ESSAYS ON THE IMPACT AND INCENTIVES OF FEDERAL FUNDING IN MEDICARE AND MEDICAID

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A dissertation submitted to Johns Hopkins University in conformity with the requirements for the degree of Doctor of Philosophy

Baltimore, Maryland
August 2015

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Abstract

Background: Federal funding into the Medicare and Medicaid programs creates financial incentives that can have important implications for these programs and the populations that they serve. This dissertation contains three essays that explore the following topics: 1) The impact of the recent pay-for-performance payment reform, resulting from the Affordable Care Act, for Medicare Advantage plans with dual-eligible enrollees (paper 1); 2) the impact of the federal subsidy of state Medicaid programs in the form of the Federal Medical Assistance Percentages (FMAP) on the level of state Medicaid spending (paper 2); and 3) the impact of the federal subsidy of state Medicaid programs on infant mortality rates (paper 3).

Methods: All three papers utilize an instrumental variable approach to address potential unobserved factors that could result in estimation bias. In addition, the three studies utilize panel data where units are observed over time allowing for fixed-effects analyses that measures within-entity variation to control for time-invariant unobservable factors.

Results: Paper 1 finds that the share of dual-eligible enrollees within a Medicare Advantage contract is associated with a one half star lower rating in the CMS five-star quality rating system for measures that fall under the Intermediate Outcomes category.
Measures in this category are closely tied to patient health behaviors that are often outside the plan’s control.

Paper 2 finds that the FMAP does not impact the level of state Medicaid spending but increases the share of the state healthcare expenditures that is going into Medicaid. Paper 3 finds that marginal increases in the FMAP of a state are associated with lower infant mortality rates and that the effects are stronger for nonwhite infants and lower income states.

Conclusion: Results from paper 1 suggest that the current pay-for-performance structure of the Medicare Advantage market should be revised so to not place Medicare Advantage contract with dual-eligible enrollees at a disadvantage. Results from papers 2 and 3 suggest that the federal subsidy of the Medicaid program, while does not increase state spending in Medicaid, acts to reduce infant mortality rate through increased health resources within the state.

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Acknowledgements

This dissertation would not have been possible without the support, encouragement and direction of my advisor, Dr. Kevin D. Frick. His patience and steadfast guidance for the past 5 years have been invaluable in my development as a PhD student and an independent researcher. I would also like to thank Dr. David Bishai for not only generously sharing the state expenditures dataset but also being equally generous with his time throughout the entire dissertation process. Dr. Jonathan Weiner’s expertise and expansive knowledge of managed care and keen focus on public health policy also greatly improved this work. Dr. Antonio Trujillo was instrumental throughout both the proposal and dissertation processes in helping me frame my econometric strategy.

This work is also largely attributable to my coauthors. Ivy Dong and Chunwei Wang from InnovaCare were incredibly helpful in providing the data, actuarial, and industry expertise that greatly enriched and shaped paper 1. Dr. Martin Andersen, my coauthor for paper 2 and also a committee member, provided the initial idea for the paper and was an incredible wealth of knowledge in almost all things.

I owe a special thanks to my friends and family. They have been a constant source of support and encouragement throughout this entire process. I would like to especially thank Katie Martinez for her sense of humor and tough love in times of intellectual meandering and bewilderment – a PhD student could not ask for a better next-door officemate. I owe Christine Buttorff many thanks for her careful readings and edits of this
dissertation. In addition, I would like to thank Diarmuid Coughlan for his encouragement/prodding throughout. Finally, I would like to thank Peter Beyer for his constant support over the past two years, for always encouraging me, and for always being there for me.

This dissertation is dedicated to my father. He is a constant inspiration in my life; guiding me to always strive to be better, work harder and have an innate love and respect for what I do.
Table of Contents

Abstract ........................................................................................................................................ ii
Acknowledgements ................................................................................................................ iv
List of Tables ........................................................................................................................... ix
List of Figures .......................................................................................................................... x

1. Introduction, background and study rationale ........................................................................... 1
   1.1 Introduction .......................................................................................................................... 1
   1.2 Background ......................................................................................................................... 2
       1.2.1 Medicare and Medicaid Programs .................................................................................. 2
       1.2.2 Federal Funding of Medicare - Paper 1 ........................................................................ 3
       1.2.3 Federal Funding of Medicaid – Papers 2 and 3 ............................................................ 6
   1.3 Objective ............................................................................................................................ 7
       1.3.1 Paper 1 .......................................................................................................................... 7
       1.3.2 Paper 2 and 3 ................................................................................................................ 7

2. The Impact of Dual-Eligible Enrollees on the CMS Five Star Quality Rating Performance
   for Medicare Advantage Plans .................................................................................................. 9
   2.1 Abstract .............................................................................................................................. 9
   2.2 Introduction ......................................................................................................................... 9
   2.3 Background ......................................................................................................................... 12
       2.3.1 The Five Star Quality Rating System ............................................................................ 12
       2.3.2 Dual-Eligible Enrollees and Special Needs Plans .......................................................... 14
       2.3.3 Conceptual Framework ............................................................................................... 15
   2.4 Data and Estimation Strategy ............................................................................................. 17
       2.4.1 Data ............................................................................................................................. 17
       2.4.2 Empirical Model ......................................................................................................... 20
   2.5 Findings .............................................................................................................................. 23
       2.5.1 Summary Statistics for Contracts With and Without Dual-Eligible Enrollees .............. 23
       2.5.2 Star Ratings for Contracts With and Without Dual-Eligible Enrollees ........................... 23
       2.5.3 Predictors of Measure Performance .............................................................................. 24
       2.5.4 Process, Access and Patient Experience Measure Categories ..................................... 24
       2.5.5 Intermediate Outcome Category .................................................................................. 26
       2.5.6 Outcomes Category Measures ..................................................................................... 26
### Table of Contents

3. Impact of Federal Matching of State Medicaid Programs on State Medicaid Spending...41

3.1 Abstract ..........................................................................................................................41

3.2 Introduction ....................................................................................................................41

3.3 Conceptual Framework ..................................................................................................43

3.4 Data ................................................................................................................................46

3.4.1 Medicaid spending levels ........................................................................................47

3.4.2 Historical Federal Medical Assistance Percentage .........................................................47

3.4.3 Instrumented FMAP ....................................................................................................48

3.5 Estimation Strategy .........................................................................................................48

3.5.1 Fixed Effects Model ..................................................................................................50

3.5.2 Control variables .......................................................................................................50

3.6 Results ............................................................................................................................50

3.7 Discussion .......................................................................................................................52

3.7.1 Limitations ................................................................................................................52

3.7.2 Findings ......................................................................................................................52

3.8 Tables ...............................................................................................................................55

3.9 Figures ............................................................................................................................58

3.10 References .....................................................................................................................60

4. Federal Matching Funds in State Medicaid Programs: Does It Reduce Infant Mortality?...61

4.1 Abstract ..........................................................................................................................61

4.2 Introduction ....................................................................................................................61

4.3 Background & conceptual framework ............................................................................63

4.3.1 State Medicaid and the FMAP ....................................................................................63

4.3.2 The Affordable Care Act and the FMAP .................................................................64

4.3.3 Conceptual Framework for Federal Matching in State Medicaid Budgets .............64

4.4 Model, Data & Estimation Techniques ............................................................................69

vii


**List of Tables**

Table 2.7.1: Five Star Quality Rating Weights for Calculation of Overall Star Rating ........................................................................................................................................32

Table 2.7.2: Cronbach’s Alpha for Composite Measures of Each Five Star Quality Rating Category ..........................................................................................................................................................32

Table 2.7.3: Summary statistics: 2005 MA contract characteristics by share of dual-eligible enrollees in contract ........................................................................................................................................32

Table 2.7.4: Predictors of Measure Performance (OLS) ..........................................................................................................................................................................................................................33

Table 2.7.5: Model results - Process, Access and Patient Experience ..................................................................................................................................................................................................34

Table 2.7.6: Model results - Intermediate Outcomes ............................................................................................................................................................................................................34

Table 2.7.7: Model results – Outcomes Measures ..................................................................................................................................................................................................................35

Table 3.8.1: Descriptive Statistics by State ....................................................................................................................................................................................................................55

Table 3.8.2: Instrumental Variable Regression for Log Medicaid Spending ........................................................................................................................................................................56

Table 3.8.3: Instrumental Variable Regression for Log Medicaid Spending ........................................................................................................................................................................57

Table 4.8.1: State-level Descriptive Statistics by Pre- and Post- Medicaid Status ........................................................................................................................................................................80

Table 4.8.2: Instrumental Variable Regression for Infant Mortality Rates by Race: Continuous FMAP ........................................................................................................................................................................81

Table 4.8.3: Instrumental Variable Regression for Infant Mortality Rates by Race: High versus Low FMAP ........................................................................................................................................................................82

Table 4.8.4: Instrumental Variable Regression for Infant Mortality Rates by Race: Continuous FMAP and 5 and 10 Year Medicaid Implementation Lags ........................................................................................................83
List of Figures

Figure 2.8.1: Fluctuations in D-SNP Enrollment for 50 Contracts within Sample ..........36
Figure 2.8.2: Star Rating Performance Distribution of Contracts by Dual-Eligible Enrollment Status..........................................................37
Figure 2.8.3: Average Star Rating for Performance Measure Categories by Dual Eligible Enrollment Status..........................................................38
Figure 3.9.1: Distribution of State Medicaid Spending, 1980-2000.............................58
Figure 3.9.2: Average FMAP and Instrumented FMAP, 1980-2000 .............................59
1. Introduction, background and study rationale

1.1 Introduction

2015 marked the 50th anniversary of the Medicaid and Medicare programs in the US. In 2013, the US spent $2.9 trillion in healthcare spending, accounting for 17.4 percent of the nation’s Gross Domestic Product. Medicare accounted for 20 percent of the total healthcare spending ($585.7 billion), while Medicaid accounted for 15 percent of the total spending ($449.4 billion). Today, Medicare provides health insurance coverage to over 55 million people, while Medicaid covers over 71 million people. These two sources of public insurance provide an important safety net to the aged, disabled and the poor.

This manuscript contains three papers that separately examine the relationship of federal funding into the Medicaid and Medicare programs and its impact on various outcomes. Paper 1 in chapter 2 offers an examination of a recent Pay-for Performance (P4P) payment reform as a part of the Affordable Care Act within the Medicare Advantage (MA) program in Medicare. Papers 2 and 3 both examine the federal subsidy of the state Medicaid program in the form of the Federal Medical Assistance Percentages (FMAP).

2 http://kff.org/health-reform/state-indicator/total-monthly-medicaid-and-chip-enrollment/
All three papers utilize a fixed-effects model with an instrumental variable approach to address potential unobserved heterogeneity leading to biased interpretations of causality.

1.2 Background

1.2.1 Medicare and Medicaid Programs

The Medicare and Medicaid programs began in 1965 as a federal social health insurance program for the aged and disabled (Medicare) and the impoverished (Medicaid). The Centers of Medicare and Medicaid Services (CMS), formerly known as the Health Care Financing Administration (HCFA), administer the Medicare program and monitor the Medicaid program.

The original Medicare program signed into law by President Johnson contained two parts, Medicare Part A and Medicare Part B. Medicare Part A covers hospital insurance while Part B covers medical insurance, or outpatient services. A third part, Medicare Advantage (MA), is the privatized portion of Medicare that allows beneficiaries to purchase their health plan through private insurance companies. Finally, the fourth component, Medicare Part D covers prescription drug benefits. The focus of Paper 1 is on the way the federal government reimburses MA contracts based on performance measures. Additionally, paper 1 also investigates one specific subset of beneficiaries that qualify for both Medicare and Medicaid. These beneficiaries are dual-eligible enrollees and represent some of the most vulnerable population within the US healthcare system, as they are a cross-section between being aged/disabled and poor. Paper 1 examines whether having a
larger share of dual-eligible enrollees impacts performance on quality measures for MA contracts.

Papers 2 and 3 focus on the Medicaid program. This federal safety net program for the poor began in 1965 as a federal-state partnership where states voluntarily participate and administer the program under federal guidelines and receive federal funding for program beneficiaries. More specifically, the federal government matches state Medicaid spending by a certain percentage (FMAP) that is commensurate with the level of per capita income of the state in comparison to the national average, such that higher income states receive a lower match rate than lower income states. Papers 2 and 3 focus on the impact of the FMAP on state Medicaid spending and the infant mortality rate, respectively.

1.2.2 Federal Funding of Medicare - Paper 1

Currently, the majority of the enrollment in MA contracts is in managed care plans such as Health Maintenance Organizations (HMO) and Preferred Provider Organizations (PPO); in 2014, 64% of Medicare Advantage plans were HMO plans while 31% of the plans were PPO plans. The evolution of MA plan enrollment and plan types are very closely tied to the historical payment policies of CMS.

Medicare Part C was created with the goals of increasing enrollee plan choices and reducing costs. Starting in the 1970s and the 1980s CMS began demonstration projects aimed at testing the opportunity for cost savings through capitated payments to HMOs. In 1982, the passage of the Tax Equity and Fiscal Responsibility Act (TEFRA), formalized
the way Medicare contracts with private health plans in Medicare Part C. HMOs provided services covered under Part A and Part B while receiving capitated payments from CMS. These payments were risk adjusted for the illness burden of the plan population and were also adjusted to be 95% of the traditional Medicare average, thus providing cost savings to the Medicare program.

However, the risk scores only explained 1% of health cost variation and the payments were inadequate. As a result, MA plans engaged in favorable selection by avoiding counties with relatively sicker Medicare beneficiaries and also targeting healthier beneficiaries in their marketing. As a result, even though MA plans were reimbursed at 95% of traditional Medicare, the plans did not provide cost savings to the Medicare program as a whole since sicker beneficiaries remained in traditional Medicare plans.

In 1997, the BBA of 1997 authorized other types of private plans to offer Medicare Part C plans with the goal of encouraging cost savings and efficiencies through competition. As a result, PPOs, PSOs (provider-sponsored organizations) and PFFS (private fee-for-service) plans entered the Part C market. In addition, the BBA also required CMS to revisit the risk adjustment methods - this lead to the inclusion of patient diagnoses as part of the risk adjustment formula. During this period, despite Congressional efforts, MA plans began to exit the market as enrollment in Part C plan declined due to beneficiaries losing trust in managed care plans. In reaction to this, the Medicare Modernization Act of 2003 adjusted the risk adjustment methodology and increases to the reimbursement
levels for Part C plans. Since then, enrollment grew from 5.3 million in 2003 to 15.7 million in 2014.

In addition, starting in 2006, CMS began a bidding process for MA plans to enter the market. In advance of each rating year, MA organizations that wish to participate in the Medicare Advantage market submit bids to CMS for the opportunity to offer their plans in their proposed regions. These bids include, for each plan under the contract, the proposed enrollee population, services to be covered, cost sharing and benefit structure, the proposed per member per month cost and the plan’s intended administrative fees and profit margins. Although “plan” and “contract” are often used interchangeably in MA literature, it is important to differentiate between the two in the context of our work. An MA organization, for example UnitedHealth Group, Inc., can operate one or multiple contracts and offer one or multiple plans under each contract. MA organizations often group plans within the same region into one contract. Each contract requires a separate bid to be submitted to CMS. The bids are reviewed by CMS and compared to the benchmark set by CMS and deviations that are not supported by reasonable data or assumptions may result in requested revisions before the MA contract’s plans become available on the market in the rating year.

Beginning in 2012, with the passage of the Affordable Care Act, CMS made some additional changes to the way it reimburses MA plans. Studies have been critical of the payment method, after finding that the higher level of reimbursement for MA plans
compared to the traditional fee-for-service (FFS) Medicare plans does not result in MA plans providing a higher quality of service. As a result, CMS began to cut back in 2012 on MA plan reimbursement and began rewarding quality bonus payments (QBP) for those plans that are performing well on the five star performance measures. This recent payment reform payment reform is the focus of Paper 1.

1.2.3 Federal Funding of Medicaid – Papers 2 and 3
The federal government subsidizes the cost of state Medicaid programs by matching the health care costs at the FMAP level. For example, the FMAP rate for Mississippi is 74% in 2014; this means for every dollar of the Medicaid health care spending, the federal government paid 74 cents, with the remaining 26 cents coming from the Mississippi state budget.

The formula for FMAPs was established in statute in 1965 when Medicaid was authorized and is calculated as follows:

\[
STATESHARE = 0.45 \times \left[ \frac{StatePerCapitaIncome^2}{U.S.\ PerCapitaIncome^2} \right]
\]

\[
CalculatedFMAP = 1 - 0.45 \times \left[ \frac{StatePerCapitaIncome^2}{U.S.\ PerCapitaIncome^2} \right]
\]

The calculation is based on a three year rolling average per capita income for each state and the United States from the Department of Commerce's Bureau of Economic Analysis (BEA). The statute also established a minimum FMAP of 50 percent, so that no matter how wealthy a state might be compared to the national average its Medicaid expenditure
will always be matched by the federal government dollar for dollar. The FMAP is also capped at 83% in accordance to the following formula:

\[
Actual FMAP = \begin{cases} 
83\% & \text{if } CalculatedFMAP \geq 83\% \\
CalculatdFMAP & \text{if } 50\% < CalculatedFMAP < 83\% \\
50\% & \text{if } CalculatedFMAP \leq 50\% 
\end{cases}
\]

This formula has been unchanged since its inception with the exception of a few instances where special cases were made for specific states due to circumstances and need.

1.3 Objective

1.3.1 Paper 1

Paper 1 has the objective of examining the impact of the share of dual-eligible enrollees within a Medicare Advantage contract on the performance of the contract on the CMS five star quality rating. The five star quality rating contains a set of quality measures by which CMS determines bonus payments for MA contracts. Paper 1 aims to determine whether dual-eligible enrollees within a contract causes MA contract to perform worse on these measures.

1.3.2 Paper 2 and 3

The objective of paper 2 is to examine the relationship between marginal increases in the level of the FMAP and the state’s spending level on Medicaid. The paper examines both the state’s absolute level of spending in Medicaid and the portion of a state’s spending on healthcare that is going towards Medicaid.
The objective of paper 3 is to determine whether the FMAP received by the state Medicaid programs towards Medicaid enrollee expenditures acts to reduce infant mortality rate. It will examine separately the overall infant mortality rate, the infant mortality of white infants, and the infant mortality of black infants.
2. The Impact of Dual-Eligible Enrollees on the CMS Five Star Quality Rating Performance for Medicare Advantage Plans

2.1 Abstract

Pay-for-performance (P4P) is one of the main ways we financially incentivize higher quality from providers. This paper focuses on a recent example of P4P within the Medicare Advantage (MA) program and its potential impact on the dual-eligible Medicare population. We examine the impact of the share of dual-eligible enrollees within a contract and a contract’s performance in the CMS star quality measures. We address the potential endogeneity of the share of dual-eligible enrollees within a contract by employing an instrumental variable analysis. We show that MA contracts with a higher share of dual-eligible enrollees perform worse on measures in the Intermediate Outcome category, which includes medication adherence and blood pressure control. The current design of the P4P scheme provides a source of financial disincentive to MA contracts to provide coverage for dual-eligible beneficiaries and potentially impact plan selection for this population.

2.2 Introduction

Provider reimbursement based on performance, often referred to as pay-for-performance (“P4P”) or value-based purchasing, has become the mainstay method in improving quality in health care (Blumenthal & Dixon, 2012). This reimbursement scheme is aimed

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3 Co-authors: Ivy Dong, FSA, and Chunwei Wang, PhD from InnovaCare Health
at addressing the principal-agent problem within health care delivery where providers act as “agents” for the purchasers (“principals”) of health care, be it health plans or patients. Agents may not always make decisions that result in quality levels that are desired by the principals (Ellis & McGuire, 1986). Employing pay-for-performance is one way to financially induce providers to provide higher quality care by reimbursing providers at a higher level for meeting certain quality metrics. However, a major challenge lies in how to properly define and design how quality is measured (Rosenthal & Frank, 2006). A recent review of P4P programs shows the return on investment varies widely across programs and depends heavily on the design of the program (Van Herck et al., 2010); additionally, potential unintended consequences can occur when providers choose to avoid high risk patients in order to maximize incentive payments (McGuire, Newhouse, & Sinaiko, 2011). This paper focuses on a recent example of P4P within the Medicare Advantage (MA) program and its potential impact on the dual eligible Medicare population.

Historically, payment reforms in MA reimbursement have produced inconsistent results regarding beneficiary access and cost savings - the two main goals of MA plans (Medicare Advantage Fact Sheet, 2015). Recently, as a part of the passage of the Affordable Care Act in 2010, the Centers for Medicare and Medicaid Services (CMS) began to attach incentive payments to the Five Star Quality Rating System for Medicare Advantage plans. The goal is to create financial incentives for MA plans to provide higher quality care to Medicare beneficiaries. Since the inception of this policy, CMS has paid out approximately $8 billion dollars in bonus payments between 2012 and 2014.
Expectedly, a recent report by the Office of the Assistant Secretary for Planning and Evaluation (ASPE) shows that since the inception of this payment reform policy, MA plans have been improving in quality, enrollment in these plans remains high, and plan profitability remains strong (2014).

However, there is some concern that the current design of the quality measures might pose additional challenges to those MA contracts that have a higher share of dual-eligible enrollees within their population. Dual-eligible enrollees are low-income individuals who qualify for both Medicare and Medicaid and can pose unique challenges to managed care organization in care coordination and population health management (Cassidy, 2012). In this study we examine whether there is a relationship between the share of dual-eligible enrollees within a contract and a contract’s performance in the CMS five star quality measures. While a number of studies and industry reports have shown that there are correlations between dual-eligible enrollees and lower quality star ratings, none have shown a causal relationship (Inovalon Inc., 2013; National Quality Forum, 2014).

The main challenge in establishing causality lies in the potential unobserved factors that could be influencing the MA contract’s exposure to dual-eligible enrollees and their overall five star rating performances. Contracts that are simpler better at disease/case management due to organizational resources could choose to have a higher exposure to dual-eligible enrollees. We are able to address this threat to the validity of establishing
causality through an instrumental variable approach as well as a fixed effects panel model.

The structure of the paper is as follows: Section 3 reviews the structure of the five star quality rating system and outlines a conceptual framework for the potential impact of dual-eligible enrollees on a plan’s star rating performance. Section 4 describes the data and estimation strategy. Section 5 presents the findings and section 6 discusses limitations of the study, the results, and policy implications.

2.3 Background

2.3.1 The Five Star Quality Rating System

As part of the effort to provide more information to Medicare consumers during the plan selection process, starting in 2008, CMS developed the Five Star Quality Rating System to provide market signals to consumers around plan quality. The five star rating system rates MA contracts on a scale of 1 to 5 stars, with half star increments. CMS evaluates Medicare Advantage contracts based on data from these sources:

- Member surveys conducted by CMS
- Information from clinicians
- Plan-submitted information
- Results from CMS monitoring activities

CMS develops the overall star rating of a contract by evaluating each contract on over 50 specific quality measures spanning 5 (CMS-defined) categories:
• Process (i.e. cancer screening, cholesterol control, pain screening, improving bladder control etc.),
• Access (i.e. beneficiary access and performance problems, plan makes timely decisions about appeals etc.),
• Patient Experience and Complaints (i.e. Overall rating of health care quality, complaints about the health plan etc.),
• Intermediate Outcomes (i.e. Diabetes care-blood sugar controlled, controlling blood pressure, medication adherence etc.),
• Outcomes (i.e. plan all-cause readmissions, health plan quality improvement etc.)

Separations between half ratings are based on thresholds for each measure that are developed using statistical modeling approaches (Medicare 2014 Part C & D Star Rating Technical Notes, 2014). Each measure is also then assigned a weight (Table 2.7.1) and the weighted average of a plan’s performances across all individual criteria is the plan’s overall star rating. Finally, an integration factor (i-factor) that accounts for the variance of contract performance scores over time is applied to reward plans with consistently high performance.

One important aspect of the CMS star rating system is CMS’s utilization of case-mix adjustments. In calculating the individual star ratings, CMS applies a case-mix adjustment to the CAHPS (Medicare Consumer Assessment of Health care Providers and Systems) measures. Most CAHPS measures fall under the Patient Experience category and are based on survey responses. The case-mix adjustment takes into consideration differences in the characteristics of enrollees that may potentially impact survey
responses. Case-mix variables include dual eligible status, education, age, and general health status. Aside from CAHPS measures, other five-star quality measures are not case-mix adjusted, and all contracts are measured using identical rating thresholds. Since only Patient Experience measures are case-mix adjusted, we expect the impact of the share of dual-eligible enrollees in a contract to be smaller for the Patient Experience and Complaints measures.

2.3.2 Dual-Eligible Enrollees and Special Needs Plans

Special needs plans (SNP) were established in 2006 by the Medicare Modernization Act. These plans target three particular types of special-needs populations within the Medicare beneficiary pool: 1) those individuals who are institutionalized, 2) those individuals with severe or disabling chronic conditions, and 3) those individuals who qualify for both Medicare and Medicaid services. The last set of individuals is referred to as dual-eligible enrollees and make up most of the SNP population at about 80% (Medicare Advantage Fact Sheet, 2014). DE enrollees are typically enrolled in a Dual-Eligible Special Needs Plan (D-SNP) that allows dual-eligible enrollees to have coordinated, Medicaid and Medicare reimbursement for their health expenditures.

Dual-eligible enrollees are more likely to be disabled, have multiple chronic conditions and be more costly (CBO, 2013). While dual-eligible enrollees comprise 21 percent of the total Medicare enrollment, they are responsible for 36 percent of total Medicare spending. Similarly with Medicaid, dual-eligible enrollees make up only 15 percent of Medicaid enrollment while their spending represents 39 percent of total Medicaid annual
expenditures. SNP plans are reimbursed at a higher rate from CMS because SNP individuals have higher than average risk scores and have more complex health needs.

### 2.3.3 Conceptual Framework

We hypothesize that the share of dual-eligible enrollees would impact a plan’s performance in the Patient Experience, Intermediate Outcomes, and Outcomes categories and have no impact on the measures in the Process and Access categories.\(^4\) We motivate our thinking as follows.

The Process category includes those measures that are related to standards of care at the point of service. These measures are designed to capture whether providers are giving beneficiaries the appropriate screenings and examinations during an office visit. Since the performance of these measures are largely motivated by physician behavior that should not be linked with the dual-eligible status of their patient, we do not expect that a MA plan with a higher share of dual-eligible enrollees would perform worse or better than other plans.

The Access category includes measures related to the health plan administration issues that might create barriers to beneficiaries accessing the care that they need, an example being whether the health plan makes timely decisions on member appeals. Similar to the reasoning for the Process category, performance measures here are largely measuring the

\(^4\) This reasoning is the main motivation behind using the five rating categories as separate outcome categories within our analysis.
overall administrative functioning of the health plan and should be largely independent of the dual-eligibility status of the beneficiary.

For the Patient Experience category, we do hypothesize a relationship between dual-eligible enrollees and the plan’s performance on these factors. From the classic Aday and Andersen behavioral model on access to care, we know that an individual’s socioeconomic factors (income, education, occupation) can influence the way they interact with the healthcare system, as well as their overall level of satisfaction with the care they receive (Aday & Andersen, 1974). However, since CMS already adjusts for dual-eligibility status in calculating these performance metrics we do not expect to see a large impact in this category.

The final two categories are Intermediate Outcomes and Outcomes. While Outcomes measures focus on the improvements in a member’s overall health, Intermediate Outcomes are proximal measures that would lead to improvements in the Outcomes, such as blood pressure management. We hypothesis that plan performance on these two categories would be impacted by the share of dual-eligible enrollees, as the ultimate health of an individual can be largely influenced by an individual’s socioeconomic characteristics. One main pathway is the influence of an individual’s socioeconomic status on the individual’s health behavior (Adler & Newman, 2002).
2.4 Data and Estimation Strategy

2.4.1 Data

Our analyses are at MA contract level since that is the level at which CMS evaluates five star rating performances. We use the 2012 - 2015 Part C and D Performance Data that contains contract-level star rating performance for each of the individual star measures. The data are publicly available from the CMS website\(^5\). We also use the Monthly Enrollment by County/Plan/State data sets from the CMS website for county-level enrollment for each plan under each contract\(^6\). In order to identify the share of dual eligible population within each contract, we use the Special Needs Plan Data from the website\(^7\). We use county-level socioeconomic variables from the United States Department of Agriculture (USDA) Economic Research Service and the United States Census Bureau that get at education level.

For star rating data we began with the CMS website and obtained contract-level historical ratings for individual performance measures for rating years 2012 through 2015, which reflects actual plan data from 2010 through 2013. We limit our data set to only those plans that received an overall rating score from CMS\(^8\). This ranged from 440 contracts in 2012 to 395 contracts to 2015. Within the four years of panel data, 69% of the contracts

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\(^5\) http://www.cms.gov/Medicare/Prescription-Drug Coverage/PrescriptionDrugCovGenIn/PerformanceData.html


\(^8\) CMS does not provide an overall rating score for a contract when the minimum number of measures having a rating is not met for each contract type
were in our sample for all four year and 78% of the contracts were in our sample for at least 3 years.

For the outcome variables, we constructed composite scale variables from individual rating measure variables within each of the 5 measurement categories. The composite performance variables are constructed as scales using all measures that fall into the measurement category. The Cronbach’s alpha was calculated for each scale created and these are presented in Table 2.7.2.

The Cronbach’s alpha measures the internal consistency of the constructed scale and provides a score for how well the measures within the composite scale fit together in measuring the underlying latent construct. We note that the Cronbach’s alpha is low for the Access and Outcomes composite measures. We address this by running each of the performance measures under Outcomes in separate regressions.

In order to quantify the share of dual-eligible enrollees within each contract, we used the Special Needs Plan (SNP) data from the CMS website. The SNP data from CMS flags all SNP plans under each contract and provides the SNP type for each of these plans, with each SNP falling into one of three categories: 1) Chronic or Disabling Condition, 2) Dual Eligible and 3) Institutional. With this data, we were able to identify all plans under each contract that were a D-SNP plan, or a SNP plan in general. To calculate the percentage
of a contract’s enrollment that is in a D-SNP plan, we used the enrollment data from CMS to map the number of members that are enrolled in each plan for each rating year. We then calculate the percentage of a contract’s enrollment that is in a D-SNP plan.

We utilized a similar process to develop a contract-level Medicare Part C risk score. We obtained the plan level average Medicare Part C risk score from CMS and weighted the risk score for each plan by its enrollment and summed the weighted risk score across all plans under a contract to get at the weighted average risk score for each contract.\textsuperscript{9}

We included in our data several socioeconomic variables:\textsuperscript{10} education level (percentage of adults age 25 and older without a high school diploma in the counties in which the contracts are located), poverty level (percentage of people of all ages below the federal poverty level in the US), and county-level median household income (annual median household income in the US). We merged these data with the MA enrollment data by linking the Federal Information Processing Standards (FIPS) state and county codes. We then calculated the weighted average of the socioeconomic factors by enrollment for each contract.\textsuperscript{11}

\textsuperscript{9} For the 2015 rating year, we utilized the risk score data from the 2014 rating year as the 2015 risk score data is not yet available.
\textsuperscript{10} Ultimately, we only included the education level variable in our final models due to overlapping nature of the poverty and income variables with the dual-eligible measure.
\textsuperscript{11} For 2015 rating year we used poverty level and median household income in 2012 since it is the latest available data in the US Census Bureau website; in addition, the 2008 - 2012 average percentages were used as the education level for all years in our analysis.
2.4.2 Empirical Model

In order to identify the causal relationship between the percentage of dual-eligible enrollees and the performance of MA plans in the CMS Five Star Quality Rating System, we employ a fixed effects panel model. The advantage of panel data is that it allows us to control for omitted characteristics of each MA contract that are different across contracts but are constant over time. The fixed effects model is only looking at the within-contract variations when estimating the coefficients of interest. There are a number of contract-level characteristics that can influence a contract’s five star rating performance that are unobservable to the researcher, such as the MA organization’s health-informatics capabilities and its provider contracting negotiating powers. By using the fixed effects panel model, the within estimator model, we are only looking at the relationship between the predictor and outcome variables within each contract.

We estimate the following model:

\[
\text{OutcomeCategory}_{i,t} = \alpha_i + \lambda_t + \rho \text{PercentageDualEligibles}_{i,t} + \delta \text{RiskAdjustmentScore}_{i,t} + \\
\gamma \text{education}_{i,t} + \mu_{i,t}
\]

where

\[
\alpha_i \equiv \alpha + A_i \eta
\]

OutcomeCategory_{i,t} is the score in a particular measure category for plan \( i \) at time \( t \). The variable PercentageDualEligibles_{i,t} is the main variable of interest, with \( \rho \) representing the causal impact of the percentage of dual-eligible enrollees in a contract. In addition, we
control for a contract’s overall population risk level with RiskAdjustmentScore\textsubscript{i,t} and the prevalence of low education levels in a contract’s service area with education\textsubscript{i,t}.

The key assumption for identification is that the unobserved $A_i$ does not have a time subscript. In the fixed effects panel model, we estimate the coefficient $\alpha_i$ for each MA contract and eliminate the effects of unobserved $A_i$ on the outcome variables. We similarly control for time trends by using a rating-year fixed effect, $\lambda_t$. In order for identification in a fixed effects panel model, we need to have enough variation in the variable of interest, the percentage of dual-eligible enrollees in a contract. Approximately 84% of the contracts with dual-eligible plans within our sample experience fluctuations in the percentage of dual eligible enrollment percentage. Figure 2.8.1 shows the year-to-year fluctuation in D-SNP enrollment for 50 contracts within our sample. One challenge to causality that isn’t addressed by our model is the potential endogeneity of the share of dual-eligible enrollees of a contract. It is possible that contracts are choosing their level of exposure to dual-eligible enrollees in their contract in response to their performance levels. We address this issue through the utilization of an instrumental variable (IV).

The IV analysis instruments for the share of dual-eligible enrollees in a contract by using the proportion of dual-eligible beneficiaries in the service area of each contract. The instrument is constructed using CMS Part C enrollment files. We calculate, for each county, the total D-SNP enrollment and the total overall enrollment for all plan types for
all contracts. For each MA contract, we then calculate the percentage of dual-eligible enrollees for the service area of the contract.

We estimate the following IV two-stage least squares (2SLS) model:

\[
Percentage\text{Dual\ Eligibles}_{i,t} = \beta \times Percentage\text{Dual\ Eligibles}\text{InServiceArea}_{i,t} + \delta \text{controls}_{i,t} + \epsilon_{i,t}
\]

\[
Outcome\text{Category}_{i,t} = \tau_{i} + \rho \times Percentage\text{Dual\ Eligibles}_{i,t} + \delta \text{controls} + \mu_{i,t}
\]

We next examine the validity of the instrument. The first criterion for a valid instrument is that of instrument exogeneity. For this, we reason that the proportion of dual-eligible enrollees in the overall enrollment of the service area of a contract (IV) influences the share of dual-eligible enrollees for a given contract in two ways: One, contracts with plans in service areas with higher concentration of dual-eligible enrollees are more likely to offer D-SNP plans so to capture revenue from this population. Two, contracts with D-SNP plans in areas of higher concentrations of dual-eligible enrollees are more likely to have higher enrollment of dual-eligible enrollees in their plans. We next examine whether the IV satisfies the exclusion restriction, or that the IV does not have an effect, either directly or through omitted variables, on the star rating performance of the contracts. To the extent that we believe that the MA contracts are not choosing the concentration of dual-eligible enrollees within the service area of their contracts, it is plausible to believe that the IV is unrelated to the dependent variable. This is not an unreasonable assumption since we are considering the service area of the entire MA contract, which in most cases
includes multiple plans of various types (SNP and non-SNP). It is therefore not likely that the contract is choosing the service area for the entire contract based specifically on dual-eligible enrollee concentration. Next, we consider whether there are reverse effects of the dependent variable on the instrument. We can rule this out since it does not make much conceptual sense that a contract’s star rating performance would influence the concentration of dual-eligible enrollees in its service area.

For the next criterion of a valid instrument, we test instrument relevance by testing for a possibly weak instrument and underidentification using the Cragg-Donald Wald F statistic and the Anderson canonical correlation LM statistic, respectively. These test statistics are presented with the model estimates in the findings section.

2.5 Findings

2.5.1 Summary Statistics for Contracts With and Without Dual-Eligible Enrollees
Table 2.7.3 shows the variation across plans in rating year 2015. Those plans with a non-zero dual eligible enrollment are generally performing at a lower level than those plans without any dual eligible enrollment.

2.5.2 Star Ratings for Contracts With and Without Dual-Eligible Enrollees
Consistently by year, those contracts without any dual-eligible enrollees have a higher proportion of star ratings above 3 (Figure 2.8.2). For those contracts with a non-zero number of dual-eligible enrollees, the distribution of star ratings is comparatively much more clustered at the lower ratings. Additionally, we also note that there is a general
increase over time in star ratings across all contracts as higher proportions of contracts receive star ratings above 3.

Figure 2.8.3 shows the average star rating of contracts with and without dual-eligible enrollees. Those contracts with dual-eligible enrollees have lower average star ratings for all measures, but with the biggest difference in the Intermediate Outcomes categories.

2.5.3 Predictors of Measure Performance

Table 2.7.4 presents the results from the OLS regression for the 5 performance measure categories. The coefficient on the share of a contract’s dual eligible population is highly significant and negative in all performance categories, except Access. We note that % DSNP is a significant predictor for Patient Experience measures despite earlier discussion of CMS’ case-mix adjustment for CAHPS measures that include dual-eligibility status. A flaw in this analysis is the failure to control for contract-level characteristics that may be influencing performance. We next present our results for the fixed effects and IV models.

2.5.4 Process, Access and Patient Experience Measure Categories

Table 2.7.5 presents our findings for the performance measures under Process, Access and Patient Experience categories. We show both the fixed effects model and the IV model. In the first stage estimates of the IV models, we see the expected effects: the proportion of dual-eligible enrollees in a contract’s service area has a positive and significant correlation with the share of dual-eligible enrollees a contract has in their beneficiary population. The instrument tests show that the instrument is not weak with a Cragg-Donald F Statistic of 22.54 (with the rule of thumb that the F statistic should be
>10). Furthermore, the underidentification test shows a p-value <0.05, which indicates the model is not underidentified.

Measures under the Process category include screening measures (colorectal cancer screening, cholesterol screening for cardiovascular care, cholesterol screening for diabetes care etc.), measures for older adults (medication review, function status assessment, pain screening), measures related to diabetes (eye exam, kidney disease monitoring) and other general measures such as improving bladder control and reducing the risk of falling. For this measure category, we find no relationship between the share of dual-eligible enrollees in a contract and its performance in the fixed effects model and the IV model, as we expected in our conceptual framework.

Measures under the Access category include: whether beneficiaries are having problems getting access to services, whether plans are making timely decisions about beneficiaries’ appeals, whether plan call centers have foreign language interpreters, etc. For this category of measures, we find a negative relationship in the fixed effects model between the percent of dual-eligible enrollees and performance; but we find no effect in the instrumented model.

The last two columns in the table show the results for Patient Experience measures. In the fixed effects model, we find no significant relationship between the share of a contract’s
dual eligible population and Patient Experience measures. However, second stage estimations of the IV model shows a positive and significant relationship between the percentage of D-SNP enrollees and the contract’s performance in Patient Experience measures where a 10% increase in a MA contract’s DE enrollees causes a 0.7 increase in average star ratings.

2.5.5 Intermediate Outcome Category

Table 2.7.6 presents our results for the Intermediate Outcome category. Within this category are measures that include medication adherence (whether beneficiaries are taking/refilling oral diabetes/blood pressure/cholesterol medication as directed), measures around diabetes care (blood sugar control, cholesterol control), whether beneficiaries have their blood pressure under control, and whether beneficiaries are getting the appropriate drugs. The fixed effects model shows a significant and negative coefficient of -0.055 for the percent of dual-eligible enrollees in a contract. When we look at the IV model, this effect is even larger with a coefficient of -0.607. This indicates that when the percentage of DE enrollees increases 10% within a contract, the average star rating for Intermediate Outcome measures fall by a little over a half star. The larger magnitude of the instrumented fixed effects model might be an indication that in the uninstrumented model, the coefficient was downwardly biased due to MA contracts that were generally higher five star rating performers choosing to have a higher exposure to dual-eligible enrollees.

2.5.6 Outcomes Category Measures

We next present the results for the five measures within the Outcomes category:
- Improving or Maintaining Physical Health
- Improving or Maintaining Mental Health
- Plan All-Cause Readmissions
- Health Plan Quality Improvement
- Drug Plan Quality Improvement

In the first stage estimates of the IV models (Table 2.10.7), we again see the hypothesized effects: the proportion of dual-eligible enrollees in a contract’s service area has a positive and significant correlation with the share of dual-eligible enrollees a contract has in their beneficiary population. However, the instrument tests show mixed results. While the underidentification test shows significant p-values for all five measures indicating no issues with underidentification, the weak instrument test shows that the IV is weak (with the Cragg-Donald F Statistic <10) for the models for the last 3 measures within the Outcomes category (these are detailed later in this section).

For the first measure of “Improving or Maintaining Physical Health,” the fixed effects model shows no significant relationship between dual eligible enrollment in a contract and the contract’s performance. The IV model reflects a similar finding. For “Improving or Maintaining Mental Health,” the fixed effects model shows a positive association between dual-eligible enrollees and the contract’s performance. This effect goes away in the IV model (because of standard errors).
For the next three measures, we note that the IV model shows a potentially weak instrument. The fixed effects model for “Plan All-Cause Readmission” indicates that a higher share of dual-eligible enrollees in a contract leads to a lower star rating on this measure. This effect is not mirrored in the IV model. For the two Plan Quality Improvement measures, we find that the fixed effects model finds no significant relationship between our main causal variable and the outcome. This is also reflected in the IV models.

2.6 Discussion

2.6.1 Limitations

Our analysis utilizes a number of econometric techniques to overcome potential threats to biased interpretations of causality. However, we are utilizing a relative short panel of 4 years, which limits the amount of within-contract variation to be exploited. In addition, the fixed effects model is only able to control for time-invariant unobserved heterogeneity and thus will not be able to control for within MA contract changes, such as changes in adoption of informatics, that vary over time. While we use an IV to address the endogeneity of the percent of dual-eligible enrollees in the contract, this instrument does not prove to be a strong instrument in all of our models. This is likely due to the reduction in sample size when we examine individual performance measures in the Outcomes category. In addition, the magnitude of the IV models seems unreasonable given the outcome variable range of 1 to 5. A possible reason for this is that both our endogenous variable and IV are probability variables ranging from 0 to 1 and a linear estimation model might not be the most appropriate. Similarly, our outcome variables are
non-negative and range from 1 to 5, it is possible that a linear model may not be the most appropriate.

We further note that the dynamics of the entry and exit of the Medicare Advantage market can be quite complex. Without studying a contract’s entry and exit from the MA market in association to its star rating, it is difficult to say that there isn’t selection bias occurring within the model. Although if poor-performing contracts are exiting the market, this would only work to attenuate our results towards more conservative estimates. Intended future work will include examining whether contracts choose to terminate D-SNP plans within their contracts in response to rating performances.

2.6.2 Findings

The share of dual-eligible enrollees in a MA contract negatively impacts the contract’s performance on Intermediate Outcome measures. These measures are weighted heavily with a factor of 3, similar to those measures in the Outcome category. Measurements within this category include those that are closely associated with patient behavior, such as medication adherence. Many studies have shown that an individual’s socioeconomic characteristics are closely tied to their health behaviors and outcomes (Adler & Newman, 2002; Link & Phelan, 1995). These factors are often outside the control of the plan and can require additional costs for a plan to meet the performance standards set by CMS.
In our earlier discussion, we noted that CMS utilizes case-mix adjustments for measures that fall under the Patient Experience category. The case-mix adjustment includes whether or not the beneficiary is dual-eligible. As such, we expected that the percentage of dual-eligible enrollees in a contract should not influence a contract’s performance in this area. We were partially correct in our hypothesis in that there is no negative impact but there was a positive impact. So plans with higher dual-eligible enrollees actually perform better for measures under Patient Experience. Could this be a potential over-adjustment on CMS’ part? Whether that’s true or not, we do observe the importance of case-mix adjustment in our results.

2.6.3 Policy Implications

Dual eligible Medicare enrollees are the most vulnerable and costly group among all Medicare beneficiaries. The creation of D-SNP plans was an important step in better managing the health and costs of this group. However, the success of D-SNP plans requires that the P4P design does not act to disincentivize MA organizations from entering the dual eligible market. If contracts begin to drop their D-SNP plans because they are unable to achieve higher star ratings, we will observe the MA market become more concentrated while the level of competition decreases with a small number of contracts dominating the D-SNP market. This will act to decrease beneficiary choice and can potentially reduce market efficiencies.

One way for CMS to address this issue is to adjust the way it currently calculates thresholds for star rating separations (i.e. what separates 3 stars from 3.5 stars or 3.5 stars from
4 stars). In order to account for the drivers of quality measure performances not under plan control, MA plans can be stratified into groups with similar SES and demographic factors during the CMS rating process. Separate cut points for each measure can then be established and applied to all plans within each of these groups. Such stratification could be based on the percentage of dual eligible members, or other SES factors. This can potentially result in a P4P scheme that is fairer for those contracts that operate dual eligible plans.
2.7 Tables

Table 2.7.1: Rating Year 2015 Five Star Quality Rating Weights for Calculation of Overall Star Rating

<table>
<thead>
<tr>
<th>Process</th>
<th>Access</th>
<th>Patient Experience</th>
<th>Intermediate</th>
<th>Outcomes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Weights</td>
<td>1.00</td>
<td>1.50</td>
<td>1.50</td>
<td>3</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>3</td>
</tr>
</tbody>
</table>

Table 2.7.2: Cronbach’s Alpha for Composite Measures of Each Five Star Quality Rating Category

<table>
<thead>
<tr>
<th>Process</th>
<th>Access</th>
<th>Patient Experience</th>
<th>Intermediate</th>
<th>Outcomes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cronbach’s Alpha</td>
<td>0.84</td>
<td>0.50</td>
<td>0.88</td>
<td>0.81</td>
</tr>
</tbody>
</table>

Table 2.7.3: Summary statistics: 2005 MA contract characteristics by share of dual-eligible enrollees in contract

<table>
<thead>
<tr>
<th>Overall Star Rating</th>
<th>Overall (Mean (SE))</th>
<th>No Dual Eligibles (Mean (SE))</th>
<th>Some Dual Eligibles (Mean (SE))</th>
</tr>
</thead>
<tbody>
<tr>
<td>Overall Star Rating</td>
<td>3.64 (0.61)</td>
<td>3.79 (0.56)</td>
<td>3.28 (0.61)</td>
</tr>
<tr>
<td>Dual Eligible %</td>
<td>0.18 (0.32)</td>
<td>0.00 (0.00)</td>
<td>0.44 (0.37)</td>
</tr>
<tr>
<td>Risk Score</td>
<td>0.999 (0.30)</td>
<td>0.93 (0.29)</td>
<td>1.09 (0.28)</td>
</tr>
<tr>
<td>Low Education</td>
<td>14.011 (4.62)</td>
<td>12.85 (3.77)</td>
<td>15.67 (5.20)</td>
</tr>
<tr>
<td>N</td>
<td>395</td>
<td>232</td>
<td>163</td>
</tr>
</tbody>
</table>
### Table 2.7.4: Predictors of Measure Performance (OLS)

<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>Process</th>
<th>Access</th>
<th>Patient Experience</th>
<th>Intermediate Outcome</th>
<th>Outcome</th>
</tr>
</thead>
<tbody>
<tr>
<td>% DSNP</td>
<td>-0.510***</td>
<td>0.0515</td>
<td>-0.610***</td>
<td>-0.919***</td>
<td>-0.182***</td>
</tr>
<tr>
<td></td>
<td>(0.0509)</td>
<td>(0.0838)</td>
<td>(0.0778)</td>
<td>(0.0630)</td>
<td>(0.0549)</td>
</tr>
<tr>
<td>Risk score: 0.7-0.8†</td>
<td>-0.00689</td>
<td>0.310*</td>
<td>-0.283*</td>
<td>0.0250</td>
<td>-0.168</td>
</tr>
<tr>
<td></td>
<td>(0.101)</td>
<td>(0.168)</td>
<td>(0.156)</td>
<td>(0.125)</td>
<td>(0.109)</td>
</tr>
<tr>
<td>Risk score: 0.8-0.9</td>
<td>0.00266</td>
<td>0.469***</td>
<td>-0.318**</td>
<td>-0.0477</td>
<td>-0.0550</td>
</tr>
<tr>
<td></td>
<td>(0.0857)</td>
<td>(0.150)</td>
<td>(0.139)</td>
<td>(0.111)</td>
<td>(0.0968)</td>
</tr>
<tr>
<td>Risk score: 0.9-1.0</td>
<td>0.138</td>
<td>0.531***</td>
<td>-0.146</td>
<td>0.102</td>
<td>-0.0716</td>
</tr>
<tr>
<td></td>
<td>(0.0896)</td>
<td>(0.149)</td>
<td>(0.139)</td>
<td>(0.111)</td>
<td>(0.0967)</td>
</tr>
<tr>
<td>Risk score: 1.0-1.1</td>
<td>0.211**</td>
<td>0.615***</td>
<td>-0.0309</td>
<td>0.182</td>
<td>-0.119</td>
</tr>
<tr>
<td></td>
<td>(0.0914)</td>
<td>(0.152)</td>
<td>(0.142)</td>
<td>(0.113)</td>
<td>(0.0987)</td>
</tr>
<tr>
<td>Risk score: 1.1-1.2</td>
<td>0.273***</td>
<td>0.682***</td>
<td>0.0366</td>
<td>0.211*</td>
<td>-0.0682</td>
</tr>
<tr>
<td></td>
<td>(0.0979)</td>
<td>(0.163)</td>
<td>(0.151)</td>
<td>(0.121)</td>
<td>(0.105)</td>
</tr>
<tr>
<td>Risk score: 1.2-1.3</td>
<td>0.297***</td>
<td>0.627***</td>
<td>-0.0868</td>
<td>0.146</td>
<td>0.0101</td>
</tr>
<tr>
<td></td>
<td>(0.113)</td>
<td>(0.187)</td>
<td>(0.174)</td>
<td>(0.140)</td>
<td>(0.122)</td>
</tr>
<tr>
<td>Risk score: 1.3-1.4</td>
<td>0.505***</td>
<td>0.630***</td>
<td>0.318*</td>
<td>0.510***</td>
<td>0.0552</td>
</tr>
<tr>
<td></td>
<td>(0.118)</td>
<td>(0.196)</td>
<td>(0.182)</td>
<td>(0.146)</td>
<td>(0.128)</td>
</tr>
<tr>
<td>Risk score: 1.4+</td>
<td>0.506***</td>
<td>0.798***</td>
<td>0.644***</td>
<td>0.610***</td>
<td>-0.121</td>
</tr>
<tr>
<td></td>
<td>(0.113)</td>
<td>(0.196)</td>
<td>(0.182)</td>
<td>(0.146)</td>
<td>(0.128)</td>
</tr>
<tr>
<td>Low Education</td>
<td>-0.0231***</td>
<td>0.00658</td>
<td>-0.0610***</td>
<td>-0.0827***</td>
<td>-0.00288</td>
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<tr>
<td></td>
<td>(0.00278)</td>
<td>(0.00457)</td>
<td>(0.00424)</td>
<td>(0.00344)</td>
<td>(0.00301)</td>
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<tr>
<td>2013 Rating Year</td>
<td>0.111***</td>
<td>-0.513***</td>
<td>0.0254</td>
<td>0.127***</td>
<td>-0.0529</td>
</tr>
<tr>
<td></td>
<td>(0.0343)</td>
<td>(0.0565)</td>
<td>(0.0524)</td>
<td>(0.0425)</td>
<td>(0.0371)</td>
</tr>
<tr>
<td>2014 Rating Year</td>
<td>0.292***</td>
<td>-0.442***</td>
<td>0.126**</td>
<td>0.171***</td>
<td>0.185***</td>
</tr>
<tr>
<td></td>
<td>(0.0346)</td>
<td>(0.0570)</td>
<td>(0.0530)</td>
<td>(0.0429)</td>
<td>(0.0374)</td>
</tr>
<tr>
<td>2015 Rating Year</td>
<td>0.378***</td>
<td>2.215***</td>
<td>0.390***</td>
<td>0.218***</td>
<td>0.236***</td>
</tr>
<tr>
<td></td>
<td>(0.0359)</td>
<td>(0.0592)</td>
<td>(0.0550)</td>
<td>(0.0445)</td>
<td>(0.0388)</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.173</td>
<td>0.636</td>
<td>0.195</td>
<td>0.382</td>
<td>0.065</td>
</tr>
</tbody>
</table>

Standard errors in parentheses

* p<0.01, ** p<0.05, * p<0.1

†Reference group is the risk score below 0.7
Table 2.7.5: Model results - Process, Access and Patient Experience

<table>
<thead>
<tr>
<th>Model Results</th>
<th>Process</th>
<th>Access</th>
<th>Patient Experience</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Fixed Effects</td>
<td>Instrumental Variable</td>
<td>Fixed Effects</td>
</tr>
<tr>
<td>First Stage for D-SNP %</td>
<td>---</td>
<td>0.242***</td>
<td>---</td>
</tr>
<tr>
<td></td>
<td>(0.086)</td>
<td>(0.086)</td>
<td>(0.086)</td>
</tr>
<tr>
<td>D-SNP %</td>
<td>-0.001</td>
<td>-0.237</td>
<td>-0.062</td>
</tr>
<tr>
<td></td>
<td>(0.025)</td>
<td>(0.158)</td>
<td>(0.056)</td>
</tr>
</tbody>
</table>

Note: Robust standard errors in parentheses. Regressions include contract-level and rating year fixed effects, prevalence of low education and risk scores.

*** p <0.01
**  p <0.05
*   p <0.1

Table 2.7.6: Model results - Intermediate Outcomes

<table>
<thead>
<tr>
<th>Model Results</th>
<th>Intermediate Outcomes</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Fixed Effects</td>
</tr>
<tr>
<td>First Stage for D-SNP %</td>
<td>---</td>
</tr>
<tr>
<td></td>
<td>(0.086)</td>
</tr>
<tr>
<td>D-SNP %</td>
<td>-0.055*</td>
</tr>
<tr>
<td></td>
<td>(0.032)</td>
</tr>
</tbody>
</table>

Note: Robust standard errors in parentheses. Regressions include contract-level and rating year fixed effects, prevalence of low education and risk scores.

*** p <0.01
**  p <0.05
*   p <0.1
Table 2.7.7: Model results – Outcomes Measures

<table>
<thead>
<tr>
<th>Regressions for individuals in the Outcomes category</th>
<th>Improving or Maintaining Physical Health</th>
<th>Improving or Maintaining Mental Health</th>
<th>Plan All-Cause Readmissions</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Fixed Effects</td>
<td>Instrumental Variable</td>
<td>Fixed Effects</td>
</tr>
<tr>
<td>First Stage for D-SNP %</td>
<td>---</td>
<td>0.208**</td>
<td>(0.099)</td>
</tr>
<tr>
<td>D-SNP %</td>
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<td>0.187</td>
<td>0.122</td>
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<td>(0.431)</td>
<td>(0.082)</td>
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<th>Drug Plan Quality Improvement</th>
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<td>Fixed Effects</td>
</tr>
<tr>
<td>First Stage for D-SNP %</td>
<td>---</td>
</tr>
<tr>
<td>D-SNP %</td>
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</tr>
<tr>
<td></td>
<td>(0.173)</td>
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</table>

Note: Robust standard errors in parentheses. Regressions include contract-level and rating year fixed effects, prevalence of low education and risk scores.

*** p < 0.01
** p < 0.05
* p < 0.1
2.8 Figures

Figure 2.8.1: Fluctuations in D-SNP Enrollment for 50 Contracts within Sample
Figure 2.8.2: Star Rating Performance Distribution of Contracts by Dual-Eligible Enrollment Status
Figure 2.8.3: Average Star Rating for Performance Measure Categories by Dual Eligible Enrollment Status

AVERAGE STAR RATING BY MEASUREMENT CATEGORY, RATING YEAR 2015

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2.9 References


Medicare Part C. Milbank Quarterly, 89(2), 289-332.


3. Impact of Federal Matching of State Medicaid Programs on State Medicaid Spending

3.1 Abstract

This paper examines the relationship between federal matching into state Medicaid programs and the level (both absolute and proportional) of Medicaid spending for 1980 to 2000. Using an instrumental variable model while controlling for state fixed-effects, the results do not show a significant relationship between the level of Medicaid spending and the level of FMAP. However, there is a positive and significant relationship between the level of a state’s FMAP and the proportion of the healthcare spending by the state that is going into Medicaid services.

3.2 Introduction

This study examines the relationship between Federal funding of state Medicaid programs and the level of Medicaid spending within a state, both at the absolute level and the proportional levels. The Federal government subsidizes each state’s Medicaid program in the form of the Federal Medical Assistance Percentage (FMAP) at levels that are commensurate with the relative income level of the state. States that are poorer than the national average receive a higher matching percentage that is capped at 83%, while higher income states receive as low as 50% (Peterson, 2010). While Medicaid is run at the state level, the subsidy received by these states has the potential to influence the allocation of funds within the state budget. I examine the change in Medicaid spending level in two ways: 1) The absolute level of Medicaid spending in the state budget and 2) the relative share of healthcare spending by the state that is going towards Medicaid.
In the same spirit as other empirical works examining state budgeting behavior, I utilize the median voter model to motivate how states make their budgets and respond to government subsidy (Gramlich & Rubinfeld, 1982; Baicker 2001). In this model, state policymakers are assumed to be rational decision-makers who maximize the utility of their median voter.\(^{12}\) Politicians often choose to maximize the preferences of the median voter as a way to gain the majority of the votes. In addition, I test the Ricardian equivalence theory of state consumption in the face of federal government budget constraint (Barro, 1988)\(^ {13}\). Given that the theory holds, states should not alter the level of Medicaid spending in response to the federal subsidy of Medicaid expenditures.

This utility function contains two parts, the voter’s utility from private consumption and also the utility of transfers to other individuals through Medicaid, which can be interpreted to be an altruism function. Using this framework, I motivate the impact of the FMAP on state spending on Medicaid.

This is the only study to examine the relationship between the state’s level of FMAP and Medicaid spending. In order to address the bias of unobservable factors that correlate with the FMAP and state Medicaid spending, an instrumental variable model is used for the FMAP.

\(^{12}\) The median voter is defined to be voter that holds the preferences that lie at the median of all voter preferences if all voter preferences can be ordered on a continuous line. This applies in situations where the political issue can be measured with a continuous variable, such as tax rates and in this instance, how much to spend on Medicaid.

\(^{13}\) The Ricardian Equivalence theorem, as proposed by Ricardo, De Viti and Barro, hypothesizes government budgetary actions in the form of taxes and issuing bonds will not impact consumer behavior such that tax cuts and spending increases by the federal government will not influence aggregate demand.
The structure of the paper is as follows: Section 3 provides the conceptual framework for the potential impact of FMAP on state Medicaid spending. Sections 4 and 5 describe the data and econometric approach. Section 6 presents the results. Section 6 discusses the results, policy implications, and limitations.

3.3 Conceptual Framework

Federal subsidies for the state Medicaid programs have the effect of decreasing the price of Medicaid for states as well as freeing up state budget for other state expenditures. One would hypothesize that the injection of federal funds into the state Medicaid programs will increase the states’ spending on Medicaid through income and substitution effects. However, a major challenge to this hypothesis is the potential fungible nature of these federal monies within the state.\textsuperscript{14} This would predict that state governments, when faced with federal subsidies that free up money for the state Medicaid program, would redirect the funds to other portions of the state budget. This would be reflected as a decrease in the state Medicaid spending since as the FMAP increases, the state government would be responsible for a smaller proportion of the Medicaid expenditures.

I begin with the assumption of the state being a rational decision maker that acts to maximize the utility of the median voter (Gramlich & Rubinfeld, 1982; Baicker 2001). Here the median voter is defined to be the voter whose views on a political agenda are at

\textsuperscript{14}A clear example of fungible state funds can be found in the relationship between state lotteries and education funding. State lottery programs are often touted to be the solution for education funding, with the proceeds of the lottery programs going towards education. However, empirical studies have shown that state lottery funds are fungible and often do not increase education funding as promised. Even when lottery funds are earmarked for education, as lottery funds flow into education, other funds are flowing out of education (Pantuosco, Seyfried, & Stonebraker, 2007).
the middle of spectrum. The Median Voter Theorem, as formalized by Duncan Black, predicts that the median voter will be the one casting the decisive vote in a political election and as such politicians vying for the majority of votes from the group will be best off when they act to appeal to the median voter directly (1948).  

The utility of the median voter is given as follows:

\[ U = u(y - \tau) + \alpha(\vec{X}, \vec{T}) \]

where the \( u(.) \) is utility derived from personal consumption, which is a function of income \( y \) net taxes \( \tau \). The second part of the voter’s utility function is the individual’s level of utility that is derived from the transfers to other individuals through the Medicaid program. This altruism function is determined by a vector of demographic differences between the individual and the recipients and also a vector of the transfers.

I next define total taxes to be the total of state and federal taxes as \( \tau = \tau_s + \tau_f \). In addition, we simplify the model and define the total state population \( (N) \) to be total sum of those individuals whose taxes fund Medicaid, or median voters \( (N_M) \), and those individuals who receive Medicaid \( (N_R) \), such that \( N = N_M + N_R \) and \( N_R \) is a function of the size of the transfer \( (T) \).

As such the median voter’s budget constraints are as follows:

\[ N_M \tau_s \geq N_R (T)(1 - FMAP) \]
\[ N \tau_f \geq N_R (T)(FMAP) \]

\[ ^{15} \text{This is similar to the Hotelling theory about voters/shoppers willing to travel to the option with the least distance from themselves.} \]
Where the $N_M$ is the number of voters of the “median” variety and $N_R$ is the number recipients of Medicaid, which is a function of the size of the transfer, $T$. The first budget constraint (equation 2), dictates that the total cost of the Medicaid program less the federal discount does not exceed the total tax revenue collected from all median voters. The second budget constraint imposes that the total federal subsidy into the state subsidy program does not exceed total tax revenue from \emph{all} voters in the state.\footnote{I utilize this specification due to the assumption that while the state policymaker receives taxes from taxpayers of all types, including those of non-median type, the budget constraint is from the perspective of the median voter as politicians have an incentive to make decisions on behalf of the median voter; such that, the taxes collected from the median voters influences the selection of $T$. I then further extend the budget constraint from Baicker’s 2001 paper to include the federal component of the median voter’s taxes. I define equation 3 to reflect that the median voter recognizes that while they are the median voter within their state, they are not necessarily the median voter from the federal government’s perspective and as such equation 3 contains all voters in the median voter’s state.}

Solving for $\tau$, I get the following:\footnote{For simplicity, $N_R(T)$ is assumed to be $NxT$, where $N$ is some constant.}

$$
\tau = \tau_s + \tau_f = NT^2 \left( \frac{FMAP}{N} + \frac{1 - FMAP}{N_M} \right)
$$

Maximizing (1), subject to (2) and (3):

$$
U = u \left[ y - NT^2 \left( \frac{1}{N_M} - \left( \frac{1}{N_M} - \frac{1}{N} \right) FMAP \right) \right] + \alpha(\tilde{x}, \tilde{T})
$$

Solving for $T^*$, I get:

$$
\frac{\partial U}{\partial T} = \frac{\partial u}{\partial c} \left\{ -2NT \left[ \frac{1}{N_M} - \left( \frac{1}{N_M} - \frac{1}{N} \right) FMAP \right] \right\} + \frac{\partial \alpha}{\partial T} = 0
$$

where $c = y - \tau$.

$$
T^* = \frac{\frac{\partial \alpha}{\partial T}}{2NT \left[ 1 - \left( 1 - \frac{N_M}{N} \right) FMAP \right] \frac{\partial u}{\partial c}}
$$

I next look at the first order condition of $T^*$ with respect to changes in the FMAP.
\[
\frac{\partial T^*}{\partial FMAP} = \frac{\partial \alpha}{\partial T} \left[ P - P \left( 1 - \frac{N_M}{N} \right) FMAP \right]^2 \left[ P \left( 1 - \frac{N_M}{N} \right) \right]
\]

where \( P = 2NT \frac{\partial u}{\partial c} \)

Since \( N \) is always larger than \( N_M \), \( 1 - \frac{N_M}{N} \) is always positive and nonzero. And \( P \) is also always positive and nonzero since \( N \) and \( T \) are always positive. As such, the denominator is always positive. I further make the assumption that the individual’s marginal utility is positive in the transfer payment. Thus \( T \) increases in the FMAP as long as the median voter’s marginal altruistic utility from the transfer payment is nonzero. This is in contradiction to the Ricardian Equivalence theorem, which would dictate that consumers would not be responsive in demand for a good in response to governmental stimulus (Barro, 1976). As such, the conceptual framework would predict that states would either increase or not decrease the level of Medicaid spending in the face of a higher federal matching rate.

### 3.4 Data

The analysis is at the state-level with panel data spanning 1980 through 2000. The main source of data is the United States Census Bureau. Title 13, United States Code, Section 182 authorizes the United States Census Bureau to collect an annual survey of state and local government finances.\(^{18}\) Data included in this analysis are summarized in Table 3.8.1 and described below.

\(^{18}\) [http://www2.census.gov/govs/estimate/2009_Local_Finance_Methodology.pdf](http://www2.census.gov/govs/estimate/2009_Local_Finance_Methodology.pdf)
3.4.1 Medicaid spending levels

In this analysis, two separate outcome measures of state Medicaid spending are utilized. First, I use a log-transformed level of Medicaid spending; log transformation of healthcare expenditures is a commonly employed methodology to address the positive-skewness, and nonnegative measurement of the outcome - shown in Figure 3.9.1 (Manning & Mullahy, 2001).¹⁹

Second, I calculate the relative percentage of a state’s health care costs that are going towards Medicaid. This variable is calculated by dividing the Medicaid spending of each state by the total healthcare expenditures of the state government.²⁰ The policy question addressed here is whether a state will allocate a larger portion of its healthcare spending to the Medicaid population if the price of Medicaid decreases.

3.4.2 Historical Federal Medical Assistance Percentage

The main independent variable of interest is the FMAP level of the state. This data is available as compiled by the Office of the Assistant Secretary for Planning and Evaluation (ASPE).²¹ For ease of interpretation within this analysis, the FMAP variable is log transformed so that the estimated coefficient can be interpreted as the elasticity of the FMAP on the Medicaid spending.

¹⁹ Within this data, we have evidence of positive-skewness as the mean (1,251.04) is to the right of the median (593.47) and a nonnegative measure of outcome.
²⁰ Total healthcare expenditures includes the following: Outpatient health services, other than hospital care, including: public health administration; research and education; categorical health programs; treatment and immunization clinics; nursing; environmental health activities such as air and water pollution control; ambulance service if provided separately from fire protection services; and other general public health activities such as mosquito abatement. School health services provided by health agencies (rather than school agencies) are included here.
²¹ http://aspe.hhs.gov/health/fmapearly.htm
3.4.3 Instrumented FMAP

The challenge in establishing the relationship between the FMAP and state Medicaid spending is the possibility of unmeasured confounders that are co-related with these two variables. Since states that receive higher levels of the FMAP are systematically poorer, they may have a higher proportion of residents who are Medicaid-eligible. Alternatively, these states may also face additional fiscal challenges and face the need to limit Medicaid spending by reducing provider reimbursement rates or limiting eligibility. This endogeneity is addressed by using an instrumental variable approach (Cameron & Trivedi, 2005). Data from the Bureau of Economic Analysis (BEA) is used with historical state-level per capita income broken out by industry type. The FMAP was constructed for each state each year by using per capita income that reflect the industry composition of each state in 1958 and annual national growth trends in income in each of those industries for each year subsequent to 1958. The calculated state per capita incomes are then used to calculate the instrument variable for the FMAP using the FMAP formula as in section 3.2. The idea is that, by holding the occupational composition of a state fixed, we measure a state’s exposure to sector-specific, exogenous economic shocks that affect state income and the FMAP. The instrument relevance condition is satisfied by the fact that economic shocks are correlated with income and the FMAP. The exogeneity (exclusion) requirement is satisfied by the fact the shocks are “simulated” using national economic trends, which is reasonably uncorrelated with state Medicaid spending levels. This method is similar to the IV used in Bartik’s paper (1991).

3.5 Estimation Strategy

The following two-stage models are estimated for the two outcome variables:
Logged Medicaid Spending

\[
\text{LogFMAP}_{it} = \beta_0 + \beta_1 \text{LogFMAP}_{Bartik} + \beta_2 \text{population}_{it} + \beta_3 \text{LogStateRevenue}_{it} + u_i + u_t + \zeta_{it}
\]

\[
\text{LogMedicaid}_{it} = \alpha_0 + \alpha_1 \text{LogFMAP}_{it} + \alpha_2 \text{population}_{it} + \alpha_3 \text{LogStateRevenue}_{it} + u_i + u_t + \epsilon_{it}
\]

for each state \(i\) in year \(t\), where \(\zeta_{it}\) and \(\epsilon_{it}\) are not correlated.

The main coefficient of interest is \(\alpha_1\), which measures the percentage change in Medicaid spending levels in response to a percentage change in the FMAP level.

Share of Healthcare Spending by State on Medicaid

\[
\text{LogFMAP}_{it} = \gamma_0 + \gamma_1 \text{LogFMAP}_{it} + \gamma_2 \text{population}_{it} + \gamma_3 \text{LogStateRevenue}_{it} + u_i + u_t + \zeta_{it}
\]

\[
\text{ShareMedicaid}_{it} = \gamma_0 + \gamma_1 \text{LogFMAP}_{it} + \gamma_2 \text{population}_{it} + \gamma_3 \text{LogStateRevenue}_{it} + u_i + u_t + \theta_{it}
\]

for each state \(i\) in year \(t\), where \(\zeta_{it}\) and \(\theta_{it}\) are not correlated.

In this regression, the main coefficient of interest is \(\gamma_1\), which measures the change in the percentage of share of Medicaid spending in response to a percentage change in the FMAP level.
3.5.1 Fixed Effects Model

The regressions are at the state-level where each observation is for state $i$ in year $t$. State fixed-effects, $u_t$, within the regression addresses time-invariant unobservable factors that potentially bias estimates. Year fixed effects, $u_i$, allows for the control of general state-level trends as well as year specific variations.

3.5.2 Control variables

The regressions control for the varying population sizes of the state, by including the state population as a control variable. This method accomplishes the same effect as estimating per capita spending without introducing endogeneity since we would in that case include the same denominator in the outcome variables (LHS) as the independent variable (RHS) thus creating a built in relationship. In addition, the regressions also control for the total state revenue for each state so to control for states’ tax income levels.

3.6 Results

Figure 3.9.2 presents a plot of the average FMAP and the average instrumented FMAP from 1980 through 2000. The instrumented FMAP while consistently higher than the average actual FMAP exhibits similar time trends. The just-identified instrumental variable passes the under-identification test with a Kleibergen-Paap rk LM statistic of 5.837 ($p<0.05$) and a Cragg-Donald Wald F statistic of 29.037, passing the threshold of a weak instrumental variable (Stock & Yogo, 2005).

Logged Medicaid Spending
Table 3.8.2 presents the results for the log Medicaid spending levels. Columns 1 and 2 are results for the fixed effects model, while columns 3 and 4 present results for the instrumental variable fixed-effects models. Columns 1 and 3 do not control for the logged population of the state and the log total state revenue of the state.

Results show that in both the fixed effects only model and the fixed effects with instrumental variable models, the level of the FMAP received by the state does not have a significant relationship with the level of Medicaid spending by the state.

**Share of Medicaid Spending**

Table 3.8.3 presents the results for the share of the state health spending that is going towards Medicaid. Columns 1 and 2 are results for the fixed effects model, while columns 3 and 4 present results for the instrumental variable models. Columns 1 and 3 do not control for the logged population of the state and the log total state revenue of the state.

In the fixed effects model, there is not a significant relationship between the level of the FMAP and the share of Medicaid in the state’s health spending. The instrumental variable model that does not control for population and state revenue, indicates a positive and significant relationship between the level of log FMAP and the share of Medicaid in the state health spending. The coefficient of 0.00247 (SE: 0.00117) indicates that for every 10% increase in the FMAP of the state the state increases the percent of the share of
Medicaid spending by 0.0247%. This effect is larger when the model further controls for log population of the state and the total state revenue at 0.0317%.

3.7 Discussion

3.7.1 Limitations

This study has a number of limitations. The fixed effects model is effective in controlling for unobserved heterogeneity that is time invariant. But it is unable to address potential unobserved factors that may change with time, such as the political climate of the state, local economic shocks, and other constraints on the state budget. This study also faces the challenge of a relatively small sample, as it is a state-level analysis. This could potentially be the reason for the lack of significant finding on the level of Medicaid spending. Additionally, as with any IV analysis, there is the concern that the instrument is potentially weak or inappropriate. Although this is not reflected in the test statistics, there is no set of tests that can fully determine the appropriateness of an IV.

3.7.2 Findings

This study set out to examine the relationship between the state’s level of federal matching from the federal government for the Medicaid program and the level of Medicaid spending for that state. Using the median voter model, I motivate that an increase in the FMAP should result in an increase or a non-decrease in the state’s Medicaid spending. Classic economic theory of Ricardian equivalence would indicate a negative relationship as the consumer (in this case the state policymaker maximizing the consumer’s utility) is forward looking and internalizes the federal budget constraints (Barro, 1988). The difference in the two theories lies in whether the policymaker, with
foresight, makes consumption decisions on behalf of all consumers (Ricardian equivalence) or only the median voters.

The approach to the estimation is robust to account for bias associated with unobservables correlated with state level Medicaid spending and FMAP levels. By using a fixed effects model, the estimations control for time-invariant unobservable factors related to each state. The instrumental variable approach allows for the estimation of the local average treatment effect rather than the average treatment effects. Per the work of Angrist and Imbens (1994), the linear IV estimate here can be interpreted as a weighted average of the local average treatment effects, with the weights determined by the elasticity of the endogenous variable to changes in the IV.

The combination of the empirical findings would indicate that the FMAP is not changing the Medicaid spending within states as much as it is leading to cost savings for the state in healthcare costs. The reasoning is as follows: As the federal portion of the Medicaid program increases in the form of the FMAP, the state’s level of Medicaid spending remains steady. This would indicate that even though the federal government is paying for a larger percentage of each dollar of Medicaid spending (leaving the state responsible for a smaller proportion), the state does not lower its level of Medicaid spending. So that in essence, there is an overall increase in Medicaid resources in the state, even though the state does not change its level of Medicaid spending. Additionally, I also find that state Medicaid spending is accounting for a larger portion of the healthcare expenditure by the state. This could be a reflection of the reduction of non-Medicaid spending due to states
saving on uncompensated medical services as overall Medicaid spending increases.

While the analysis shows a relatively small percentage increase in the percentage of total health care spending going towards Medicaid, in the US health care environment where states spent over $2.9 trillion in 2013\(^2\), this translates to a nontrivial amount of healthcare spending.

### 3.8 Tables

Table 3.8.1: Descriptive Statistics by State

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<th>Table 1: Descriptive Statistics by State</th>
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Table 3.8.2: Instrumental Variable Regression for Log Medicaid Spending

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<td></td>
<td>FE</td>
<td>FE</td>
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<td>FE + IV</td>
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<td>---</td>
<td>-0.227***</td>
<td>-0.227***</td>
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<tr>
<td></td>
<td></td>
<td></td>
<td>(0.0563)</td>
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<tr>
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<td>-0.0288</td>
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<td>-0.274</td>
<td>0.32</td>
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<td>Log Population</td>
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<td>1.140**</td>
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<td>0.487</td>
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Note: Regressions include state-level and year fixed effects and excludes Alaska, Arizona and District of Columbia. Regressions are clustered at the state level and robust errors are used.

*** p<0.01
** p<0.05
* p<0.1
### Table 3.8.3: Instrumental Variable Regression for Log Medicaid Spending

<table>
<thead>
<tr>
<th>Medicaid Share of Total Health Spending</th>
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<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>FE</td>
<td>FE</td>
<td>FE + IV</td>
<td>FE + IV</td>
</tr>
<tr>
<td>First Stage for log FMAP</td>
<td>---</td>
<td>---</td>
<td>-0.227***</td>
<td>-0.227***</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.0563)</td>
<td>(0.0563)</td>
</tr>
<tr>
<td>Log FMAP</td>
<td>-0.0000726</td>
<td>-0.000135</td>
<td>0.00247**</td>
<td>0.00317*</td>
</tr>
<tr>
<td></td>
<td>(0.000108)</td>
<td>(0.000103)</td>
<td>(0.00117)</td>
<td>(0.00184)</td>
</tr>
<tr>
<td>Population</td>
<td>---</td>
<td>-0.00334*</td>
<td>---</td>
<td>0.00178</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.00192)</td>
<td></td>
<td>(0.00363)</td>
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<tr>
<td>Log Total Revenue</td>
<td>---</td>
<td>0.000226</td>
<td>---</td>
<td>0.000463</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.000070)</td>
<td></td>
<td>(0.00112)</td>
</tr>
<tr>
<td>Observations</td>
<td>783</td>
<td>783</td>
<td>633</td>
<td>633</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.62</td>
<td>0.64</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Number of states</td>
<td>44</td>
<td>44</td>
<td>36</td>
<td>36</td>
</tr>
</tbody>
</table>

Note: Regressions include state-level and year fixed effects and excludes Alaska, Arizona and District of Columbia. Regressions are clustered at the state level and robust errors are used.

*** p<0.01

** p<0.05

* p<0.1
3.9 Figures

Figure 3.9.1: Distribution of State Medicaid Spending, 1980-2000
Figure 3.9.2: Average FMAP and Instrumented FMAP, 1980-2000
3.10 References


4. Federal Matching Funds in State Medicaid Programs: Does It Reduce Infant Mortality?^{23}

4.1 Abstract

This paper examines the relationship between the Federal Medical Assistance Percentages (FMAPs) to state Medicaid programs and infant mortality for 1961 to 2001. The FMAPs formula determines the level of federal “matching” a state Medicaid program receives for each $1 of Medicaid expenditure. States with lower per capita income receive higher levels of matching than the higher income states. It isn’t clear, however, whether federal subsidy of state Medicaid programs acts to reduce mortality, particularly given that states that receive higher federal matching are systematically poorer than states with low matching rates. We use an instrumental variable model to control for endogeneity arising from unmeasured factors that influence the relationship between state per capita income (utilized in FMAP calculations) and mortality outcomes. We find that states that bear less of the burden of funding Medicaid have lower infant mortality rates, all else equal.

4.2 Introduction

The federal subsidy of state Medicaid programs is referred to as the Federal Medical Assistance Percentages (FMAP) and helps to reduce the financial burden of Medicaid programs for individual states. In recent years individual states have been given the

^{23} Co-author: Martin Andersen, PhD, University of North Carolina Greensboro
option to expand Medicaid as a part of the Affordable Care Act (ACA). In support of the expansion, those states that choose to expand Medicaid receive 100% FMAP from the federal government for the newly eligible Medicaid enrollees, while those states that do not expand pass up on the federal subsidy. The rejection of the FMAP has surprised some researchers, citing the positive impacts of the FMAP on a state’s general economic health (Glied & Ma, 2013). But does the FMAP, lowering the cost of Medicaid for state governments, have an impact on health outcomes? Motivated by this recent debate, this paper takes a look back at the historical impact of the FMAP on state Medicaid programs on all-cause infant mortality rate (IMR). While motivated by the recent events of the ACA, this paper focuses on pre-ACA era Medicaid. A major challenge to this analysis is the presence of unmeasured factors that act to confound the relationship between the FMAP, which is based on a state’s per capita income, and health outcomes. We address the endogeneity of the FMAP by using an instrumental variable (IV) approach. We use state-level panel data spanning 1961 through 2001 to capture the pre-Medicaid and post-Medicaid expansion periods and examine the impact of FMAP on IMR through the state Medicaid programs.

The structure of the paper is as follows: Section 3 reviews the structure of Medicaid and outlines a conceptual framework for the potential impact of FMAP on IMR. Section 4 describes the data and econometric approach. Section 5 presents the results. Section 6 discusses the results, policy implications, and limitations.
4.3 Background & conceptual framework

4.3.1 State Medicaid and the FMAP

Established in 1965 under President Lyndon Johnson, the Medicaid insurance program is one of the most important safety nets in place within the US healthcare system in providing the poor and near poor with access to health and long-term care services. As of January 2015 total Medicaid enrollment is estimated to be close to 70 million enrollees (Centers for Medicare & Medicaid Services, 2015). The Medicaid program, while run by individual states, receives federal matching funds that are commensurate with its relative level of per capita personal income as compared to the national average. These matching funds from the federal government are set at levels that are formally referred to as the Federal Medical Assistance Percentages (FMAPs), the formula for which is designed to provide a higher level of matching to states with lower per capita income and a lower level of matching to the wealthier states. An additional nuance to the FMAP formula also caps the FMAP at 50% and 83% on the low and high ends, respectively. In 2015, for example, 13 states received an FMAP of 50% while none reached the upper limit of 83%. It was estimated in 2012 that federal dollars accounted for approximately 57% of the overall Medicaid spending in this country at approximately $239 billion dollars, while per enrollee spending ranged from $3,728 in Nevada to $9,474 in Alaska.

26 http://kff.org/medicaid/state-indicator/medicaid-spending-per-enrollee/
4.3.2 The Affordable Care Act and the FMAP

One important exception to the FMAP’s determination process arises from the Medicaid expansion proposed by the Affordable Care Act (ACA), which redefined Medicaid eligibility for all non-disabled adults as 138% of the Federal Poverty Line (FPL). For all the newly eligible Medicaid enrollees through this historic expansion, the federal government is committed to a FMAP of 100%. This level of federal matching is set to continue through 2016 with a slow phase down to 90% by the year 2020 (Affordable Care Act, 2010). However, the Supreme Court’s ruling in the case of *National Federation of Independent Business v. Sebelius* stated that it is unconstitutional for the federal government to withhold current federal matching dollars from those states that do not expand Medicaid as prescribed by the ACA. This in turn caused a split amongst the states on the expansion of Medicaid, allowing states to opt out of the expansion. Currently, only thirty states including the District of Columbia have decided to expand Medicaid to the ACA's newly Medicaid eligibles. The twenty states that have elected not to expand Medicaid have in essence turned down billions in federal matching funds, as estimated by a RAND report (Price & Eibner, 2013). It has been estimated, for example, by the Commonwealth Fund that the state of Texas will be forgoing about $9.6 billion in federal Medicaid funding in 2022 (Glied & Ma, 2013).

4.3.3 Conceptual Framework for Federal Matching in State Medicaid Budgets

Federal subsidies for the state Medicaid programs have the effect of decreasing the price of Medicaid for states as well as freeing up state budget for other state expenditures. It is important to assess whether these federal funds actually lead to better health outcomes.
We hypothesize that the injection of federal funds into the state Medicaid programs will have two important economic pathways in affecting IMR, namely through the income effect and the substitution effect of cheaper Medicaid. However, a major challenge to this hypothesis is the potential fungible nature of these federal monies within the state. This would predict that state governments, when faced with federal subsidies that free up money for the state Medicaid program, would redirect the funds to other portions of the state budget.

We begin with the assumption of the state being a rational decision-maker that acts to maximize the utility of the median voter (Gramlich & Rubinfeld, 1982; Baicker 2001). Here the median voter is defined to be the voter whose views on a political agenda is at the middle of spectrum. The Median Voter Theorem, as formalized by Duncan Black, predicts that the median voter will be the one casting the decisive vote in a political election and as such politicians vying for the majority of votes from the group will be best off when they act to appeal to the median voter directly (1948).

The utility of the median voter is given as follows:

\[(1) \quad U = u(y - \tau) + \alpha(\bar{X}, \bar{T})\]
where the $u(.)$ is utility derived from personal consumption, which is a function of income $y$ net taxes $\tau$. The second part of the voter’s utility function is the individual’s level of utility that is derived from the transfers to other individuals through the Medicaid program.\textsuperscript{28} This altruism function is determined by a vector of demographic differences between the individual and the recipients and also a vector of the transfers.

We next define total taxes to be the total of state and federal taxes as $\tau = \tau_s + \tau_f$. In addition, we simplify the model and define the total state population ($N$) to be total sum of those individuals whose taxes fund Medicaid, or median voters ($N_M$), and those individuals who receive Medicaid ($N_R$), such that $N = N_M + N_R$ and $N_R$ is a function of the size of the transfer ($T$).

As such the median voter’s budget constraints are as follows:

\begin{align}
(2) \quad N_M \tau_s & \geq N_R(T)T(1 - FMAP) \\
(3) \quad N \tau_f & \geq N_R(T)T(FMAP)
\end{align}

The first budget constraint (equation 2), dictates that the total cost of the Medicaid program less the federal discount does not exceed the total tax revenue collected from all median voters, while the second budget constraint imposes that the total federal subsidy

\textsuperscript{28} We assume here that the median voter does not meet the income requirements for Medicaid benefits.
into the state subsidy program does not exceed total tax revenue from all voters in the state.\(^{29}\)

Solving for \(\tau\), we get the following\(^{30}\):

\[
\tau = \tau_s + \tau_f = NT^2 \left( \frac{FMAP}{N} + \frac{1 - FMAP}{N_M} \right)
\]

Maximizing (1), subject to (2) and (3):

\[
U = u \left[ y - NT^2 \left( \frac{1}{N_M} - \left( \frac{1}{N_M} - \frac{1}{N} \right) FMAP \right) \right] + \alpha(\bar{X}, \bar{T})
\]

Solving for \(T^*\), we get:

\[
\frac{\partial U}{\partial T} = \frac{\partial u}{\partial c} \left\{ -2NT \left[ \frac{1}{N_M} - \left( \frac{1}{N_M} - \frac{1}{N} \right) FMAP \right] \right\} + \frac{\partial \alpha}{\partial T} = 0
\]

where \(c = y - \tau\).

\[
T^* = \frac{\frac{\partial \alpha}{\partial T}}{2N \left[ 1 - \left( \frac{N_M}{N} \right) FMAP \right] \frac{\partial u}{\partial c}}
\]

We next look at the first order condition of \(T^*\) with respect to changes in the FMAP.

---

\(^{29}\) We utilize this specification because we assume that while the state policymaker receives taxes from taxpayers of all types, including those of non-median type, the budget constraint is from the perspective of the median voter as politicians have an incentive to make decisions on behalf of the median voter; such that, the taxes collected from the median voters influences the selection of \(T\). We then further extend the budget constraint from Baicker’s 2001 paper to include the federal component of the median voter’s taxes. We set equation 3 to reflect that the median voter recognizes that while they are the median voter within their state, they are not necessarily the median voter from the federal government’s perspective and as such equation 3 contains all voters in the median voter’s state.

\(^{30}\) For simplicity, \(N_a(T)\) is assumed to be \(N \times T\), where \(N\) is some constant.
\[ \frac{\partial T^*}{\partial \text{FMAP}} = \frac{\frac{\partial \alpha}{\partial T}}{P - P \left(1 - \frac{N_M}{N}\right) \text{FMAP}} \left[P \left(1 - \frac{N_M}{N}\right)\right]^2 \]

where \( P = 2N \frac{\partial u}{\partial c} \)

Since \( N \) is always larger than \( N_M \), \( 1 - \frac{N_M}{N} \) is always positive and nonzero. And \( P \) is also always positive and nonzero since \( N \) is always positive. As such, the denominator is always positive. We further make the assumption that the individual’s marginal utility is positive in the transfer payment. Thus \( T \) increases in the FMAP as long as the median voter’s marginal altruistic utility from the transfer payment is positive and nonzero. This is in contradiction to the Ricardian Equivalence theorem, which would dictate that consumers would not be responsive in demand for a good in response to governmental stimulus (Barro, 1976).

Finally, we propose the following production function of the infant mortality rate:

\[ IMR = f(T, X) \]

where the IMR is a function of the \( T \), the size of the transfer in the Medicaid program, and \( X \), a set of exogenous factors. We would expect that IMR would increase in \( T \) as higher levels of \( T \) increase subsidized the delivery, prenatal and postnatal care for infants and mothers in the Medicaid population. In addition, we would further expect that \( \frac{\partial IMR}{\partial T} \) would be greater for those infants who were identified to be the more vulnerable and of higher need and as such we further hypothesize that the FMAP would have a greater
protective impact for nonwhite infants, as black infants are especially vulnerable to low birth weight and maternal stressors (Centers for Disease Control and Prevention, 2000).

4.4 Model, Data & Estimation Techniques

We estimate panel data structured at the state level. Our data spans 1961 through 2001. The dependent variable is the annual infant mortality rate for each state. This data is obtained from the US Census Bureau’s annual report of state vital statistics. Since the 1940s, annual infant mortality rates have been collected for Whites and Non-Whites for all states.

In order to estimate the effect of the FMAP on state IMR, we face the challenge of the potential endogeneity of the FMAP and mortality rates arising from unmeasured confounders. One can imagine that there are any number of potential unmeasured factors that can influence a given state’s per capita income and infant deaths. At a state level, a higher income state would have a higher level of resources to be allotted for neonatal care and other enabling social resources; similarly, higher income individuals will have enabling resources to obtain better care and produce better health (Andersen & Aday, 1978).

We address this by using an instrumental variable approach. We use data from the Bureau of Economic Analysis (BEA) with historical state-level per capita income broken out by industry type. We construct the FMAP for each state each year by using per capita
income that reflect the industry composition of each state in 1958 and annual national 
growth rate in each of those industries for each year subsequent to 1958. The idea is that, 
by holding the occupational composition of a state fixed, we measure a state’s exposure 
to sector-specific, exogenous economic shocks that affect state income and the FMAP. 
The instrument relevance condition is satisfied by the fact that economic shocks are 
correlated with income and the FMAP. The exogeneity (exclusion) requirement is 
satisfied by the fact the shocks are “simulated” using national economic trends, which 
should be uncorrelated with state-level mortality. We then used the calculated state per 
capita incomes to calculate the instrument FMAP using the FMAP formula. This method 
is similar to the IV used in Bartik’s paper (1991).

We estimate the following two-stage model with the Bartik instrument \( z_{it} \):

\[
\begin{bmatrix}
FMAP_{it} \\
FMAP_{it} \times Post_{it}
\end{bmatrix}
= 
\begin{bmatrix}
\alpha_0 + \alpha_1 z_{it} + \alpha_2 Post_{it} + u_t + u_i + \eta_{it} \\
\pi_0 + \pi_1 z_{it} \times Post_{it} + \mu_3 Post_{it} + u_i + u_t + \zeta_{it}
\end{bmatrix}
\]

\[
IMR_{it} = \beta_0 + \beta_1 Post_{it} + \beta_2 FMAP_{it} + \beta_3 FMAP_{it} \times Post_{it} + u_i + u_t + \varepsilon_{it}
\]

where we have a separate observation for each state \( i \) and year \( t \) and control for year and 
state fixed effects (\( u_i \) and \( u_t \), respectively). The variables \( \eta_{it} \) and \( \zeta_{it} \) are errors in the 
first-stage regressions that are correlated with \( \varepsilon_{it} \) in the second-stage model. Additionally, 
we estimate our models with robust standard errors clustered at the state level.
For the second part of our analysis, we examine the differential impact of FMAP for those states receiving a relatively high FMAP, versus those states receiving a relatively lower FMAP.\textsuperscript{31} Do states that receive on average a higher matching rate have better health outcomes than low dose states? We define states to be receiving “high” federal funds to be those states that were receiving higher than the median FMAP in 1965. We estimate the following second-stage instrumented difference-in-difference model for state $i$ and year $t$:

$$IMR_{it} = \beta_0 + \beta_1 Post Medicaid_{it} + \beta_2 High FMAP_i + \beta_3 Post_{iu} \times High FMAP_i + u_i + u_t + \nu_{it}$$

\textbf{4.5 Results}

\textbf{4.5.1 Descriptive statistics}

Table 4.8.1 summarizes the pre-Medicaid expansion and post-Medicaid expansion statistics of the FMAP for each state as well as the average infant mortality level for all infants, white infants and non-white infants. In addition, we also included the year in which each state implemented Medicaid. We see that in general pre-Medicaid infant mortality rates are higher than post-Medicaid infant mortality rates. We also see that FMAP levels increase and decrease depending on the state pre- and post-Medicaid implementation.

\textsuperscript{31} We examine this high versus low relationship partly as a sensitivity analysis due to the ceiling and floor structure within the FMAP formula; by looking at the FMAP at a high versus low levels, we are able to bypass the cutoffs of the data at both ends.
4.5.2 Instrumental variables regressions for infant mortality with continuous FMAP

Table 4.8.2 presents the regression results for the Fixed Effects Model (FEM) and the IV analyses instrumenting for the actual FMAP with a calculated FMAP that uses the instrumented state per capita income in its formula. This instrument removes the potential endogeniety of the FMAP by utilizing per capita income that is stripped of unobserved state-level factors. Furthermore, we do not note any pathways by which the instrumented FMAP would influence IMR, except through the actual FMAP. Overall, we find that the instrument performs well under the standard tests for weak instruments and underidentification. First stage results show that the IV has a negative and significant relationship to the actual FMAP. We note here that simple regression of the actual FMAP and the IV show a positive and significant relationship (0.45, p<0.01). However, with the inclusion of all other control variables as well as the interaction term between the IV and the post-Medicaid variable in the first stage, the IV ended up with a negative and significant relationship while the IV and post-Medicaid interaction term has a positive correlation.

All Race Infant Mortality

For the all race infant mortality rate, we see that a one percentage increase in the FMAP for a state decreases IMR by 0.82 per 1000 live births (p=0.001) in the IV model.\textsuperscript{32} This is a stronger effect than the non-instrumented FEM with a reduction of 0.17 deaths per

\textsuperscript{32} With a just identified model, the instruments have an F statistic of 24.07, passing the weak instrument test.
1000 live births. This indicates that the uninstrumented FMAP attenuated the relationship between the FMAP and infant mortality rates. This makes sense as states with higher FMAP are systematically poorer and have other determining variables related to worse infant mortality outcomes in general. That is, after controlling for unobserved variables that are positively related to both the FMAP and infant mortality, we identify a stronger protective effect of FMAP funds directed through a Medicaid program on infant mortality.

**White Infant Mortality**

The FEM model does not show a significant decrease associated with the FMAP and the implementation of Medicaid. The IV model does, however, show a decrease of 0.0785 deaths per 1000 live births (p=0.1). Again, we observe that the IV model has stronger, both in magnitude and significance, effects.

**Non-White Infant Mortality**

For the models for Non-White IMR, we exclude years 1969 and 1971 through 1973 as we were unable to obtain Non-White IMR data for these years. The results of the FEM and IV models are consistent with the other two outcomes but are larger in magnitude. The FEM model shows a 0.212 reduction in deaths per 1000 live births while the IV model indicates a larger reduction of 0.315 deaths for 1000 live births.
4.5.3 Instrumental variables regressions for infant mortality with high/low FMAP

We define states with a high FMAP to be those states that have a FMAP level in 1965 that were above the median. We want to compare high FMAP states to low FMAP states as we hypothesize that those states who receive a higher matching rate from the federal government would have a larger reduction in infant mortality. By averaging above and below the mean, we are able to test the robustness of our results in the face of left and right censoring of our data at 50% and 83%.

Table 4.8.3 presents the regression results for the difference-in-difference model. We see that poorer states with a high FMAP (defined to be above the median) experience an additional reduction of 1.94 infant deaths per 1000 live births. This relationship is smaller and not significant when considering white infants. For Non-White infants, we see that high FMAP states show a borderline significant (p<0.1) decrease of 3.27 deaths per 1000 live births.

4.5.4 Instrumental variables regressions for infant mortality with 5 and 10 years post-Medicaid lags

We further extend our model to include 5 years and 10 years post-Medicaid expansion variables to test the lagged effects of the FMAP on infant mortality through Medicaid. Table 4.8.4 presents the results for the set of regressions. We find that there are reductions to IMR 5 years after Medication expansion and that the effects are stronger in magnitude and significance for Non-White IMR (-2.666, SE: 1.429) than White IMR (-
0.281, SE: 0.377). We also note that this reduction in IMR is persistent after 10 years of Medicaid expansion for Non-White infants at -1.266 (SE: 0.766).

Looking at the effect of FMAP post-Medicaid, we note that there are reductions in IMR overall (-0.303, SE: 0.102) and for both White and Non-White infants but the reduction is larger for Non-Whites (-0.285, SE: 0.169) and Whites (-0.130 SE: 0.0586). However, we do note that the effects do not persist after 5 and 10 years.

4.6 Discussion

4.6.1 Findings

In general, we find Ricardian Equivalence does not hold and that federal funds do have an impact on state behavior. We find that the injection of federal monies into the state Medicaid programs in the form of the FMAP reduced infant mortality. We also found a larger effect for Non-White infants. In addition, we found that states that receive a higher level of the FMAP experience a larger reduction in infant mortality. Additionally, we find that reductions in IMR from the FMAP are still persistent for Non-White infants.

4.6.2 Policy Implications

The FMAP acts to lower the price of Medicaid for states and as our results show leads to a reduction to the IMR. Currently there are a number of states who are not expanding Medicaid as prescribed by the ACA and are turning down 100% matching of the FMAP for those individuals who are newly eligible. This has the potential to translate into negative health outcomes for lower income states. This then leads to the policy question
of whether it makes sense to cap the FMAP at 50% for higher income states when the funds could be allocated to states with lower per capita income that benefit more from the FMAP. The GAO has studied the appropriateness of the FMAP formula for many years and has found that the FMAP formula is limited by considering per capita income in its calculation as it does not account for state-specific challenges, such as higher healthcare costs or Medicaid utilization (Government Accountability Office, 2011). A potential way to address this is by utilizing more state specific factors to adjust the FMAP level for each state and removing or lowering the FMAP floor of 50% for higher income states.

4.6.3 Limitations

In our analysis and discussions, we utilized three slightly differently looks at the relationship between the FMAP and infant mortality. Our data spans pre- and post-Medicaid expansion where there was a shift from no FMAP matching to some FMAP matching. In our research question, we examined the impact of marginal increases in the FMAP and its impact on the infant mortality rate. Finally within our policy discussion, we include the discussion of the ACA Medicaid expansion that would include no FMAP matching to full FMAP matching to the newly eligible enrollees. These three ways to examine the FMAP are slightly different and can be imprecise in its policy interpretations. We utilized the pre-Medicaid era data to control for any pre-Medicaid trends that existed in the outcome variable. However, we have a relatively short pre-Medicaid period. An expanded pre-Medicaid period would address this issue but accurate infant mortality data by race was not available at the time of this project. Additionally, in order to better examine the potential impact of the 100% matching for the newly eligible Medicaid enrollees, data on a previous such expansion would be useful but also not available.
In performing this analysis, we face the challenge of addressing the endogeneity of the FMAP and infant mortality. We addressed this by using an instrumental variable and a fixed effects model. As with any instrumental analysis, we face the challenge of a potentially weak instrument. However, we find little evidence of this within our analyses with the just identified model having an F statistic that is above 10. These results are robust even after clustering the errors at the state level.

We also face some data limitations in not having data beyond 2001. However, in this analysis we are interested in the impact of the Medicaid program and the price reduction effect of the FMAP on infant mortality rates and our study period of 1961 through 2001 provides sufficient pre- and post-Medicaid implementation data to address the question. One challenge lies in examining white and non-white IMR; more recent data may present evidence of the gap between the two groups closing. Additionally, the categorization of non-white is very broad and does not allow us to disentangle all the potential racial groups that are included.

Within our analyses, we were not able to isolate the mortality outcomes of infants who received Medicaid versus those who did not. As such our results reflects a conservative estimate of the reductions in infant mortality and not the true effect.
4.7 Conclusion

The federal government subsidizes state Medicaid programs through FMAP funds. While there have been studies that examine the impact of Medicaid insurance on access to care and mortality, none have looked at whether the subsidization of Medicaid influences health outcomes as well. The FMAP formula, established in 1965 along with the Medicare and Medicaid programs, is designed to provide higher matching for poorer states based on the state per capita income. The main challenge in our analysis is addressing the endogeneity of the FMAP to infant mortality rates due to omitted variables. We address this by using an instrumental variable approach. We use an IV methodology developed by Bartik (1991) to remove regional variations from per capita income shocks. We also use state fixed-effects to further control for time-invariant unobservable factors associated with IMR.

We find that the FMAP leads to a reduction to infant mortality through the state Medicaid programs. We also find that the impact is larger for non-white infant mortality than white infant mortality. When we examine the impact of poorer states (those with high FMAP) versus higher income states, we find that the protective effects of the FMAP are significant for non-white infants. In addition, we find that reductions in IMR are sustained in non-white infants 10 years post Medicaid implementation. As such, it seems that states with lower income have more to gain marginally than higher income states.
This study has two areas of policy implication: 1) States need to reconsider their
decisions to reject these federal dollars for newly eligible Medicaid enrollees when it has
the potential to lead to protective positive health outcomes for its population; 2) the
FMAP formula currently has a floor of 50% for all states and does not account for state-
specific challenges in running the Medicaid program. Rethinking the FMAP formula to
adjust the floor downwards for higher income states and the ceiling upwards for the
lowest income states and including additional factors that better reflect the Medicaid
landscape of the state would potentially make the federal subsidies work more efficiently
within the system.
4.8 Tables

Table 4.8.1: State-level Descriptive Statistics by Pre- and Post-Medicaid Status

<table>
<thead>
<tr>
<th>Medicaid Implementation Year</th>
<th>SNAP</th>
<th>FPL</th>
<th>Post-Medicaid</th>
<th>All Race</th>
<th>White Non-Medicaid</th>
<th>White Pre-Medicaid</th>
<th>Black Non-Medicaid</th>
<th>Black Pre-Medicaid</th>
</tr>
</thead>
<tbody>
<tr>
<td>Alabama</td>
<td>1973</td>
<td>1.02</td>
<td>1.28</td>
<td>2.70</td>
<td>1.89</td>
<td>1.89</td>
<td>1.89</td>
<td>1.89</td>
</tr>
<tr>
<td>Alaska</td>
<td>1974</td>
<td>0.80</td>
<td>0.93</td>
<td>1.63</td>
<td>0.90</td>
<td>0.90</td>
<td>0.90</td>
<td>0.90</td>
</tr>
<tr>
<td>Arkansas</td>
<td>1975</td>
<td>0.85</td>
<td>1.08</td>
<td>2.13</td>
<td>1.03</td>
<td>1.03</td>
<td>1.03</td>
<td>1.03</td>
</tr>
<tr>
<td>Arizona</td>
<td>1976</td>
<td>0.91</td>
<td>1.14</td>
<td>2.58</td>
<td>1.12</td>
<td>1.12</td>
<td>1.12</td>
<td>1.12</td>
</tr>
<tr>
<td>California</td>
<td>1977</td>
<td>0.96</td>
<td>1.20</td>
<td>3.05</td>
<td>1.18</td>
<td>1.18</td>
<td>1.18</td>
<td>1.18</td>
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Note: Regressions include state-level and year fixed effects and excludes Alaska, Arizona and District of Columbia. Regressions are clustered at the state level and robust errors are used.

*** p<0.01
** p<0.05
* p<0.1
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Note: Errors are clustered at the state level. Regressions include year fixed effects.

*** p<0.01  
** p<0.05 
* p<0.1
Table 4.8.4: Instrumental Variable Regression for Infant Mortality Rates by Race: Continuous FMAP and 5 and 10 Year Medicaid Implementation Lags

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Note: Regressions include state-level and year fixed effects and excludes Alaska, Arizona and District of Columbia. Regressions are clustered at the state level and robust errors are used.

*** p<0.01
**  p<0.05
*   p<0.1
4.9 References


Glied, S., & Ma, S. (2013). How States Stand to Gain or lose federal funds by opting In or out of the Medicaid Expansion. Issue brief (Commonwealth Fund), 32, 1-12.


85
5. Conclusion

5.1 Summary of Results

This dissertation explores three separate research questions related to the federal financing of the Medicare and Medicaid programs. The first paper examined the Medicare program and a recent P4P payment reform established by the ACA. The second and third papers examined the Medicaid program and the level at which the federal government subsidizes the state program in the form of the FMAP.

The first paper (Chapter 2) analyzed the impact of the share of dual-eligible enrollees within a Medicare Advantage contract and its performance on the CMS five star quality rating system. We explore this relationship along the five main CMS-defined categories of quality measures: Process, Access, Patient Experience, Intermediate Outcomes, and Outcomes. We find that having a higher share of dual-eligible enrollees negatively impacts a MA contracts’ performance on the Intermediate Outcome measures, reducing a contract’s performance by little over half of a star with a 10% increase in dual-eligible enrollment within a contract. As such, these contracts would systematically receive lower bonus payments than contracts with lower shares of dual-eligible enrollees.

The second paper (Chapter 3) examined the impact of the FMAP on state Medicaid spending, both in absolute levels and as a proportion of all healthcare expenditures by the state. I find that the FMAP does not decrease the level of state Medicaid spending even
though it decreases the state’s responsibility in funding Medicaid. In addition, I find that the FMAP increases the proportion of the healthcare expenditure by the state that is going towards Medicaid. This study however is not set up to determine why these changes are occurring.

The third paper (Chapter 4) examined the impact of the FMAP on the infant mortality rate over time. Overall, we find that the FMAP lowers infant mortality rates, all else equal. We also found a larger effect for Non-White infants. In addition, we found that states that receive a higher level of the FMAP experience a larger reduction in infant mortality. Finally, we find that reductions in the infant mortality rate from the FMAP are still persistent for Non-White infants 10 years post Medicaid implementation.

5.2 Policy Implication

The policy implications of this study pertain to some of the ways by which the federal government injects money into the Medicare and Medicaid programs. Findings from paper 1 indicate that CMS should consider redesigning the P4P program to ensure not placing MA contracts with dual-eligible enrollees at a disadvantage in terms of performance on the quality measures and bonus payment calculations. This could be accomplished by reconsidering how thresholds for establishing star ratings are defined. In order to account for the drivers of quality measure performances not under plan control, MA plans can be stratified into groups with similar SES and demographic factors during the rating process. Separate cut points for each measure can then be established and applied to all plans within each of these groups.
Results from papers 2 and 3 indicate that the FMAP increases the level of Medicaid resources within a state and has a protective effect on infant health that leads to lower infant mortality rates. The two papers also present evidence against Ricardian equivalence as states increase Medicaid spending (unsubsidized portion) in response to government subsidy, which then translated into improved infant health and reduced infant mortality. Given these findings, it would be important for the federal government to reconsider the current FMAP formula and consider possibly lowering the FMAP floor so that high income states can receive a lower rate of matching, thus freeing up these important federal monies for lower income states by increasing the ceiling cap.
6. Curriculum Vitae

CURRICULUM VITAE
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CURRENT STATUS:
PhD Candidate
Department of Health Policy and Management
Health Economics Track
Johns Hopkins School of Public Health

Advisor: Kevin D. Frick, PhD

EDUCATION

Johns Hopkins Bloomberg School of Public Health
Department: Health Policy and Management
Track: Health Economics, Applied Economics
Degree: PhD
Year: August 2010 – Summer 2015 (expected)
Honors: AHRQ Training Grant, ONC Tuition Support for Certificate in Health Informatics, CareFirst Hal Cohen Endowed Memorial Scholarship, Outstanding Teaching Assistant Award (2012-2013) – Department of Health Policy and Management

Columbia University
Degree: M.A. in Statistics
Year: 2005

New York University
Degree: B.A. in Economics and Mathematics
Year: 2000
Honors: Omicron Delta Epsilon – Honor Society in Economics
RESEARCH

“The Impact of Dual Eligible Enrollees on the CMS Five Star Quality Rating Performance for Medicare Advantage Plans” (job market paper)

“The Impact of the Federal Medical Assistance Percentages for Medicaid on State Mortality” with Martin Andersen (work in progress)

RELATED EXPERIENCE

Congressional Budget Office
Associate Analyst
Washington, DC
August 2015–present

Agency for Healthcare Research & Quality
Center for Financing, Access, and Cost Trends
Rockville, MD
May 2014 – August 2014

Junior Service Fellow
June 2013 – September 2013
June 2012 – September 2012

Conceptualized and lead research on trauma-related expenditures, conducted literature reviews, performed data analyses using the MEPS dataset, drafted reports, and provided support in various journal submission processes

MITRE Corporation
Summer Intern
Windsor Mill, MD
June 2011 – August 2011

Provided support on various teams, including Visio workflow mapping as part of a strategic planning for a CMS fraud assessment project, data analysis and research for a CMS ESRD data monitoring improvement project

Health Leads
Volunteer
Baltimore, MD
October 2010 – December 2011

Patient advocacy work that aims to address health-essential needs that are both health and non-health related, including providing primary care access education to uninsured and Medicaid patients at the Johns Hopkins Bayview Emergency Department who present with non-emergency medical problems, helping qualifying patients apply for public assistance programs such as Medicaid and food stamps, and following up with clients to ensure that their needs are met.

Deloitte Consulting
Senior Consultant
New York, NY
June 2005 – July 2010

Provided actuarial and strategy consulting work on numerous projects that span the healthcare industry with employer clients, as well as health insurance companies and government agencies such as CMS, the Maine Medicaid Agency and SAMHSA
TEACHING ASSISTANT EXPERIENCE

State Health Policy – Prof. David Helms (3rd quarter, 2015)


Health Economics I – Prof. Doug Hough (2nd quarter 2013)

Econometrics I - Prof. Antonio Trujillo (4th quarter 2013, 2014)

Exercises in Cost Effectiveness – Prof. Kevin Frick (4th quarter 2013)

Health Economics II – Prof. Kevin Frick (3rd quarter 2013)

Public Health Economics Seminar – Prof. John Bridges (1st – 4th quarter 2012-1013)

Mathematical Economics - Prof. John Bridges (1st quarter 2012)

Introduction to SAS - Prof. Lucy Meoni (4th quarter, 2012)

Economic Evaluation II – Prof. Krishna Rao (3rd quarter 2011)

Economic Evaluation I – Prof. Kevin Frick (2nd quarter 2011, 2012)

Health Economics I – Prof. Kevin Frick (2nd quarter 2011, 2012)

Obesity Economics – Prof. Kevin Frick (Summer Session 2011, 2012)

PUBLICATIONS AND PAPERS


CONFERENCE ABSTRACTS

Podium presentation at iHEA’s 2015 World Congress in Milan, Italy. “Examining a Pay-for-Performance Program in the US: The Impact of Dual Eligible Enrollees on the CMS Quality Performance of Medicare Advantage Contracts”

Discussant at 5 Biennial Conference of the American Society of Health Economists, June 2014.

Poster Presentation at AcademyHealth’s Annual Research Meeting, June 2014. “Do Health Attitudes Vary Among Health Individuals and Individuals with Chronic Conditions?”

Podium presentation at iHEA’s 2013 World Congress in Sydney, Australia. “The Role of Time Preference and Risk Aversion on Self-management of Diabetes”


LANGUAGES

English
Mandarin

REFERENCES

Kevin Frick, PhD, Professor at Bloomberg School of Public Health and Vice Dean for Education and Professor at Johns Hopkins University Carey Business School
410 614-4018
Jonathan Weiner, DrPh, Professor of Health Policy & Management and Health Informatics, Director Center for Population Health Information Technology, Director Public Health Informatics Certificate Program  
410 955-5661

Didem Bernard, PhD, Senior Economist at the Agency for Healthcare Research and Quality, Center for Financing, Access, and Cost Trends  
301 427-1682

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