use such drugs, then this estimated difference makes intuitive sense (i.e., men having larger gains compared to women).

I also conduct two specification tests. First is that since the hospital controls used in my analysis (i.e., bed size, location, and teaching status) tend to be constant for each hospital over time, excluding these variables (but keeping hospital fixed effects in the model) should produce estimates similar with my initial results. Conversely, dropping hospital fixed effects and keeping hospital characteristic should produce slightly different results if these hospital characteristics are important and several of them are unobserved.

Table 3.5. Difference-in-Difference Results by Population Sub-Group

	Population sub-group						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	All	White	Black	Asian/Pacific Islander	Hispanic	Men	Women
DD coeff. (Std. Err.) *per 100k*	-213.9*** (23.5)	-157.3*** (19.5)	-468.6*** (97.3)	-203.4*** (56.4)	-251.3*** (79.9)	-267.8*** (34.8)	-158.0*** (24.4)
Pre-Jan 2006 mean of dep. Var. *per 100k*	377	326	652	113	502	419	337
Coeff as % of mean	-56.74%	-48.25%	-71.87%	-180.00%	-50.06%	-63.91%	-46.88%
No. of obs.	5,604,448	4,163,687	733,330	116,085	416,027	2,765,807	2,838,641

Notes: *, **, *** denote significance levels of 10%, 5%, and 1%, respectively. HCUP discharge weights used. Discharge-level characteristics, hospital characteristics, state characteristic, hospital fixed effects, state fixed effects, and year-quarter fixed effects included in the models. Hospital-clustered standard errors in parentheses.

I also consider the possibility that treating OUD might be a gradual process. To test this, I use progressively shorter age ranges for comparison. The underlying idea here is that, with briefer exposure to treatment, we might observe more modest results. This approach is in line with the FDA's acknowledgment that there's no specified maximum recommended duration for maintenance treatment (FDA, 2023). This absence of a time limit suggests the possibility that the positive effects of the treatment could unfold over the long term.

In Table 3.6 Column 2, we see that when the time-varying hospital characteristics (i.e., hospital bed size, location, and teaching status) are dropped (but hospital fixed effects remain included), results do not significantly change. The estimated effect of the policy went down from

-56.74% to -56.71%. Table 3.6 Column 3 shows the results when I run specifications keeping hospital characteristics and removing hospital fixed effects (-60.11%) while Table 3.6 Column 4 shows the result when I remove both hospital characteristics and fixed effects (-60.08%). As expected, we see slightly different results, implying that observed and unobserved hospital characteristics are important. Statistical tests show that Table 3.6 Columns 3 and 4 are not statistically different from each other, but are statistically different compared to Table 3.6 Column 1. This suggests that including fixed effects significantly produces more accurate results.

Table 3.6. Difference-in-Difference Results (Inclusion and Exclusion of Hospital Controls and Hospital Fixed Effects)

	(1)	(2)	(3)	(4)
	With hospital characteristics, with hospital fixed effects	No hospital characteristics, with hospital fixed effects	With hospital characteristics, no hospital fixed effects	No hospital characteristics, no hospital fixed effects
DD coef.	-213.9***	-213.8***	-226.6***	-226.5***
(Std. Err.)	(23.5)	(23.5)	(26.4)	(26.4)
Pre-Jan 2006 mean of dep. var. per 100k	377	377	377	377
Coeff as % of mean	-56.74%	-56.71%	-60.11%	-60.08%
Hospital controls?	Y	N	Y	N
Hospital FE?	Y	Y	N	N
No. of obs.	5,604,448	5,604,448	5,604,448	5,604,448

Notes: *, **, *** denote significance levels of 10%, 5%, and 1%, respectively. HCUP discharge weights used. Discharge-level characteristics, state characteristic, state fixed effects, and year-quarter fixed effects included in the models. Hospital-clustered standard errors in parentheses.

Table 3.7. Difference-in-Difference Results (Different Age Ranges)

	Age range				
	60 to 69	61 to 68	62 to 67	63 to 66	64 to 65
DD coeff.	-213.9***	-187.8***	-153.6***	-174.1***	-167.4***
(Std. Err.) *per 100k*	(23.5)	(21.9)	(21.6)	(30.1)	(38.3)
Pre-Jan 2006 mean of dep. Var. *per 100k*	377	349	328	389	405
Coeff as % of mean	-56.74%	-53.81%	-46.83%	-44.76%	-41.33%
No. of obs.	5,604,448	4,589,108	3,580,736	1,995,679	991,801

Notes: *, **, *** denote significance levels of 10%, 5%, and 1%, respectively. HCUP discharge weights used. Discharge-level characteristics, hospital characteristics, state characteristic, hospital fixed effects, state fixed effects, and year-quarter fixed effects included in the models. Hospital-clustered standard errors in parentheses.

Table 3.7 shows the results when I consider other age ranges for my analysis, namely 61 to 68, 62 to 67 years old, 63 to 66, and 64 to 65. As expected, the estimated effects get smaller in magnitude as the age range gets narrower. Furthermore, statistical tests show that I cannot reject the null hypothesis that these effects are equal.

3.6. Discussion and Conclusion

In this paper, I find that the incidence of OUD-related hospital discharges among the treatment group went down by -56.74% relative to its pre-2006 mean. This figure represents the first causal estimate of the effects of Medicare Part D on OUD-related hospital discharges. My results are potentially explained by the increased use of MAT drugs for OUD among the elderly after Medicare Part D's implementation. By having improved access to medications, as well as access to providers that could give these individuals proper guidance on how to use such drugs, OUD complications in the form of hospital discharges are reduced. However, it is important to note that I was not able to empirically test changes in MAT drugs utilization among individuals in the NIS following Part D's implementation. Incorporating this in the analysis can be explored in a future work.

I also looked at the effect of the policy by specific OUD type (i.e., opioid dependence, opioid abuse, opioid poisoning), and observed differences in effects, with the effects largest for opioid abuse, followed by opioid dependence, and opioid poisoning, respectively. This is potentially explained by the differing severity levels associated with each type. Medicare Part D had more substantial marginal effects in reducing hospitalizations associated with opioid abuse compared to opioid dependence and poisoning.

I also contextualize my main results (56.74% reduction in OUD-related hospital discharges) by comparing it with other works that look into the effect of Part D on *other* types of

discharges. Other authors find more modest estimates, ranging from 4.1% (Afendulis et al., 2011) to 19% (Kaestner et al., 2019) declines in hospital admissions, depending on discharge type. This merits further investigation into my approach given the relatively large effect that I find in this paper. Meanwhile, those that explore the effects of another policy (i.e., ACA's Medicaid expansion) on OUD-related discharges estimate effects ranging from a 9.7% (Wen et al., 2020) to a 12% (Decker et al., 2023) declines in admissions.

Lastly, I also observed differential effects by race/ethnicity and gender. I found that non-whites benefited the most from the policy, and understand this to be due to them having worse initial outcomes compared to white individuals. The policy providing equal benefits in magnitude across all race/ethnic groups yielded larger relative marginal benefits for non-white individuals. I also found that men had larger declines in OUD-related discharges compared to women. As men have higher tendencies to misuse opioid analgesics (McHugh et al., 2021), they likely benefited more when Part D made it easier for them to acquire opioids from licit sources as well as acquire it from providers that could give them proper guidance on how to use such drugs.

These results contribute to the literature by estimating the currently unknown impacts of the Medicare Part D on OUD complications in the form of hospital discharges using an all-payer, nationally representative dataset of hospital discharges in the country. These findings may aid policymakers in crafting laws that make MAT drugs more accessible, as well as improve guidelines in terms of opioid prescription monitoring. In addition, my heterogeneity results suggest that policymakers may want put in place measures to protect the population subgroups that benefit less from the policy. Overall, my results suggest that Medicare Part D led to a decrease in the incidence of OUD-related discharges after its implementation.

Appendix A. Conceptual Framework

Figure A.1. Optimal Choice of Type L Hospitals When Dealing with CAUTI and CLABSI Outcomes Under the 2008 Policy

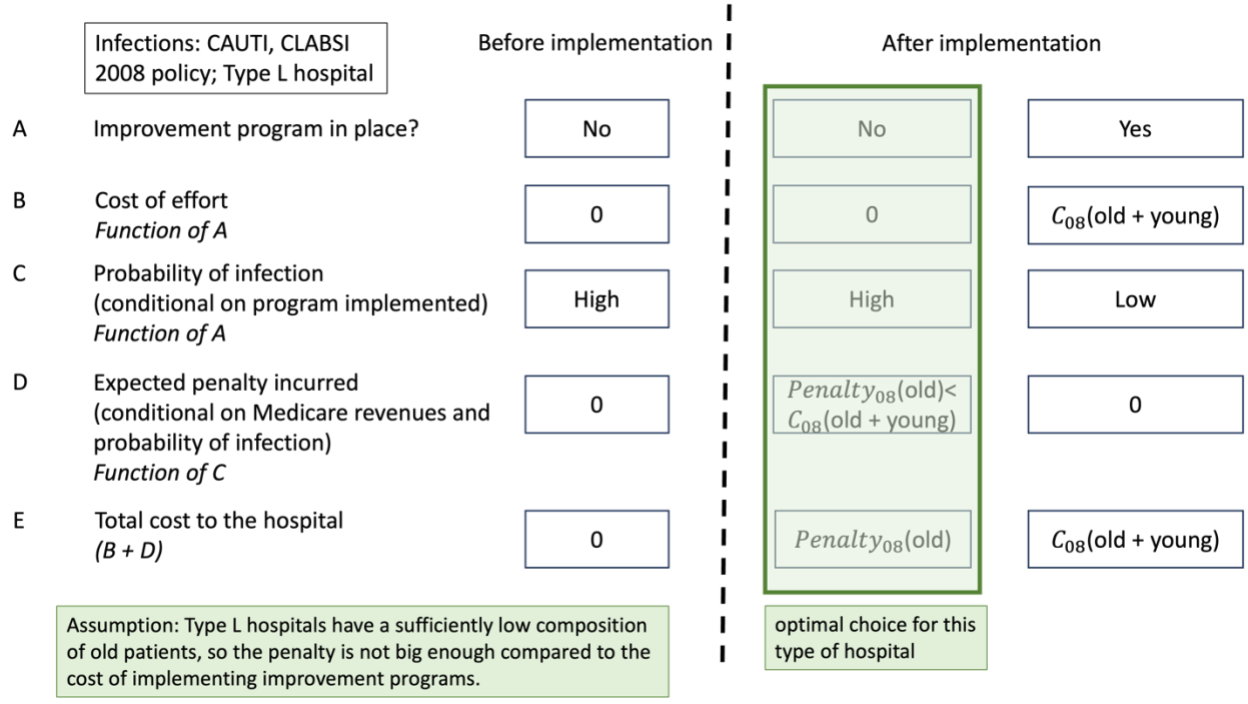


Figure A.2. Optimal Choice of Type H Hospitals When Dealing with CAUTI and CLABSI Outcomes Under the 2008 Policy

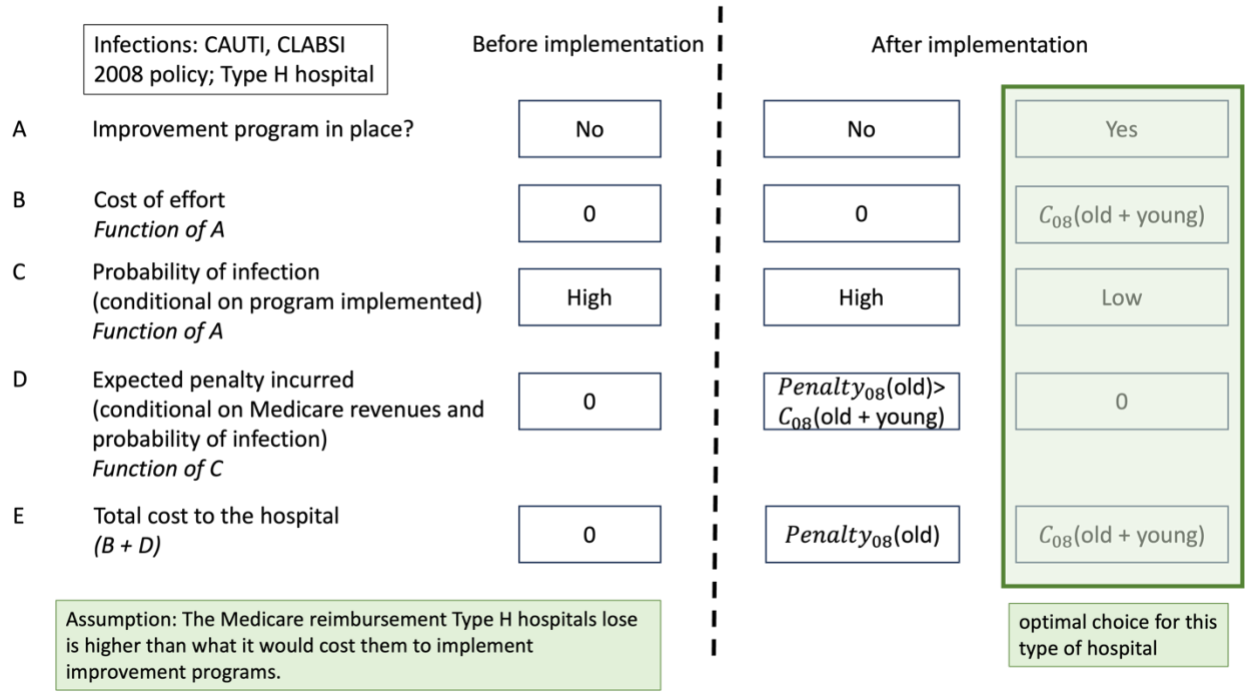


Figure A.3. Optimal Choice of Type L Hospitals When Dealing with CAUTI and CLABSI Outcomes Under the 2014 Policy

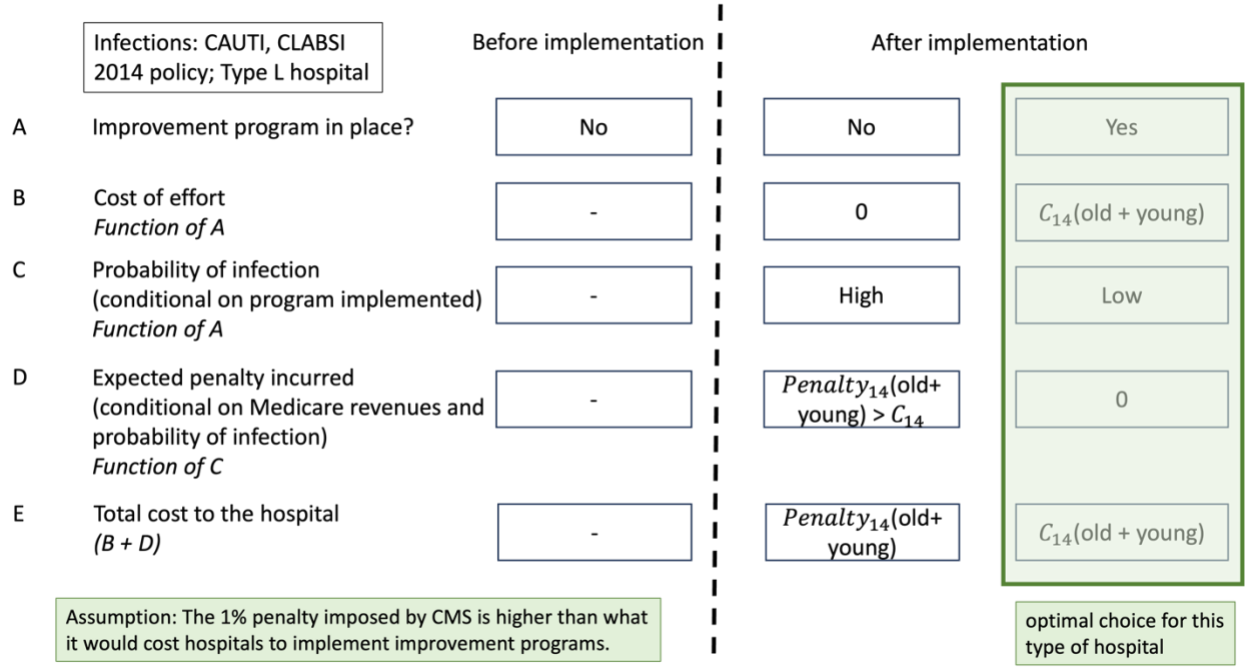


Figure A.4. Optimal Choice of Type H Hospitals When Dealing with CAUTI and CLABSI Outcomes Under the 2014 Policy

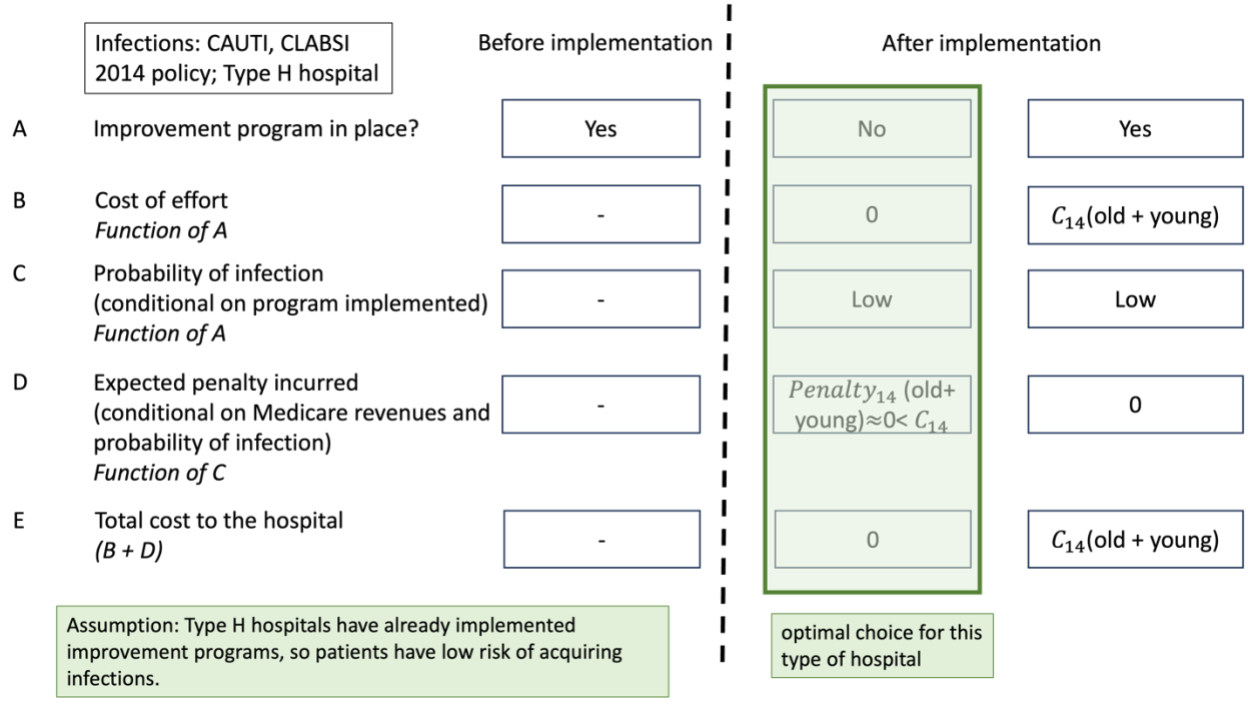


Figure A.5. Optimal Choice of Type L Hospitals When Dealing with CDI and MRSA Outcomes Under the 2008 Policy

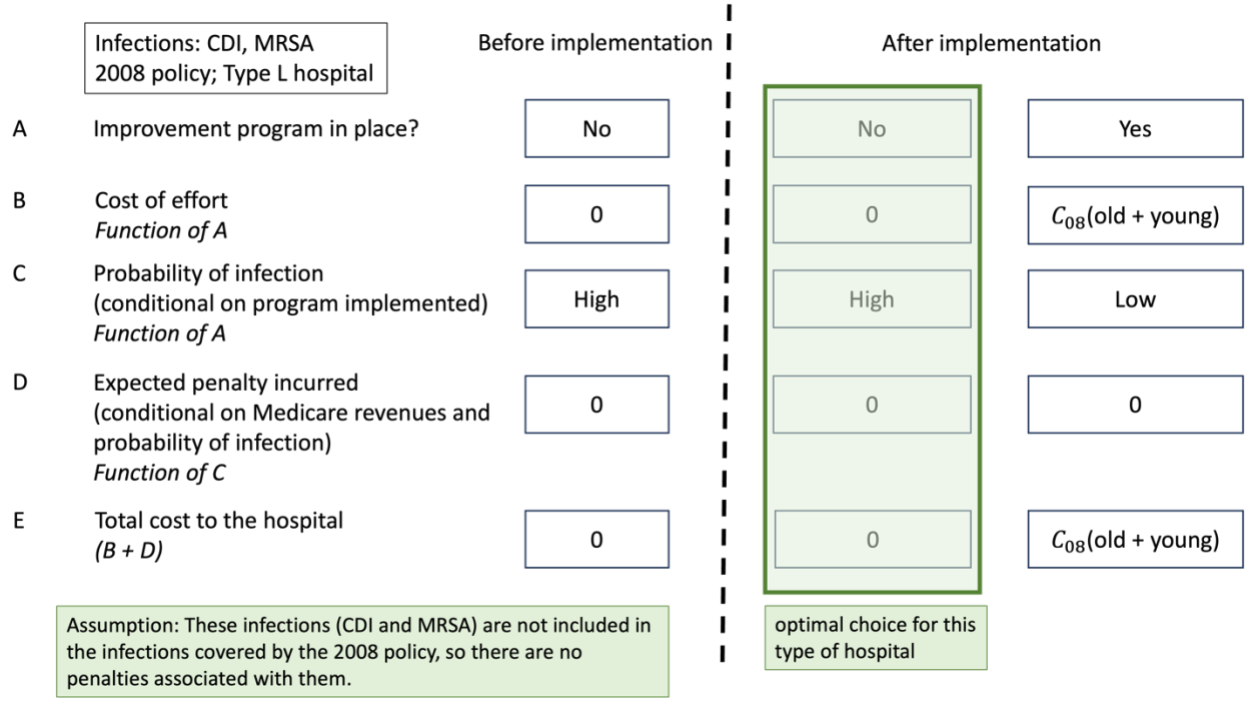


Figure A.6. Optimal Choice of Type H Hospitals When Dealing with CDI and MRSA Outcomes Under the 2008 Policy

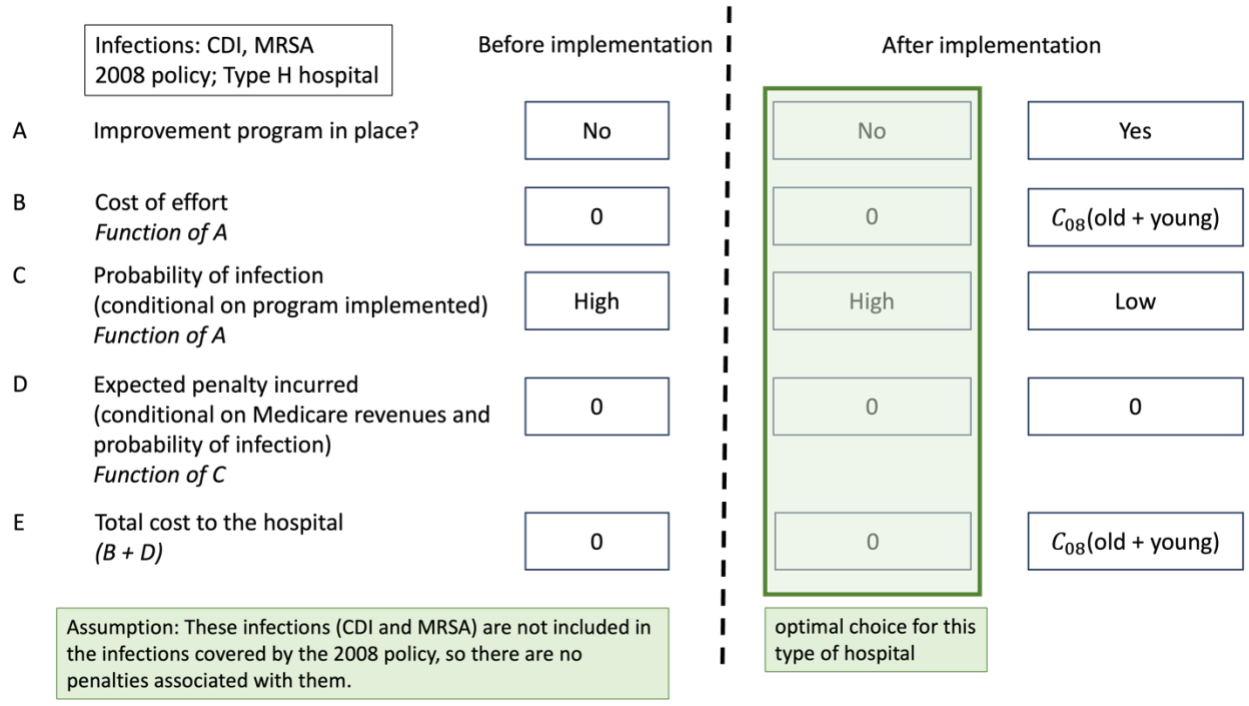


Figure A.7. Optimal Choice of Type L Hospitals When Dealing with CDI and MRSA Outcomes Under the 2014 Policy

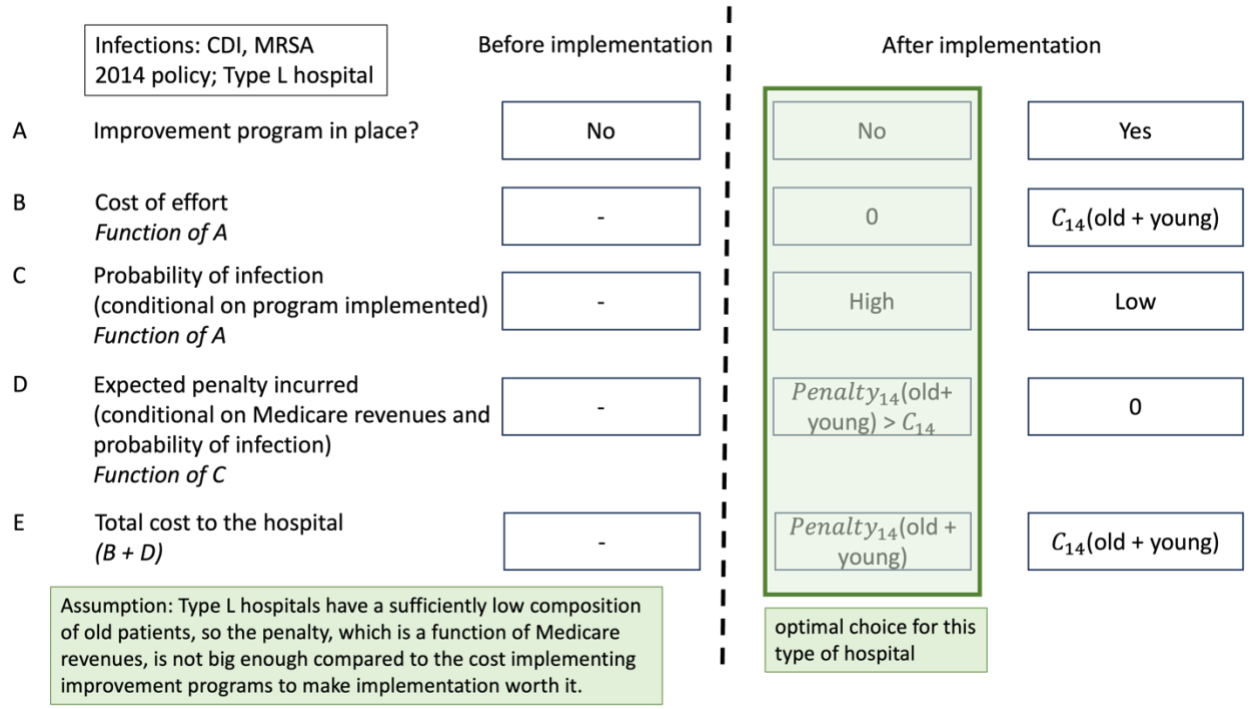
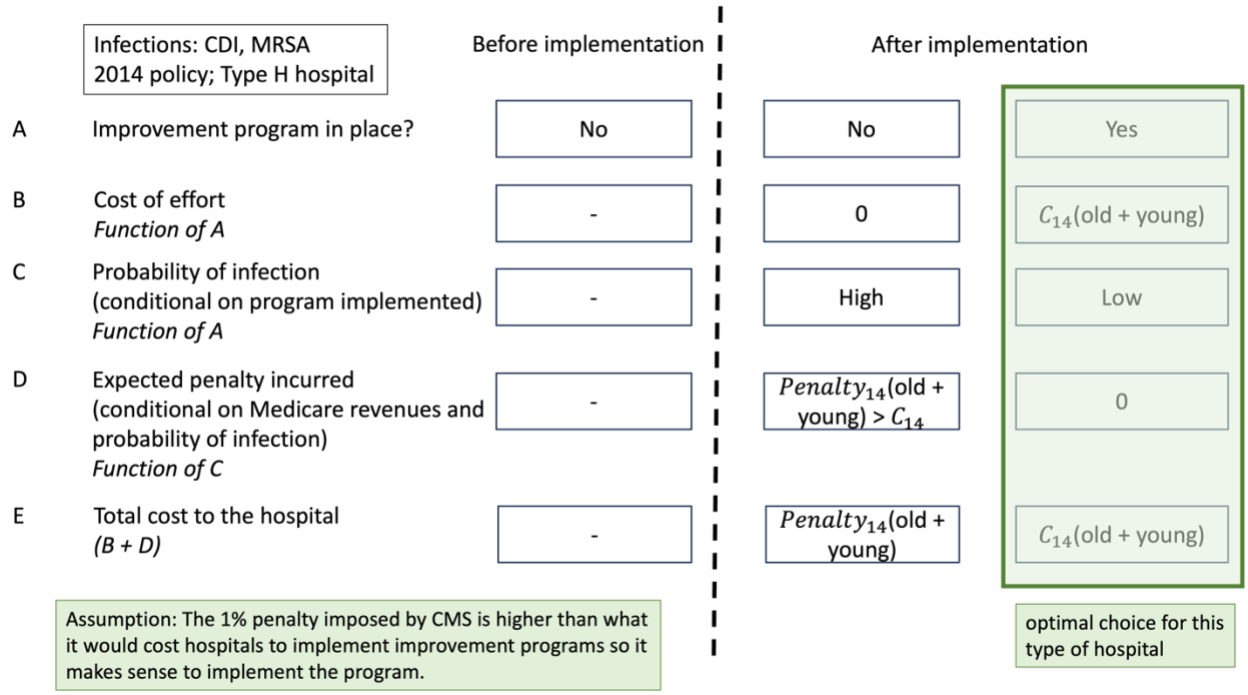


Figure A.8. Optimal Choice of Type H Hospitals When Dealing with CDI and MRSA Outcomes Under the 2014 Policy



Appendix B. Estimating the Effects of the Hospital-Acquired Conditions–Present on Admission (HAC-POA) Reporting Provision on the Incidence of CAUTI and CLABSI

Here I look at the effects the HAC-POA reporting provision had on the incidence of CAUTI and CLABSI[14] by exploiting the differences in Medicare revenue shares across hospitals in the 2008 to 2011 NIS. I restrict my sample to hospitals with Medicare revenue shares less than 30% and greater than 70% to emphasize the differential impacts on hospitals that were most likely affected by the policy and those that were least likely affected. I use a difference-in-differences model of the form

$$y_{iht} = \xi_0 + \xi_1 \mathbf{1}\left(Post_{2008Q4}\right)_t + \xi_2 MEDICARE Share_{ht} + \xi_3 \mathbf{1}\left(Post_{2008Q4}\right)_t \times MEDICARE Share_{ht} + \mathbf{X}'_{iht}\boldsymbol{\xi}_4 + \delta_h + \eta_t + \epsilon_{iht}, \quad (B1)$$

where ξ are coefficients, $y_{iht} = 1$ if discharge i in hospital h records a HAI in year-quarter t, and 0 otherwise, $\mathbf{1}\left(Post_{2008Q4}\right)_t = 1$ in year-quarters after the fourth quarter of 2008, and 0 otherwise, $MEDICARE Share_{ht}$ = hospital h's Medicare reimbursements (as percent of total revenues) in quarter-year t, $\mathbf{X}$ = vector of controls (individual and hospital characteristics mentioned in Section 1.4), δ_h = hospital FE, η_t = year-quarter FE, and ϵ_{iht} = error term.

The main coefficient of interest in this case is ξ_3. Economic theory tells us that hospitals with bigger exposure to the policy (i.e., higher $MEDICARE Share_{ht}$) are likely to respond more compared to those with smaller exposure (i.e., lower $MEDICARE Share_{ht}$), and hence display a larger decrease (or smaller increase) in HAI incidence in the post period. This means that in Equation B1, we expect that coefficient ξ_3 will be less than 0.

[14] I exclude CDI and MRSA since these infections are not part of the list of HAIs covered by the HAC-POA reporting provision.

Running Equation B1, I find that for every 1 standard deviation increase in a hospital's Medicare revenue share (as % of total revenues), the probability of a patient having CAUTI and CLABSI went down by -0.87% and -0.76%, respectively after the policy went into effect (Table B.1). These support my assumption that in analyzing the impacts of HACRP (policy that came after the HAC-POA reporting provision) on the incidence of CAUTI and CLABSI, hospitals with relatively higher Medicare reimbursements are to be considered as part of the control group rather than the treatment group.

Table B.1. Difference-in-Differences Coefficients for Equation B1

	HAI Type	
	CAUTI	CLABSI
DD coeff.	-1.12***	-1.07***
(Std. Err.) per 100k	(0.14)	(0.21)
Pre-policy implementation mean of dep. var. per 100k	99	136
Change in probability of infection for every 1 SD increase in Medicare share	-0.87%	-0.76%
No. of obs.	9,227,653	9,227,653

Notes: *, **, *** denote significance levels of 10%, 5%, and 1%, respectively. HCUP discharge weights used. Discharge-level characteristics, hospital-level characteristics, stratum fixed effects, and year-quarter fixed effects included in the models. Robust standard errors in parentheses.

Appendix C. Supplemental Tables

Table C.1. Summary Statistics of CAUTI and CLABSI (per 100 Thousand Discharges) by Medicare Revenue Share

Outcome variable	75% to 100% ("More control")			50% to 75% ("Less control")			25% to 50% ("Less treatment")			0% to 25% ("More treatment")		
(per 100k discharges)	Pre	Post	Δ	Pre	Post	Δ	Pre	Post	Δ	Pre	Post	Δ
CAUTI	110	154	+40.00%	115	156	+35.65%	96	130	+35.42%	74	85	+14.86%
	(3319)	(3926)		(3395)	(3941)		(3096)	(3609)		(2710)	(2921)	
CLABSI	57	34	-40.35%	80	53	-33.75%	128	85	-33.59%	105	78	-25.71%
	(2379)	(1853)		(2824)	(2297)		(3572)	(2920)		(3242)	(2796)	
No. of obs.	102,461	460,006		4,427,541	24,326,105		2,210,256	12,126,258		208,132	935,727	

Notes: Post period begins 2013 Q2. HCUP discharge weights used. Standard deviations in parentheses. We expect that hospitals in the treatment group see smaller increases in infections or larger decreases in infections.

Table C.2. Summary Statistics of CDI and MRSA (per 100 Thousand Discharges) by Medicare Revenue Share

Outcome variable	75% to 100% ("More treatment")			50% to 75% ("Less treatment")			25% to 50% ("Less control")			0% to 25% ("More control")		
(per 100k discharges)	Pre	Post	Δ	Pre	Post	Δ	Pre	Post	Δ	Pre	Post	Δ
CDI	682	643	-5.72%	741	702	-5.26%	733	701	-4.37%	472	477	+1.06%
	(8231)	(7990)		(8575)	(8349)		(8531)	(8345)		(6856)	(6890)	
MRSA	1370	1132	-17.37%	1064	966	-9.21%	970	950	-2.06%	848	790	-6.84%
	(11623)	(10578)		(10260)	(9781)		(9800)	(9700)		(9171)	(8853)	
No. of obs.	163,608	398,859		6,962,716	21,790,930		3,534,355	10,802,159		323,506	820,353	

Notes: Post period begins 2014 Q1. HCUP discharge weights used. Standard deviations in parentheses. We expect that hospitals in the treatment group see smaller increases in infections or larger decreases in infections.

Table C.3. Summary Statistics of Discharge and Hospital-Level Controls

	Full		Type H		Type L	
	Pre-2014	Post-2014	Pre-2014	Post-2014	Pre-2014	Post-2014
Age	57.43	57.93	59.77	60.13	53.09	53.74
	(20.58)	(20.32)	(20.39)	(20.05)	(20.23)	(20.16)
Female	0.59	0.58	0.59	0.58	0.60	0.59
	(0.49)	(0.49)	(0.49)	(0.49)	(0.49)	(0.49)
Race/Ethnicity						
White	0.69	0.68	0.75	0.74	0.58	0.56
	(0.46)	(0.47)	(0.43)	(0.44)	(0.49)	(0.5)
Black	0.15	0.15	0.12	0.13	0.19	0.19
	(0.35)	(0.36)	(0.32)	(0.33)	(0.39)	(0.4)
Asian/Pacific	0.02	0.03	0.02	0.02	0.03	0.04
Islander	(0.15)	(0.16)	(0.13)	(0.14)	(0.18)	(0.19)
Native American	0.01	0.01	0.01	0.01	0.01	0.01
	(0.08)	(0.08)	(0.08)	(0.07)	(0.08)	(0.08)
Hispanic	0.10	0.11	0.08	0.08	0.14	0.16
	(0.30)	(0.31)	(0.27)	(0.27)	(0.35)	(0.37)
Income Quartile						
First	0.31	0.31	0.31	0.30	0.30	0.32
	(0.46)	(0.46)	(0.46)	(0.46)	(0.46)	(0.47)
Second	0.26	0.26	0.27	0.28	0.22	0.23
	(0.44)	(0.44)	(0.45)	(0.45)	(0.42)	(0.42)
Third	0.24	0.24	0.23	0.24	0.24	0.23
	(0.42)	(0.42)	(0.42)	(0.43)	(0.43)	(0.42)
Fourth	0.20	0.20	0.18	0.18	0.24	0.22
	(0.40)	(0.40)	(0.39)	(0.39)	(0.43)	(0.41)
Ownership						
Government, non-	0.12	0.12	0.09	0.08	0.18	0.19
federal	(0.33)	(0.32)	(0.28)	(0.27)	(0.39)	(0.4)
Private, non-profit	0.73	0.73	0.74	0.76	0.70	0.67
	(0.45)	(0.44)	(0.44)	(0.42)	(0.46)	(0.47)
Private, invest-own	0.15	0.15	0.17	0.16	0.11	0.14
	(0.36)	(0.36)	(0.38)	(0.37)	(0.32)	(0.34)
Bed size						
Small	0.14	0.20	0.15	0.21	0.12	0.17
	(0.35)	(0.40)	(0.36)	(0.41)	(0.33)	(0.37)
Medium	0.26	0.29	0.27	0.30	0.26	0.27
	(0.44)	(0.46)	(0.44)	(0.46)	(0.44)	(0.44)
Large	0.60	0.51	0.58	0.48	0.62	0.56
	(0.49)	(0.50)	(0.49)	(0.5)	(0.49)	(0.5)
Location/teaching status						
Rural	0.11	0.09	0.15	0.12	0.04	0.04
	(0.31)	(0.29)	(0.36)	(0.32)	(0.19)	(0.18)
Urban, non-	0.40	0.24	0.46	0.29	0.29	0.15
teaching	(0.49)	(0.43)	(0.5)	(0.45)	(0.45)	(0.36)
Urban, teaching	0.49	0.67	0.39	0.59	0.68	0.81
	(0.50)	(0.47)	(0.49)	(0.49)	(0.47)	(0.39)
No. of observations	10,984,185	33,812,301	7,126,324	22,189,789	3,857,861	11,622,512

Notes: HCUP discharge weights used. Type H hospitals are those with Medicare revenue shares of at least 50%. Type L hospitals are those with Medicare revenue shares less below 50%.

Table C.4. Event Study Coefficients for Equation 6

Quarter	Coeff. (std. err.)
2004 Q1	-28.3 (80.7)
2004 Q2	25.2 (82.8)
2004 Q3	-44.8 (85.2)
2004 Q4	118.6 (84.8)
2005 Q1	-10.2 (83.6)
2005 Q2	-25.9 (89.1)
2005 Q3	-117.1 (86.9)
2006 Q1	88.3 (84.1)
2006 Q2	-53.0 (80.0)
2006 Q3	-55.5 (85.6)
2006 Q4	25.9 (83.5)
2007 Q1	-164.8* (84.8)
2007 Q2	-52.2 (87.8)
2007 Q3	-29.3 (88.0)
2007 Q4	-33.5 (89.8)
2008 Q1	5.27 (84.4)
2008 Q2	-63.0 (83.6)
2008 Q3	-128.0 (86.3)
2008 Q4	-55.6 (90.4)
2009 Q1	-187.3** (90.3)
2009 Q2	-166.3* (87.1)
2009 Q3	-33.9 (91.0)
2009 Q4	-143.5* (87.0)
2010 Q1	-55.3 (88.9)
2010 Q2	-90.1 (87.9)
2010 Q3	-92.2 (88.7)
2010 Q4	-52.6 (92.6)
2011 Q1	-193.6** (84.6)
2011 Q2	-174.2** (86.5)
2011 Q3	-306.5*** (92.2)
2011 Q4	-164.5* (86.7)

Notes: *, **, *** denote significance levels of 10%, 5%, and 1%, respectively. HCUP discharge weights used. Discharge-level characteristics, hospital characteristics, state characteristic, state fixed effects, and year fixed effects included in the models. Hospital-clustered standard errors in parentheses.

Table C.5. Event Study Coefficients for Equation 8

Quarter	DD coeff. (Std. Err.)			
	(1)	(2)	(3)	(4)
	Any OUD type	Opioid dependence	Opioid abuse	Opioid Poisoning
2004 Q1	48.2 (53.0)	20.0 (42.5)	13.7 (22.7)	26.0 (21.2)
2004 Q2	45.7 (51.0)	33.9 (40.5)	16.6 (21.4)	11.2 (21.8)
2004 Q3	66.4 (55.9)	53.1 (46.4)	23.7 (20.6)	4.40 (21.3)
2004 Q4	18.1 (55.4)	-14.8 (45.8)	20.2 (21.2)	16.1 (21.6)
2005 Q1	60.1 (43.1)	62.3* (34.3)	4.22 (19.4)	11.4 (21.9)
2005 Q2	-28.1 (52.5)	-16.7 (38.0)	-20.8 (22.3)	12.8 (22.7)
2005 Q3	46.1 (50.7)	38.0 (39.8)	-16.8 (23.4)	24.5 (22.4)
2006 Q1	-109.5** (55.8)	-54.4 (43.5)	-46.6** (23.2)	-3.67 (23.4)
2006 Q2	-92.1 (63.0)	-19.1 (48.4)	-46.4 (28.3)	-14.5 (22.6)
2006 Q3	-158.5** (63.2)	-93.4* (48.8)	-55.0* (29.3)	3.27 (21.4)
2006 Q4	-115.3* (67.1)	-21.6 (53.6)	-93.1*** (27.5)	-12.3 (23.2)
2007 Q1	-31.1 (59.6)	2.05 (42.7)	-26.1 (28.7)	8.32 (24.2)
2007 Q2	-81.0 (61.6)	4.32 (47.8)	-78.8*** (30.5)	0.63 (21.9)
2007 Q3	-151.6** (63.9)	-61.8 (46.5)	-45.0 (29.3)	-49.6* (26.4)
2007 Q4	-139.9** (62.6)	-89.1* (49.3)	-65.9*** (23.9)	5.16 (25.2)
2008 Q1	-21.2 (53.2)	-16.5 (44.5)	-22.7 (23.5)	11.7 (22.4)
2008 Q2	-50.2 (52.8)	-6.55 (42.5)	-22.1 (23.6)	-17.2 (23.1)
2008 Q3	-115.7** (58.4)	-82.6* (46.8)	-36.4 (24.4)	6.83 (24.9)
2008 Q4	-158.0*** (54.7)	-86.3* (45.4)	-42.9* (22.9)	-23.2 (24.8)
2009 Q1	-233.8*** (60.9)	-135.8*** (47.4)	-84.7*** (26.8)	-19.3 (22.9)
2009 Q2	-102.6* (61.0)	-10.4 (52.0)	-73.2*** (23.9)	-16.9 (25.3)
2009 Q3	-177.9*** (68.6)	-108.8* (56.9)	-58.4** (26.3)	-10.3 (24.8)
2009 Q4	-205.6*** (65.8)	-116.8** (54.6)	-59.5** (25)	-34.1 (24.6)
2010 Q1	-201.6*** (61.8)	-137.6*** (52.4)	-44.0* (23.9)	-10.5 (22.3)
2010 Q2	-229.4*** (61.8)	-143.6*** (51.9)	-49.2** (24.7)	-37.3 (24.4)
2010 Q3	-244.7*** (68.6)	-160.1*** (54.9)	-57.3** (25.9)	-33.1 (24.7)
2010 Q4	-212.9*** (66.8)	-123.5** (55.5)	-80.8*** (26.4)	-23.3 (25)
2011 Q1	-267.0*** (67.0)	-161.5*** (54.6)	-83.4*** (24.6)	-30.6 (23.4)
2011 Q2	-363.4*** (75.9)	-277.8*** (67.9)	-53.1** (25.7)	-47.3* (25.9)
2011 Q3	-286.5*** (70.4)	-144.4** (61.4)	-88.2*** (25.4)	-70.0*** (25.7)
2011 Q4	-370.9*** (71.3)	-202.3*** (58.0)	-113.2*** (25.6)	-55.2** (25.2)

Notes: *, **, *** denote significance levels of 10%, 5%, and 1%, respectively. HCUP discharge weights used. Discharge-level characteristics, state characteristic, state fixed effects, and year fixed effects included in the models. State-clustered standard errors in parentheses.

Appendix D. Event Study Results for the First-Stage Analysis

The following event study equation is based on Equation 4.

$$y_{iat} = \theta'_a + \gamma'_t + \sum_{\substack{t=2002 \\ t\neq 2005}}^{2009} \delta_t \mathbf{1}(t) \times AGE65-68 + \varepsilon_{iat}, \qquad (D1)$$

where y_{iat} is the number of antibiotic prescriptions filled by individual i at age a in year t, $\mathbf{1}(t)$ are year dummies for each t from 2002 to 2009 (except 2005), $AGE65-68$ is a binary indicator for being 65 to 68 years old, θ'_a, γ'_t are age and year fixed effects, respectively, and ε_{iat} is an error term. The estimates of δ_t in this event study are given in Table D.1.

Table D.1. Difference-in-Differences Coefficients for Equation D1

Year	Coeff. (Std. Err.)
2002	-0.0093
	(0.0165)
2003	-0.0019
	(0.0161)
2004	0.0097
	(0.0149)
2006	0.0045
	(0.0159)
2007	0.0249
	(0.0155)
2008	0.0116
	(0.0152)
2009	0.0187
	(0.0154)
Age FE?	Y
Year FE?	Y
No. of obs.	18,295

Notes: *, **, *** denote significance levels of 10%, 5%, and 1%, respectively. MEPS weights used. Individual-clustered standard errors in parentheses.

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