How Do Hospitals Respond to Managed Care? Evidence from At-Risk Newborns*

Ajin Lee†

May 2018

Abstract

Medicaid has increasingly transitioned from a government-run fee-for-service system (FFS) to a managed care system (MMC) administered by private insurers. To examine the impact of MMC, I exploit an arbitrary determinant of MMC enrollment: infants weighing less than 1,200 grams were excluded from MMC and were instead served through FFS. I find that MMC does not impact hospital practice patterns on average. However, MMC reduces hospital costs by lowering the intensity of treatment and encouraging inter-hospital transfers in an extremely dense hospital market. The structure of local hospital markets and financial disincentives associated with MMC drive the hospital responses.

*I am grateful to Douglas Almond, Tal Gross, Kate Ho, Wojciech Kopczuk, and Amy Ellen Schwartz for their invaluable support and helpful suggestions. I also thank Stacy Dickert-Conlin, Steven Haider, Hyuncheol Bryant Kim, Yogita Shamdasani, Boris Vabson, the applied microeconomics colloquium participants at Columbia University. I use the State Inpatient Databases from the Healthcare Cost and Utilization Project (HCUP), Agency for Healthcare Research and Quality, provided by the Maryland Health Services Cost Review Commission, the New Jersey Department of Health, and the New York State Department of Health. I also use the American Hospital Association (AHA) Annual Survey Database. I thank Jean Roth at the National Bureau of Economic Research for assistance with the data.

†Michigan State University: `leeajin@msu.edu`

1 Introduction

Health care spending in the US is notoriously high. In 2014, the US government spent $1.1 trillion on public health insurance programs, roughly 30% of the total federal budget. Notably, nearly half of all US children are covered by Medicaid,[1] the means-tested health insurance program funded by states and the federal government. In an effort to reduce wasteful spending and improve quality, Medicaid is transitioning from the traditional fee-for-service (FFS) system administered by the government to the Medicaid managed care (MMC) system administered by private health plans. The coverage of MMC has grown dramatically over the last 20 years—up from 10% of Medicaid enrollees in the early 1990s to 74% by 2013 (Duggan and Hayford, 2013; CMS, 2015a). Government expenditures on MMC have also increased substantially from $61 billion in 2007 to $269 billion in 2016, accounting for almost half of total Medicaid expenditures today.[2]

A priori, MMC's incentive structure might restrain the excesses of FFS. Critics suggest that the per-service reimbursement for health care providers (such as physicians and hospitals) under FFS encourages greater provision of care with dubious health benefits (Hackbarth et al. 2008; Arrow et al. 2009). Under MMC, state governments contract out the Medicaid services to intermediary health plans that accept capitation (a set fee per month per enrollee), and these health plans are responsible for reimbursing health care providers. Capitation provides health plans an incentive to reduce costs and manage quality. However, the incentive structure under MMC does not regulate payments to health care providers, and thus providers may not face the same incentive as health plans. The existing literature documents mixed impacts of MMC on both health care spending and patient health outcomes (e.g., Duggan 2004; Herring and Adams 2011), which may be driven by heterogeneous provider responses across different contexts.

In this paper, I examine the effects of MMC on hospital care and patient health focusing on infants in New York State. My focus on infants in New York State pro-

[1] 35.6 million children were enrolled in the Children's Health Insurance Program (CHIP) and Medicaid in August 2017.

[2] `https://www.healthmanagement.com/blog/medicaid-managed-care-spending-2016/`

vides a unique opportunity to examine the causal effect of MMC in comparison to FFS. Infants weighing less than 1,200 grams (2 pounds, 10 ounces) were excluded from mandatory enrollment in MMC and were instead served through the traditional FFS system for the first six months of their lives (NYSDOH, 2000, 2001).[3] I compare infants whose birth weight fell just below the 1,200-gram threshold and thus enrolled in FFS with infants whose birth weight fell just above the threshold and thus enrolled in MMC in a regression discontinuity (RD) design.

While local, my estimates focus on the most expensive and highest-risk newborn deliveries. Infants who weigh below 1,200 grams accounted for roughly one percent of the total newborn population but incurred approximately one-fourth of total newborn hospital costs in New York State between 1995 and 2013. This suggests that potential cost savings relative to FFS are large. Moreover, infants around the cutoff are at-risk newborns whose health outcomes are highly dependent on the quality of care. For example, the mortality rate of infants near the threshold is ten times higher than the overall rate. If MMC compromises the quality of care, cost savings might be traded off against health outcomes.

In the first part of the paper, I estimate the effects of MMC on hospital practice patterns and patient health outcomes. Consistent with the policy, infants above the 1,200-gram threshold are significantly more likely to participate in MMC compared to infants below the threshold. However, I find *no significant difference* in hospital costs and practice patterns between infants below and above the threshold. This surprising null result masks a stark heterogeneity by hospital markets. In New York City, infants above the threshold have significantly lower hospital costs in the first six months of their lives. I show that infants above the threshold stay fewer days at birth hospitals and they are more likely to be transferred to another facility shortly after birth. In other counties outside of New York City, I find no differences in costs, lengths of stay, and transfer rates across the threshold. However, I provide suggestive evidence that in-hospital mortality increases above the threshold in all counties, suggesting that MMC may be associated with adverse effects on health.

To complement my RD strategy, I utilize another source of variation. Specifically, I exploit the rollout of the MMC mandate across counties in New York State in

[3]The exclusion lasted until April 2012.

a difference-in-difference (DD) framework. I find that the DD estimates are comparable to my RD estimates for low birth weight infants, supporting the robustness of my RD estimates. For infants with higher birth weight, I find that hospitals achieve a similar level of cost reductions without affecting in-hospital mortality following the mandate. I provide evidence that hospitals reduce the provision of certain services to cut costs for this group of infants.

In the second part of the paper, I examine potential mechanisms through which hospitals achieve cost savings under MMC, focusing on infants around the 1,200-gram threshold in New York City. I first examine the role of distance between local hospitals, motivated by the difference in the estimates between New York City and other counties. I hypothesize that unavailability of a nearby hospital that can provide adequate care to high-risk infants keeps some hospitals from engaging in profit-driven transfers. I examine the distance from a birth hospital to the closest hospital with a NICU facility in New York City and find that the increase in transfer rates is in fact stronger for birth hospitals that have a NICU hospital nearby. This emphasizes that hospital responses to MMC can vary depending on the structure of local health care markets.

To further understand the mechanism, I hypothesize that hospitals differentially treat FFS and MMC patients due to financial *disincentives* associated with MMC. In New York State, both FFS and MMC use a prospective payment system based on diagnosis to reimburse hospitals for inpatient services. Under FFS, the state government sets the amount of prospective payment for all hospitals in a uniform manner. In contrast, under MMC each health plan negotiates with each hospital to choose the amount of prospective payment. Therefore, the difference in the level of prospective payment between MMC and FFS determines the relative profitability of infants in MMC.

I examine three dimensions along which hospitals would find MMC infants less profitable. First, I examine hospital market share as a proxy for hospitals' bargaining power in the payment negotiation with health plans. I find that the effects—the reduction in costs and the increase in transfers above the threshold—are stronger for smaller hospitals, suggesting that hospitals that are likely to receive lower payments under MMC drive the results. Second, I examine the role of capacity constraints and show that the effects are stronger in hospital-months when their Neonatal Intensive Care Unit (NICU) facilities are relatively crowded. This suggests that hospitals differentially treat infants based on their insurer when marginal costs are high due to capacity constraints. Third, I directly examine the expected costs of treatment and find that the reduction in treatment intensity as well as the increase in transfer rates are much stronger for infants with higher expected costs of treatment. This is again consistent with the hypothesis that hospitals respond to the relative profitability of MMC infants.

The remainder of the paper is organized as follows. Section 2 discusses prior literature and my contributions. Section 3 provides relevant institutional details. Section 4 describes my data and presents descriptive statistics. Section 5 describes the main empirical strategy, while Section 6 presents the policy effects of MMC along with various placebo tests and robustness checks including the difference-in-difference estimation. Section 7 investigates several mechanisms to further understand the effects of MMC and hospital behavior. Section 8 concludes.

2 Contributions to the Relevant Literature

In contrast to the widespread adoption of MMC, the previous findings on the effects of MMC on health care spending and health outcomes are inconclusive. Several papers use local MMC mandates as an exogenous source of variation in a difference-in-difference framework. Duggan (2004) finds that an MMC mandate in California led to an increase in government spending with no health improvement. In contrast, Harman et al. (2014) show that the MMC mandate in Florida led to a reduction in Medicaid expenditures. On the other hand, using nationally representative datasets, Herring and Adams (2011) and Duggan and Hayford (2013) find no overall effects of MMC implementation on expenditures.

Several papers also exploit local mandates to examine health outcomes. Aizer et al. (2007) examine prenatal care and birth outcomes in California and find that MMC actually decreased the quality of prenatal care and increased the incidence of low birth weight, pre-term births, and neonatal mortality.[4,5] On the contrary, some of the earlier findings suggest improvements in prenatal care (Krieger et al. 1992; Levinson and Ullman 1998; Howell et al. 2004).

Relatively few researchers examine the mechanisms through which MMC can achieve savings. In addition, most papers focus on the contract between the government and health plans in understanding the mechanisms, such as the baseline Medicaid reimbursement rate (Duggan and Hayford, 2013)[6] and the types of competing health plans in regional health care markets (Van Parys, 2015).[7] The lack of attention on provider-level responses limits our understanding of how MMC can achieve meaningful savings.[8]

I contribute to the literature by examining provider responses to MMC. Complicated incentive structures under FFS and MMC as well as substantial variation across different states limited our ability to understand how providers play a role in the success of MMC. My focus on newborns in New York State has two advantages in examining hospital responses. First, hospitals face a sudden change in incentives at 1,200 grams due to the exclusion from MMC enrollment for infants whose birth weight falls below the threshold, providing an ideal setting to examine hospital re-

[4]Conover et al. (2001) also find that MMC led to poor prenatal care and negative birth outcomes (lower Apgar scores, but no effect on infant mortality). In addition, Kaestner et al. (2005) document similar findings—poor prenatal care and birth outcomes—but show that their estimates are unlikely to be causal.

[5]These findings suggest that providers can respond to MMC by limiting care for certain subpopulations, resulting in adverse effects on health. Kuziemko et al. (2013) provide evidence of risk-selection under MMC. They find that the transition from FFS to MMC widened black-Hispanic (i.e., high- and low-cost infants) disparities in birth outcomes, suggesting that health plans shift their resources towards low-cost enrollees.

[6]Duggan and Hayford (2013) show that states with high baseline Medicaid reimbursement rates achieved savings, suggesting the government's ability to negotiate lower prices with health plans as a mechanism for reducing health care expenditures under MMC. Their findings are consistent with the literature on managed care in the private insurance market. For example, Cutler et al. (2000) examine the effects of managed care on price and quantity of health care for the privately insured, focusing on patients with heart disease. They show that unit prices (i.e., reimbursement payments) are lower under managed care than the traditional indemnity insurance, while they find relative modest differences in quantity (i.e., treatment patterns) and health outcomes.

[7]Van Parys (2015) examines Florida's 2006 Medicaid reform and discusses that the types of competing health plans in regional health care markets affect how health plans reduce costs.

[8]Marton et al. (2014) discusses how plans reimburse providers greatly affects the reduction in utilization and spending, suggesting that provider-level incentives play a key role in the success of MMC.

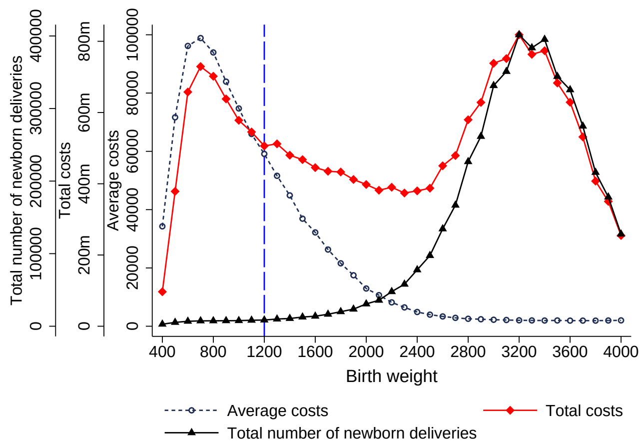


Figure 1: Hospital costs and the number of discharges by birth weight, New York State, 1995-2013

Sources: HCUP State Inpatient Databases
Notes: Average costs are computed for each 100-gram bin using total charges multiplied by cost-to-charge ratio. The total number of discharges are computed for each 100-gram bin using the number of discharges with a birth weight record. Total costs are the product of these two: average costs times the total number of discharges.

sponses. Second, health plans likely play a minimal role in hospital decisions for newborns because emergency decisions immediately following birth are generally not under health plans' supervision. For instance, health plans have limited control over hospitals' decisions on neonatal transfers, since prior authorization by insurers is not required for emergency transfers (NYSDOH, 2016).

Moreover, I contribute to the literature by focusing on a high-cost subpopulation. Newborns are one of the costliest populations treated in US hospitals. In 2011, aggregate hospital costs on newborns were ranked on top among those billed to Medicaid and private insurance (HCUP, 2013). In particular, as Figure 1 shows, only around 1% of infants weighed less than 1,200 grams at birth, but they accounted for 22.3% of total costs between 1995 and 2013 in New York State. The existing literature focuses on relatively healthier subpopulations because most of the local MMC mandates excluded disabled subpopulations, and high-cost procedures were often excluded in the benefit packages ("carve-outs").[9] However, as a num-

[9]One exception is the Florida's Medicaid reform that Van Parys (2015) studies. Florida required

ber of states expand MMC to those with critical conditions (Iglehart 2011; Libersky et al. 2013; KFF 2015), it is timely and policy-relevant to understand whether MMC can reduce costs without compromising health for these populations.

This paper also contributes to the literature by examining how hospitals respond to a change in reimbursement rates for severely ill patients (Dafny, 2005; Acemoglu and Finkelstein, 2008; Shigeoka and Fushimi, 2014). Moreover, this paper is related to the literature on returns to early life medical care. Almond et al. (2010) estimate marginal returns to medical care in early life using the very low birth weight classification at 1,500 grams and find that the higher level of medical care below the threshold results in lower mortality. Bharadwaj et al. (2013) use the same identification strategy and find that more medical care in early life leads to higher test scores in the long-term. I focus on a different cutoff at 1,200 grams to examine how different reimbursement methods affect hospitals and early life health care.

3 Background

3.1 Mandatory MMC Enrollment in New York State

New York State requires most Medicaid beneficiaries to enroll in a managed care plan. The mandatory enrollment in MMC was phased in starting in October 1997 in Albany and four other upstate counties. In New York City, the MMC mandate was introduced in August 1999 and was fully implemented in September 2002. As of November 2012, MMC was mandated in all 62 counties.

Appendix Figure B.1 shows the trends in the share of infants covered by Medicaid in New York State using inpatient discharge records. Medicaid coverage has increased over time, and around half of all births were financed through Medicaid in 2013. The composition of Medicaid coverage has changed dramatically over the last two decades. In 1995, Health Maintenance Organizations (HMOs), a type of managed care organizations (MCOs), covered 5% of Medicaid infants,[10] and by

disabled beneficiaries who received Medicaid through Supplemental Security Income (SSI) to enroll in MMC. However, Van Parys (2015) does not separately focus on examining the effects of MMC on this disabled subpopulation.

[10]Prior to the MMC mandate, Medicaid beneficiaries had an option to voluntarily enroll in MMC.

2013 83% of total Medicaid infants were enrolled in HMOs. I use Medicaid HMO and MMC interchangeably in the remainder of the paper based on the comparison between the managed care penetration published by Centers for Medicare & Medicaid Services (CMS) and the share of Medicaid infants enrolled in HMO in my sample.[11]

The measured share covered by HMO is not 100% even after the statewide implementation of the mandate due to four reasons. First, there are a few categories of infants who are still covered by Medicaid FFS due to exclusions and exemptions from the MMC enrollment. Second, some infants who are newly enrolled in Medicaid might show up as having the FFS coverage in the discharge record at birth, in case their parents fail to enroll their child in a managed care plan in a timely manner.[12] Third, even for infants who are subject to mandatory enrollment, the implementation might not be perfect or immediate due to some administrative shortcomings. Fourth, hospital discharge records might have measurement issues.

3.2 Exclusion Below the 1,200-Gram Birth Weight Threshold

Infants born to women who are receiving Medicaid on the date of delivery are automatically eligible for Medicaid for one year. If the mother is enrolled in a health plan that provides an MMC option, the child is automatically enrolled in the mother's plan in most cases. In New York State, when the infant weighs less than 1,200 grams, however, the state Medicaid system receives an alert with an indicator from the hospital noting that the infant should not be enrolled with an MCO for the first six months of their lives (NYSDOH, 2001). Instead, Medicaid services come through the FFS system. This creates a discontinuous exclusion from MMC based on birth weight, which I exploit in an RD framework to estimate the causal effects of MMC in comparison to FFS.

MMC excludes these infants with very low birth weight, along with other subpopulations that are medically complicated and expensive to treat, such as nursing

[11] According to CMS (2015b), the Medicaid managed care penetration rate in New York State increased from 61.5% in 2005 to 76.7% in 2011. In my sample of infants in New York State, the share of Medicaid infants enrolled in HMO increased from 62.1% in 2005 to 76.2% in 2011. This suggests that Medicaid HMO is a good measure of the total MMC participation in New York State.

[12] Newly enrolled Medicaid beneficiaries are given 90 days to choose a health plan.

home residents and people residing in state psychiatric facilities (Sparer, 2008). Medicaid initially excluded these groups due to several concerns raised by both health plans and beneficiaries. Health plans had little experience with severely ill subpopulations and lacked the coordinated delivery system for them. Beneficiaries were also concerned about inadequate provider networks under MMC.

However, New York State has been gradually phasing in mandatory enrollment into MMC for these subpopulations, motivated by greater cost savings. As part of the Medicaid Redesign Team (MRT) initiatives, MMC enrollment includes infants weighing less than 1,200 grams at birth since April 2012.[13]

3.3 Hospital Incentives Under MMC

Under FFS, Medicaid directly reimburses hospitals in a uniform manner without health plans. In New York State, the Medicaid FFS program uses a prospective payment system based on Diagnosis Related Groups (DRGs) for reimbursement of inpatient services.[14] Each inpatient visit is classified into a DRG based on patient conditions, and Medicaid pays a fixed rate to hospitals according to the DRG assigned to the patient (Quinn, 2008).[15]

Under MMC, Medicaid pays health plans a flat fee per month per enrollee (i.e., capitation) and health plans are responsible for providing health care services to Medicaid beneficiaries and reimbursing health care providers. This fixed fee structure under MMC incentivizes health plans to cut down unnecessary care in order to minimize cost and keep their enrollees healthy so as to avoid incurring future costs. In terms of hospital payment, health plans in New York State also use a prospective payment system based on DRGs.

Therefore, hospitals are reimbursed prospectively on a DRG basis both under FFS and MMC in New York State. The same payment method under the two sys-

[13] `http://www.health.ny.gov/health_care/medicaid/program/update/2012/2012-02.htm#infants`

[14] There are exceptions. Inpatient services at Critical Access Hospitals, rehab or cancer hospitals are reimbursed on a per diem basis. Some services such as psychiatric, medical rehabilitation, and chemical dependency are also reimbursed on a per diem basis.

[15] The use of prospective payment system for inpatient services is common in Medicaid FFS programs. More than two-thirds of states use a prospective payment system (Quinn, 2008) instead of a retrospective per-service reimbursement model, in an effort to correct perverse incentives.

tems emphasizes a rather subtle difference between FFS and MMC from the hospital's perspective, which makes it difficult to predict whether and how hospitals treat these patients differently based on the reimbursement model.

Plan-to-provider payment rates for MMC in New York State are classified as confidential and proprietary and thus not available. However, the New York State Department of Health (NYSDOH) publishes the actual hospital payment under FFS as well as the *suggested* hospital payment under MMC for each hospital.[16] The suggested hospital payments are intended to be used as base rates where adjustments can be made based on the contracts between health plans and hospitals. The suggested hospital payments under MMC are lower than the actual FFS hospital payments, indicating that hospitals may be paid less under MMC.[17] Due to the lower payments under MMC, hospitals may prefer FFS coverage to MMC coverage for otherwise comparable infants. I further investigate hospital incentives in Section 7.

4 Data

For my main analysis, I use inpatient discharge records from State Inpatient Databases (SID) of Healthcare Cost and Utilization Project (HCUP) for New York State from 2005-2011.[18] This dataset contains the universe of inpatient discharge records, thus essentially all births. This dataset contains critical information for my identification strategy such as birth weight in grams and the primary expected payer. I examine the effects of MMC on various measures of inpatient care including total charges, length of stay (LOS), disposition of patient such as transfers and mortality during hospitalization. In addition, New York State Inpatient Databases include encrypted person identifiers that enable researchers to identify multiple hospital visits of the same patient across different hospitals and years, starting in 2005. This allows me to distinguish births, transfers, and subsequent visits.

[16] `http://www.health.ny.gov/facilities/hospital/reimbursement/apr-drg/rates/ffs/index.htm`

[17] Refer to Appendix Section A for further details on hospital payments.

[18] The National Bureau of Economic Research (NBER) provided access to HCUP. The New York State SID provided by NBER spans from 1995 to 2013. I focus on periods between 2005 and 2011 to exploit encrypted person identifiers to track patients over time and to exclude the periods when the exclusion was lifted in 2012. I use years other than 2005-2011 in placebo tests.

Table 1: Summary statistics, infants in New York State from 2005-2011

	(1)	(2)	(3)
		Near the 1,200-gram threshold	
	Full sample	Birth weight∈[900,1,200)	Birth weight∈[1,200,1,500]
Birth weight (grams)	3249.778	1051.735	1356.641
Medicaid	0.445	0.567	0.528
Medicaid, non-HMO	0.131	0.515	0.238
Medicaid, HMO	0.314	0.052	0.290
Total charges (USD)	11240.017	217230.736	154895.661
Total costs (USD)	4027.966	78847.950	55165.368
Length of stay (days)	3.784	44.281	31.440
Died during hospitalization	0.003	0.046	0.023
Subsequent visits	0.047	0.164	0.137
Transfer to short-term hospital	0.009	0.097	0.082
NICU utilization	0.102	0.691	0.700
Observations	1451360	7089	8917

Notes: Total charges are list prices. Total costs are total charges multiplied by hospital-year-specific cost-to-charge ratios. Total charges and total costs are in 2011 values adjusted by CPI-U.

In addition, I use American Hospital Association (AHA) Annual Survey of Hospitals from 2005-2011.[19] This dataset contains detailed information on hospitals such as hospital name, location, staff, and facilities. I use these various hospital characteristics to understand the mechanisms through which MMC affects hospital practice.

Table 1 provides summary statistics of my main analysis sample, infants in New York State from 2005-2011. I restrict my sample to hospital discharges after the mandate was in place in each county.[20] Among the full sample of newborns in the first column, Medicaid finances 45% and Medicaid HMO covers 31.4% of the total 1.45 million discharge records.

Total charges are the sum of list prices for all services provided to each patient visit. The list price for a given service is the same for all patients regardless of their insurance status. Discounts are applied to list prices for actual payments based on contractual details between each insurer and hospital. Although total charges are not the exact payments made by insurers, they are a good proxy for the amount of services provided to a given patient. Total costs are total charges multiplied by

[19]The National Bureau of Economic Research (NBER) also provided access to AHA.

[20]In addition, I drop newborns that I cannot consistently track over time due to missing tracking variables and newborns without valid birth weight information or the initial record at birth.

hospital-year-specific cost-to-charge ratios, which better reflect how much hospital services actually cost. Total costs are considerably lower than total charges, $4,028 compared to $11,240 on average.[21] In the full sample, infants stay on average four days in the hospital. Death (during hospitalization) is a rare event, around 0.3%. Around 1% of the total newborns experience transfers, and 10% stay in a NICU facility.

The last two columns show means for the sample near the 1,200-gram threshold. Below the threshold, the majority of Medicaid beneficiaries are enrolled in a non-HMO category, which indicates that the exclusion is implemented fairly well. Hospital visits are highly expensive for these very low birth weight infants. Total charges are over $200,000 below the threshold for birth weight between 900 and 1,200 grams and over $150,000 for birth weight between 1,200 and 1,500 grams. Total costs are also high, roughly $79,000 below and $55,000 above the threshold. These infants stay hospitalized for more than a month on average. In-hospital mortality is also greater than the full sample, which is around 5% below the threshold and 2% above the threshold. Transfers occur for around 10% of these infants, and the majority of them utilize NICU (70%).

5 Empirical Strategy

To examine the effects of MMC in comparison to FFS, I exploit the 1,200-gram threshold in a regression discontinuity design. That is, I compare infants whose birth weight fell just below the 1,200-gram threshold and thus were more likely to enroll in Medicaid FFS to infants whose birth weight fell just above the threshold and thus were more likely to enroll in MMC.[22] I estimate the following regression

[21] All monetary values are in 2011 dollars adjusted by CPI-U.

[22] I do not restrict my sample to Medicaid patients due to two reasons. First, the composition of Medicaid beneficiaries might be affected due to differential selection into Medicaid following the MMC mandate. The managed care mandate can make Medicaid participation more appealing for infants above the threshold, while it does not affect those below the threshold as they are excluded from the mandate. For instance, assuming the quality of care is higher under managed care, some families who otherwise would not participate in Medicaid might decide to enroll in Medicaid (Currie and Fahr, 2005). Second, given that families covered by MMC are given time to choose a health plan, timing of Medicaid enrollment might vary at the threshold.

to examine the first stage effect of exceeding the threshold on MMC participation. Then, I proceed to examine the reduced-form effects of MMC on several discharge outcomes Y_i:

$$Y_i = \alpha + \beta D_i + f(X_i) + \phi_y + \psi_m + \eta_c + u_i \tag{1}$$

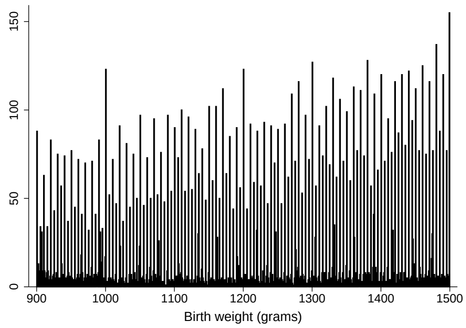
where i denotes a discharge record. D_i is a binary variable that takes one if birth weight of a record i is greater than or equal to 1,200 grams. X_i indicates a running variable, which is birth weight centered at 1,200 grams. I control for a trend in birth weight with a linear spline, $f(X_i) = X_i + D_i X_i$. Additionally, to increase precision, I control for admission year fixed effects (ϕ_y), admission month fixed effects (ψ_m), and hospital county fixed effects (η_c).[23]

For bandwidth selection, I employ a bandwidth selection method proposed by Calonico et al. (2014). This method suggests a bandwidth ranging from 100 to 200 grams for my main outcome variables. For main results, I use 150 as a bandwidth for all outcomes for easier comparisons across the outcomes. I estimate these models with Ordinary Least Squares (i.e., local linear regressions with a uniform kernel). In the tables, I report the RD estimate β with robust standard errors.[24] As a specification check, I additionally examine whether the estimates are sensitive to a range of bandwidth choices and functional forms of $f(X_i)$ in Section 6.4.1.

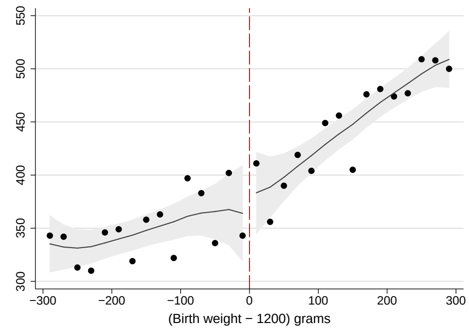
The main identifying assumption of my RD design is that control over birth weight is imprecise (Lee and Lemieux, 2010). Figure 2 shows the frequency of discharge records by birth weight. Panel (a) plots the histogram using one-gram bins. There are large heaps at multiples of 10 and smaller heaps at multiples of 5, most likely due to rounding in reporting. The data also reveals less pronounced heaps at ounce multiples (Appendix Figure B.2). Other than that, however, there is little evidence of irregular heaps around 1,200 grams. Panel (b) plots the same information using 20-gram bins along with local linear regression fitted lines. For figures, I estimate local linear regressions using the triangular kernel and a bandwidth of 150, separately for below and above the threshold. Again, it shows that the mean

[23] Excluding these additional controls has little impact on the results.

[24] Clustering standard errors at the birth weight level does not affect the results (Card and Lee, 2008).



(a) Frequency for each gram



(b) Mean frequency for each 20-g bin

Figure 2: Frequency of the running variable

Notes: Panel (a) plots the frequency of birth weight at each gram. Panel (b) plots mean frequency for each 20-gram bin (dots) along with a local linear regression fitted lines (solid lines) and the 95% confidence intervals below and above the threshold. I use the triangular kernel and a bandwidth of 150 grams for local linear regressions.

frequency is smooth across the threshold.[25]

Following McCrary (2008), I formally test for possible manipulation of birth weight around the 1,200-gram threshold. Specifically, I count the number of observations at the gram level and estimate the size of a discontinuity in this gram-level number of observations at the threshold nonparametrically. With an optimal bandwidth of 95, I estimate the RD estimate to be 3.214 with a robust standard error of 9.337, suggesting no evidence of manipulation of birth weight around the threshold.

To further test the validity of the RD design, I examine whether observable predetermined characteristics are similar around the threshold. Since it is difficult to accurately predict birth weight prior to delivery, predetermined characteristics of patients and birth hospitals are unlikely to change discontinuously across the threshold. Appendix Table C.1 summarizes the RD estimates for these baseline

[25]In addition, I examine the birth weight distribution by expected costs since hospitals might benefit most from manipulating birth weight of infants with high expected costs of treatment. Specifically, I compute predicted list prices from regressing total charges on principal diagnosis and principal procedure fixed effects. I then divide the sample by quartiles of the predicted list prices. I find no evidence of heaping across the distribution, even for infants in the top quartile of expected costs (Appendix figure B.3). Taken together, I find no evidence of manipulation around the 1,200-gram threshold.

characteristics. As expected, none of the estimates are statistically significant, indicating that the exclusion in fact created random variation in enrollment into MMC. I create an index of predicted costs and predicted in-hospital mortality using all of the covariates in Appendix Table C.1 and find that the indices are also smooth across the threshold (Appendix Table C.2). This finding also highlights that there is no evidence of selection into different hospitals across the threshold at the time of birth.

The remaining concern is that heaping in my data may be non-random, which can bias the standard RD estimates. Following Barreca et al. (2016), I examine whether heaped data is systematically different from non-heaped data. Appendix Figure B.4 plots several observable characteristics of patients and hospitals. There is little evidence of non-random heaping at multiples of 10 and 5 (shown as diamonds and triangles). However, the figures provide evidence that ounce heaps (squares) are non-random: patients are more likely to be white, hospitals are less likely to be a teaching hospital, tend to have fewer NICU beds, fewer nurses and fewer annual admissions. To address non-random heaping at ounce multiples, I conduct three robustness checks in Section 6.4.1: (1) repeat the estimations dropping ounce heaps; (2) using only heaps; and (3) a donut RD dropping observations at 1,200 grams (Barreca et al., 2011).

6 The Effects of Medicaid Managed Care

Since treatment at birth can change the course of subsequent hospital care, I distinguish visits at birth from subsequent visits. Table 2 shows the RD estimates in New York State and Appendix Figures B.5 and B.6 present the corresponding figures. Consistent with the policy, panel (a) of Appendix Figure B.5 shows that the MMC participation rate discontinuously increases above the threshold. This corresponds to an increase of 20 percentage points, which constructs a fuzzy RD design.[26] The MMC participation rate below the threshold is close to zero, which

[26] I include all patients in the estimation to minimize selection into Medicaid. Moreover, among Medicaid patients, some infants above the threshold are not categorized under MMC for several reasons. Refer to footnote 21 and Section 3.1 for further information.

Table 2: Effects of birth weight≥1,200 grams, New York State

	(1)	(2)	(3)	(4)	(5)	(6)
	MMC	Log(LOS)	Log(total charges)	Log(total costs)	Transfer	In-hospital mortality
Panel A. Discharge outcomes at birth hospitals						
Above	0.198	-0.059	-0.072	-0.073	0.019	0.025
	(0.016)	(0.044)	(0.053)	(0.055)	(0.014)	(0.010)
Observations	5920	5920	5920	5089	5920	5920
Mean below cutoff	0.031	49.860	244223.114	88735.111	0.104	0.038
	MMC	Log(LOS)	Log(total charges)	Log(total costs)	Readmission	In-hospital mortality (1-year)
Panel B. Aggregating the first six months at the individual level						
Above	0.206	-0.022	-0.026	-0.039	0.008	0.027
	(0.017)	(0.041)	(0.050)	(0.052)	(0.021)	(0.010)
Observations	5920	5920	5920	5031	5920	5920
Mean below cutoff	0.039	53.839	263807.672	95646.818	0.215	0.043

Notes: In addition to the indicator for birth weight≥1,200 g, each regression includes a linear spline of birth weight, admission year fixed effects, admission month fixed effects, and hospital county fixed effects. Robust standard errors are reported. The means of logged outcomes are reported in levels.

indicates that compliance with the exclusion from MMC enrollment based on birth weight is high.[27]

In contrast to the large policy difference at the threshold, I do not find significant differences in lengths of stay, hospital costs, and transfer rates in the pooled sample. Although point estimates indicate that infants above the threshold have shorter and less expensive hospital visits, they are insignificant and figures also provide little evidence of changes at the threshold. However, I find that in-hospital mortality increases significantly above the threshold. These results suggest that MMC may be associated with adverse health outcomes without a significant reduction in hospital costs. To further understand the results, I divide the sample by distinct hospital markets: New York City and the rest of the state.

[27]In the estimation window, 55% of infants have Medicaid, 41% have private insurance, and 4% are uninsured.

Table 3: Effects of birth weight≥1,200 grams, New York City

	(1)	(2)	(3)	(4)	(5)	(6)
	MMC	Log(LOS)	Log(total charges)	Log(total costs)	Transfer	In-hospital mortality
Panel A. Discharge outcomes at birth hospitals						
Above	0.220	-0.159	-0.202	-0.227	0.044	0.023
	(0.023)	(0.056)	(0.072)	(0.077)	(0.017)	(0.014)
Observations	3213	3213	3213	2452	3213	3213
Mean below cutoff	0.028	50.753	261746.798	98855.931	0.067	0.039
	MMC	Log(LOS)	Log(total charges)	Log(total costs)	Readmission	In-hospital mortality (1-year)
Panel B. Aggregating the first six months at the individual level						
Above	0.234	-0.074	-0.096	-0.138	0.043	0.029
	(0.023)	(0.053)	(0.067)	(0.073)	(0.030)	(0.015)
Observations	3213	3213	3213	2406	3213	3213
Mean below cutoff	0.035	54.403	280349.830	105610.288	0.230	0.045

Notes: In addition to the indicator for birth weight≥1,200 g, each regression includes a linear spline of birth weight, admission year fixed effects, admission month fixed effects, and hospital county fixed effects. Robust standard errors are reported. The means of logged outcomes are reported in levels.

6.1 New York City

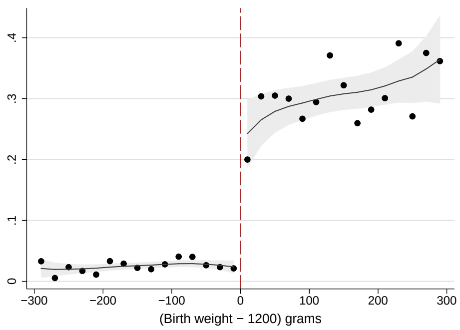
6.1.1 Hospital Care at Birth

Panel A of Table 3 shows the RD estimates at birth hospitals and Figure 3 presents the corresponding figures in the New York City subsample. I find that the higher MMC rate is associated with shorter lengths of stay, lower charges, and lower costs. Column 2 of Table 3 shows that lengths of stay drop by 16% above the threshold at birth.[28] The reductions in total charges and total costs are even larger, suggesting that the intensity of treatment would have been stronger in the "lost" days at birth hospitals.

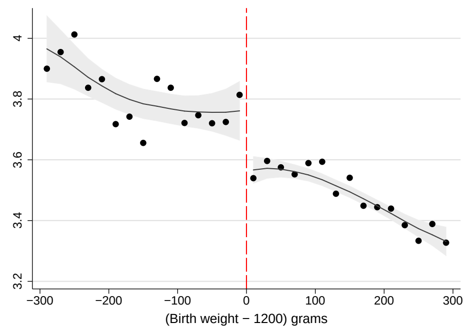
The reduction in lengths of stay could be driven by (1) faster routine discharges from a birth hospital; (2) (earlier) deaths at a birth hospital; or (3) transfers from a birth hospital to another facility for additional care.

First, I examine the transfer decision and whether it is contributing to the shorter lengths of stay. An inter-hospital transfer is an option for infants who require spe-

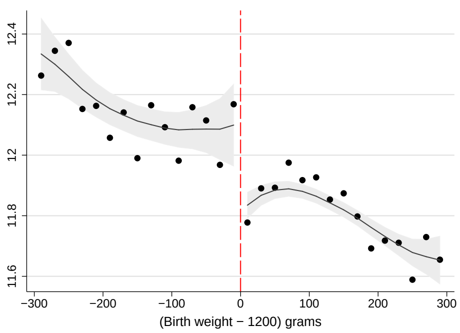
[28]To be specific, I use log(length of stay+1) as the outcome. Using the inverse hyperbolic sine transformation to avoid adding an arbitrary number one yields the same result.



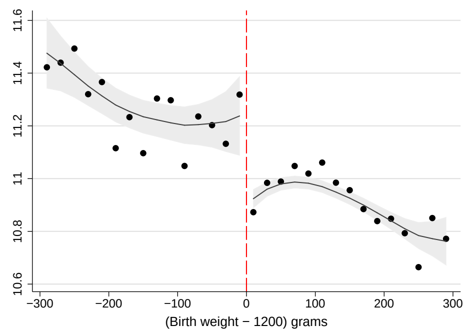
(a) MMC



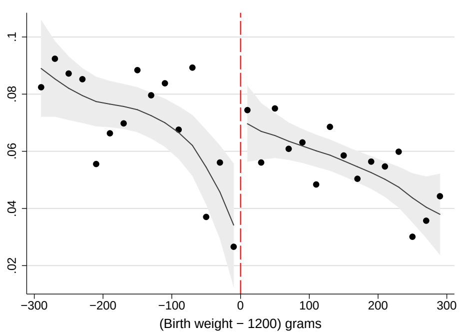
(b) Log(length of stay)



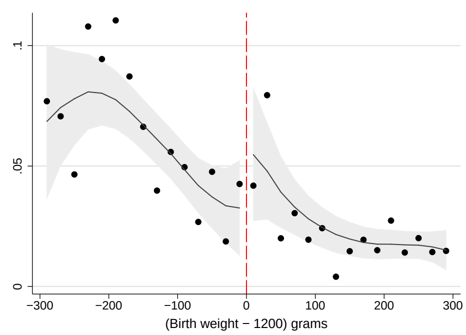
(c) Log(total charges)



(d) Log(total costs)



(e) Transfer



(f) Mortality during hospitalization

Figure 3: Effects of birth weight≥1,200 grams on discharge outcomes at birth, New York City

Notes: Panels (a)-(f) plot mean values of each outcome variable for each 20-gram bin (dots) along with a local linear regression fitted lines (solid lines) and the 95% confidence intervals below and above the threshold. I use the triangular kernel and a bandwidth of 150 grams for local linear regressions.

cialized or intensive care if they are born in inadequately-equipped facilities. However, hospitals might use inter-hospital transfers as a tool to selectively discharge certain patients who are deemed less profitable. I find that the probability of transfer to another short-term hospital in fact increases by 4.4 percentage points above the threshold, which suggests that hospitals might engage in transfers motivated by financial disincentives associated with MMC.[29]

Second, I examine whether the shorter lengths of stay are driven by faster routine discharges (i.e., home discharges). Note that there may be selection into the group of infants who are routinely discharged. For example, if hospitals selectively transfer out infants with more severe conditions, infants above the threshold who remain at the birth hospital would be positively selected and thereby have lower hospital costs. In fact, I find that lengths of stay are 8% lower and cost measures are 10-11% lower above the threshold for routinely discharged infants (panel A of Appendix Table C.3).

To examine whether lower lengths of stay or cost measures are driven entirely by selection, I impute three outcomes—lengths of stay, total charges, and total costs—using the estimates from a regression of each outcome on fixed effects of admission year, admission month, hospital county, and principal diagnosis for routine discharges. Adding non-routine discharges with these imputed outcomes to the estimations, I find that the magnitudes of the RD estimates become smaller, which is consistent with selective non-routine discharges, but the estimates are still lower above the threshold (panel B of Appendix Table C.3). The significant reduction in lengths of stay even among those who are discharged home from birth hospitals (RD estimate: -0.048; robust standard error: 0.021) is consistent with an incentive to reduce costs under MMC.

Third, I examine whether the probability of death changes at the threshold at birth hospitals. Given the reduced treatment intensity for MMC infants even among those who remain at birth hospitals, there may be adverse consequences on health for these infants. Column (6) in panel A of Table 3 shows that the in-hospital mor-

[29]The majority of transfers occur immediately after birth. In my sample, 70% of total neonatal transfers occur within the first three days of birth. This suggests that hospitals effectively change the actual location of treatment through inter-hospital transfers. In addition, hospitals are paid per diem for short stays, suggesting that hospitals have an incentive to engage in transfers shortly after birth.

tality rate increases by 2.3 percentage points, suggesting potential harm to infants' health due to the difference in treatment intensity. However, the estimate is not significant at the conventional level.

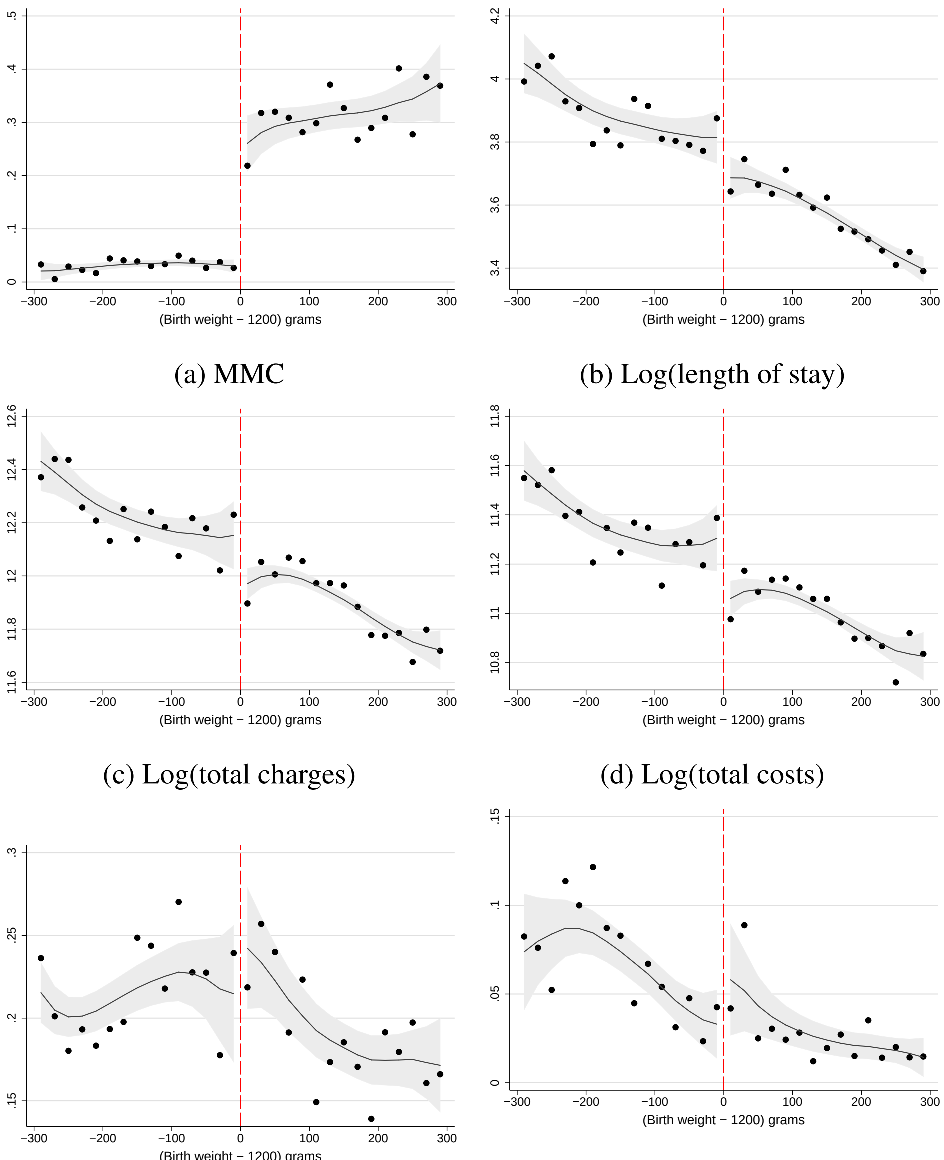
6.1.2 Subsequent Hospital Care

Exploiting the encrypted person identifiers, I further examine how MMC affects subsequent care provided to infants around the 1,200-gram threshold for the first six months after birth.[30] Panel B of Table 3 shows the effects on individual-level outcomes that aggregate outcomes at birth hospitals with outcomes at subsequent visits including transfers (if transferred) within six months. The corresponding figures are shown in Figure 4. I find that the reductions in lengths of stay, charges and costs become smaller and less precise when aggregating the amount of care provided at subsequent visits. However, the point estimates are sizable and a 14% reduction in total hospital costs is marginally significant at the 10% level.

Moreover, I track the infants over time and estimate individual-level mortality during hospitalization within one-year (column 6 of Table 3 panel B). The point estimate on one-year mortality (during hospitalization) is positive and marginally significant (RD estimate: 0.029; robust standard error: 0.015) at the 10% level. The estimate is only slightly higher than the estimate at birth hospitals, suggesting that the difference in in-hospital mortality is unlikely driven by differential care provided at subsequent visits (e.g., due to transfers). This is not surprising since more than half of all deaths I observe occur within the first three days following birth. However, the mortality effect should be interpreted with caution since the corresponding figure (panel (f) of Figure 4) shows that the positive mortality effect may be driven by an unusually high mortality rate around 1,220 grams rather than an overall shift in the level right above the 1,200-gram threshold. That said, I cannot rule out increased mortality for infants in MMC, suggesting that the reduction in costs may be traded off against worse health outcomes.

Additionally, I estimate the probability of hospital readmission within the first

[30]I focus on six months after birth since the MMC exclusion was enforced only for the first six months. After six months, infants below the threshold are supposed to enroll in MMC. Nevertheless, I still find the same results when I aggregate the outcomes for up to 6 years.



(a) MMC

(b) Log(length of stay)

(c) Log(total charges)

(d) Log(total costs)

(e) Readmission

(f) 1-year mortality during hospitalization

Figure 4: Effects of birth weight≥1,200 grams on cumulative discharge outcomes, New York City

Notes: Panels (a)-(f) plot mean values of each outcome variable for each 20-gram bin (dots) along with a local linear regression fitted lines (solid lines) and the 95% confidence intervals below and above the threshold. Each of these outcome aggregates the value at the individual level for six months including the value at transferred hospitals (if transferred). I use the triangular kernel and a bandwidth of 150 grams for local linear regressions.

six months following birth. If the reduced amount of care provided to infants above the threshold at birth was inadequate, the probability of hospital readmission might be higher above the threshold. Column 5 of Panel C in Table 3 shows that the point estimate is positive but statistically insignificant (RD estimate: 0.043; robust standard error: 0.030).[31] This suggests that initial difference in hospital care may not be substantial enough to affect the number of future hospital visits.[32]

6.2 Rest of the State

In this section, I repeat the estimations for counties outside of New York City. Table 4 summarizes the effects on discharge outcomes at birth hospitals (panel A) and aggregated outcomes at the individual level (panel B). Appendix Figures B.7 and B.8 show the corresponding figures.

In counties outside of New York City, the probability of MMC participation increases discontinuously at the threshold by 17 percentage points, which is slightly lower than the New York City estimate. Panel (a) of Appendix Figure B.7 shows that the Medicaid HMO participation is close to zero below the threshold, while it jumps discontinuously to around 20% above the threshold. Unlike New York City, however, I do not find any statistically significant difference in lengths of stay or hospital charges and costs at the threshold. I also do not find evidence of increased transfers above the threshold. Figures also show little evidence of discontinuous changes in the outcomes across the threshold.

However, I find that in-hospital mortality rates increase above the threshold and the estimates are marginally significant. The magnitudes of these mortality estimates are similar to the ones from New York City. Given that I do not find evidence of differential transfers in other counties, this suggests that the increased in-hospital mortality is likely driven by a potential shift in (unmeasurable) resources at birth

[31] However, this estimate can be downward biased if hospitals face a disincentive to admit infants above the threshold due to the contemporaneous difference in MMC participation. To address this point, I estimate the impact on hospital readmission for a subsample of infants aged 2 and older. By age 2, the MMC participation rate becomes smooth across the threshold as infants who were previously excluded from the MMC mandate enroll in MMC after the first six months. Comparing hospital admissions at age 2 and after, I still find no difference in the probability of revisiting the hospital (RD estimate: 0.001; robust standard error: 0.018).

[32] The in-hospital mortality rate also becomes smooth across the threshold by age 2.

Table 4: Effects of birth weight≥1,200 grams, rest of the state

	(1)	(2)	(3)	(4)	(5)	(6)
	MMC	Log(LOS)	Log(total charges)	Log(total costs)	Transfer	In-hospital mortality
Panel A. Discharge outcomes at birth hospitals						
Above	0.170	0.059	0.059	0.057	-0.008	0.028
	(0.023)	(0.070)	(0.079)	(0.078)	(0.025)	(0.013)
Observations	2707	2707	2707	2637	2707	2707
Mean below cutoff	0.035	48.769	222790.960	79205.657	0.150	0.036
	MMC	Log(LOS)	Log(total charges)	Log(total costs)	Readmission	In-hospital mortality (1-year)
Panel B. Aggregating the first six months at the individual level						
Above	0.171	0.048	0.046	0.047	-0.028	0.025
	(0.025)	(0.065)	(0.075)	(0.074)	(0.030)	(0.013)
Observations	2707	2707	2707	2625	2707	2707
Mean below cutoff	0.043	53.150	243575.963	86393.234	0.196	0.040

Notes: In addition to the indicator for birth weight≥1,200 g, each regression includes a linear spline of birth weight, admission year fixed effects, admission month fixed effects, and hospital county fixed effects. Robust standard errors are reported. The means of logged outcomes are reported in levels.

hospitals from infants above the threshold towards infants below the threshold.[33] Panel (f) of Appendix Figures B.7 and B.8 show that visually the discontinuities in the in-hospital mortality rate are not large, however, suggesting caution in interpreting the mortality effects.

6.3 Placebo Tests

One issue associated with identification using the birth weight threshold at 1,200 grams is that it coincides with one of the criteria that qualifies children for the Supplemental Security Income (SSI) program, which provides monthly cash payments and Medicaid to beneficiaries (Guldi et al., 2017).[34] However, I argue that SSI participation is likely to have a limited impact on medical care of newborns.

[33] I examine various outcomes associated with the quality of care and patient health, including hospital readmission due to preventable conditions (Parker and Schoendorf, 2000; Dafny and Gruber, 2005), level IV NICU stays, any NICU stays, utilization of chest X-rays, ultrasounds, and implants, as well as various therapy services (Appendix Table C.4). I do not detect any statistically significant effect on these measures

[34] Newborns can also be eligible for SSI even if their birth weight is above 1,200 grams, depending on their gestational age.

Table 5: Effects of birth weight≥1,200 grams, placebo tests

	(1)	(2)	(3)	(4)	(5)	(6)
	MMC	Log(LOS)	Log(total charges)	Log(total costs)	Transfer	In-hospital mortality
Panel A. Hospitals in New Jersey and Maryland, 2005-2011						
Above	0.034	0.018	0.032	0.071	-0.002	-0.003
	(0.027)	(0.081)	(0.088)	(0.095)	(0.025)	(0.011)
Observations	3548	3548	3542	3144	3548	3545
Mean below cutoff	0.219	43.158	232031.120	62411.637	0.157	0.030
Panel B. Infants born before the mandate (before August 1999), New York City						
Above	-0.066	0.257	0.189		-0.040	0.000
	(0.044)	(0.176)	(0.190)		(0.043)	(0.039)
Observations	614	614	614		614	614
Mean below cutoff	0.094	51.751	89010.578		0.064	0.051
Panel C. Infants born after April 2012, New York City						
Above	0.207	0.008	0.005	0.191	-0.039	0.005
	(0.080)	(0.173)	(0.210)	(0.228)	(0.049)	(0.037)
Observations	694	694	694	572	694	694
Mean below cutoff	0.436	52.993	421948.411	133077.905	0.094	0.049

Notes: Panel A shows the RD estimates from a regression of each outcome on the indicator for birth weight≥1,200 g, a linear spline of birth weight, fixed effects of admission year, admission month, and a state dummy for New Jersey. Panel B shows the RD estimates from a regression of each outcome on the indicator for birth weight≥1,200 g, a linear spline of birth weight, fixed effects of admission year, admission month, and hospital county. Panel C shows the RD estimates from a regression of each outcome on the indicator for birth weight≥1,200 g, each regression includes a linear spline of birth weight, fixed effects of admission year and admission month. Robust standard errors are reported. The means of logged outcomes are reported in levels.

First, monthly cash payments are unlikely to have a substantial impact on families' health care utilization conditional on Medicaid participation. When the child is in a medical facility, monthly cash payments are limited to $30. Since the amount of cash payments is fairly small and services provided to newborns enrolled in Medicaid are exempt from copayment, SSI payments are unlikely to alter families' incentives to utilize health care holding Medicaid participation fixed.[35]

More importantly, if SSI participation based on the birth weight qualification induces people to participate in Medicaid who otherwise would not, it can affect both

[35] Additionally, the average monthly benefit for children was $633 in December 2014 (Duggan et al., 2015). Given the substantial amount of income transfer that low-income families can expect outside of a medical facility, there may be an incentive for families to leave the facility early. However, this would go against finding a reduction in lengths of stay above the threshold.

families and health care providers by substantially changing the cost of health care services. I examine whether the probability of having Medicaid as a primary payer discontinuously increases below the threshold. I find that the effect of exceeding the threshold on the probability of Medicaid participation is small and statistically insignificant (RD estimate: 0.013; robust standard error: 0.025).[36,37] This finding suggests that SSI has minimal impacts on medical care of newborns around the 1,200-gram threshold.

Nevertheless, I conduct three placebo tests to examine whether my results are confounded by SSI participation. First, I repeat the estimations for two other states (New Jersey and Maryland) over the same period where the federal SSI rule applies but the exclusion from MMC does not.[38] I find no effects on discharge outcomes for this sample (panel A of Table 5).[39] Second, I use the periods before the mandate was introduced in New York City (prior to August 1999) and find no differences at the threshold (panel B of Table 5).[40] Third, I use the inclusion of infants weighing less than 1,200 grams into mandatory MMC enrollment since April 2012. I repeat my estimations using the discharge records of infants born after April 2012 in New York City.[41] The estimates on lengths of stay, charges, costs, and transfer rates are statistically insignificant and of opposite signs compared to my main estimates (panel C of Table 5).[42] Overall, these findings suggest that my results are not driven

---

[36]Guldi et al. (2017) examines the effects of SSI payments exploiting the 1,200-gram threshold. They also find no effect on having Medicaid as the primary payer.

[37]Little impact on Medicaid participation is likely due to a high baseline insured rate among very low birth weight infants, independent of SSI participation. Given the high costs of treatment, hospitals have a strong incentive to enroll all infants who qualify for a public health insurance program, if they do not already have one through the mother.

[38]The revisit variables are missing in these states as well as hospital county information. The regression thus includes all infants with birth weight information (regardless of the order of the visit) and I control for admission fixed effects and admission month fixed effects.

[39]Additionally, I restrict the estimation to large urban areas in these two states and still find no differences below and above the threshold (not shown).

[40]There are several caveats: (1) I have only about 600 observations in the discontinuity sample in this period; (2) the cost-to-charge ratio is not available prior to 2001; (3) revisit variables are also not available in this period. The estimation therefore includes all infants with birth weight information and I cannot separate out visits at birth from subsequent visits. Nevertheless, the estimates are of opposite signs compared to my main estimates and are not statistically significant.

[41]Note that I only have around 700 observations in this period.

[42]The hospital county information is missing for this period. The regression controls include admission fixed effects and admission month fixed effects.

by other changes at the threshold besides the exclusion from MMC.

6.4 Robustness Checks

6.4.1 Sensitivity of the Regression Specification

As a specification check, I test whether the estimates are robust to the choice of bandwidth and the degree of polynomials. I repeat the estimations varying bandwidths from 100 grams to 500 grams in 50-gram increments for each outcome. I use quadratic and cubic polynomials in addition to the linear polynomial to control for trends in birth weight. Appendix Figure B.9 shows the RD estimates by bandwidth for different degrees of polynomials. Overall, all panels show that the RD estimates are fairly stable across different choices of bandwidth and the degree of polynomials.

In addition, I include hospital fixed effects to test whether within-hospital differences in treatment depending on the insurer drive my results rather than some arbitrary aggregation of treatment differences across hospitals. Appendix Table C.5 shows that the magnitudes of the point estimates decline compared to the main estimates (Table 3), suggesting that some of the effects are driven by across-hospital differences. However, I still find large and significant differences between infants below and above the threshold with hospital fixed effects, suggesting that hospitals do respond to different insurers for otherwise comparable patients.

Following the discussion in Section 5, I examine whether non-random heaping biases my estimates. Appendix Table C.6 shows that dropping ounce heaps, using only heaps, and a donut RD approach all yield similar estimates, suggesting that non-random heaping at ounce multiples does not drive my results.

6.4.2 Dropping Births at "Out-of-Network" Hospitals

Another role of health plans under MMC is to establish a network of providers for their enrollees. The enrollees are generally required to select a health care provider such as a hospital from their health plan's network. In contrast, Medicaid beneficiaries under FFS can go to any hospital that accepts them. This raises a possibility where some of the MMC infants may be transferred to an in-network

Table 6: Effects of birth weight≥1,200 grams, robustness checks

	(1)	(2)	(3)	(4)	(5)	(6)
	MMC	Log(LOS)	Log(total charges)	Log(total costs)	Transfer	In-hospital mortality
Panel A. Dropping emergency or urgent admissions						
Above	0.224	-0.145	-0.180	-0.209	0.046	0.018
	(0.023)	(0.054)	(0.069)	(0.073)	(0.016)	(0.014)
Observations	3147	3147	3147	2391	3147	3147
Mean below cutoff	0.026	50.969	261266.288	99425.865	0.061	0.038
Panel B. Dropping hospitals with bottom-quartile share of MMC infants						
Above	0.242	-0.131	-0.193	-0.240	0.047	0.011
	(0.028)	(0.066)	(0.089)	(0.097)	(0.020)	(0.016)
Observations	2358	2358	2358	1695	2358	2358
Adjusted R^2	0.160	0.028	0.126	0.134	0.019	0.006
Mean below cutoff	0.037	50.924	259177.667	100039.295	0.076	0.039

Notes: Panel A shows the RD estimates for each outcome dropping emergency or urgent admissions. Panel B shows the RD estimates for each outcome dropping hospitals with the bottom-quartile share MMC infants. In addition to the indicator for birth weight≥1,200 g, each regression includes a linear spline of birth weight, fixed effects of admission year, admission month, and hospital county. Robust standard errors are reported. The means of logged outcomes are reported in levels.

hospital if they were born in an out-of-network hospital, which would explain the differential transfer rates across the threshold. However, this is unlikely because the infants whose birth weight is above 1,200 grams are supposed to be enrolled in the mother's plan, and as long as the mother chooses a hospital that is in-network, the infant is born in an in-network hospital.

Nevertheless, it is possible that delivery occurred unexpectedly at an out-of-network hospital, which may lead to an inevitable transfer to an in-network hospital above the threshold. I conduct two exercises to examine whether my results are robust to this alternative story. First, I drop all births whose admission type is "emergency" or "urgent" to ensure that all deliveries in the sample are planned deliveries. Panel A of Table 6 shows that the estimates barely change with this sample restriction. Second, I drop births at hospitals that have a low share of MMC infants (bottom 25 percentile). This is to exclude hospitals that are less likely to participate in the networks of MMC health plans from the estimations. Panel B of Table 6 shows that the results are not sensitive to this restriction. Taken together, hospital networks under MMC are unlikely to play a part in the differential treatment decisions across the threshold.

6.4.3 Difference-in-Difference Estimation

As is well known, RD estimates apply to those with a high probability of being near the threshold (Lee and Lemieux, 2010) and may not apply to other subpopulations. In this section, I employ a difference-in-difference approach using the MMC mandate rollout across counties in New York State to examine the robustness of the RD estimates and to examine the impact of MMC on infants with higher birth weight. I limit my sample to all newborns born between 1995 and 2011, since the exclusion of low birth weight infants was lifted in April 2012. I estimate the following regression to examine the effects of the MMC mandate on MMC participation and various discharge outcomes:

$$Y_{ict} = \lambda_c + \gamma_t + \delta D_{ct} + \theta_c t + \varepsilon_{ict} \tag{2}$$

where i denotes a discharge record, c denotes county, and t denotes year. I consider various outcomes Y_{ict} such as the probability of having Medicaid HMO as the primary expected payer, log(length of stay), log(total charges), log(total costs), the probability of transfer, and mortality during hospitalization. I include county fixed effects (λ_c) and year fixed effects (γ_t). D_{ct} is an indicator for the years following the mandate for each county. I also include county-specific time trends ($\theta_c t$) to examine whether my results are driven by differential time trends across counties. I report the coefficient of interest δ with clustered standard errors at the county level.

Panel A of Table 7 shows the estimates from the baseline DD model excluding the county-specific time trends. The DD estimates for total charges and total costs are negative and fairly close to my RD estimates. The DD estimate on lengths of stay is negative, but the magnitude is much smaller than my RD estimate. Moreover, there is no change in the probability of transfer and mortality during hospitalization following the mandate in the whole sample of newborns. Panel B shows that including the time trends has little impact on the estimates, supporting the parallel trends assumption.[43]

[43]Moreover, I employ an event study approach to examine pre-trends. Appendix Figure B.10

Table 7: Difference-in-difference estimates

	(1) MMC	(2) Log(LOS)	(3) Log(total charges)	(4) Log(total costs)	(5) Transfer	(6) In-hospital mortality
Panel A. Without county-specific time trends						
MMC mandate	0.112	-0.008	-0.077	-0.090	-0.000	-0.000
	(0.022)	(0.004)	(0.038)	(0.024)	(0.001)	(0.000)
Observations	4274138	4269911	4268952	2400405	3548836	4274127
Mean	0.175	3.800	7449.400	3587.400	0.011	0.004
Panel B. With county-specific time trends						
MMC mandate	0.065	0.001	-0.104	-0.054	-0.001	0.000
	(0.015)	(0.003)	(0.031)	(0.025)	(0.001)	(0.000)
Observations	4274138	4269911	4268952	2400405	3548836	4274127
Mean	0.175	3.800	7449.400	3587.400	0.011	0.004

Notes: Panel A presents difference-in-difference estimates for each outcome without including the county-specific trends. Panel B shows the estimates including the county-specific trends. The means of logged outcomes are reported in levels.

To compare the DD estimates with my RD estimates, I repeat the DD estimations (equation (2)) by birth weight groups. Given the small number of infants, I aggregate all infants weighing between 600 and 1,200 grams for the DD estimation below the threshold. Above the threshold, I repeat the estimation for each birth weight group in 150-gram increments. In Appendix Figure B.11, I plot the DD estimates for each birth weight group along with the 95% confidence intervals. For the comparison, I plot the RD estimates from panel B of Table 3 in red bars along with the 95% confidence intervals at the 1,200-1,350 gram bin.

Panels (b)-(f) show that the DD estimates are similar to the RD estimates for infants with birth weight between 1,200 and 1,350 grams. The DD estimates are imprecise for these low birth weight infants, but the RD estimates are generally within the confidence intervals of the DD estimates. Since both DD and RD models identify the effects using infants with the same range of birth weight, the similarity between these estimates supports my main RD estimates.

The DD estimates for infants with higher birth weight suggest that hospitals do reduce costs in response to the MMC mandate for infants across the whole distri-

shows that there is no evidence of pre-trends in the probability of MMC participation. These results suggest that differential time trends across counties are unlikely to drive my findings.

bution of birth weight, but potentially using different methods. Both total charges and total costs decline, while lengths of stay and the probability of transfer barely change following the mandate among heavier infants.[44] This suggests that hospitals may achieve cost reductions for these infants by adjusting the amount of care on the intensive margin (i.e., conditional on retaining at birth hospitals). Specifically, I consider other measures of health and the quality of care as outcomes (Appendix Table C.7) and find reductions in the utilization of chest X-rays and ultrasounds. I also find suggestive evidence that the utilization of respiratory and speech therapy services declines following the MMC mandate.

7 Discussion of the Mechanisms

Motivated by the difference between New York City and other counties, I first consider the feasibility of inter-hospital transfers as a potential mechanism. Even though hospitals may face differential financial incentives across the threshold, they might not be able to engage in inter-hospital transfers if they do not have a nearby hospital that can provide adequate care for high-risk patients. Since New York City is unique in many aspects compared to the rest of the state, there could be numerous channels through which MMC affects hospitals, such as plan-level competition.[45] I consider the role of distance between local hospitals as one channel in Section 7.1.

To further understand how hospitals in New York City differentially treat infants below and above the threshold, I hypothesize that hospitals respond to the different level of payments under MMC versus FFS for otherwise comparable infants. I conduct three analyses to examine whether the differential treatment of infants across the threshold is prominent in the subsamples of hospitals that are likely to face stronger disincentives under MMC in Sections 7.2-7.4.

[44]The mean length of stay for an average infant is 3.8 days.

[45]Unfortunately, simple comparisons by the number of plans are fraught with the endogeneity of plan entry and exit, and I do not have a valid instrument for the number of plans to further investigate this mechanism in the current project.

7.1 Does Distance Between Local Hospitals Matter?

In this section, I consider proximity to a local hospital as one potential mechanism that drives the differences between New York City and the rest of the state. The costs of transfer may be lower in New York City due to shorter distances between hospitals. The costs may include transportation costs, transaction costs between originating and receiving hospitals, and potential harm to infants' health. There are risks associated neonatal transfers,[46] and the literature documents that the longer duration of transport is associated with increased neonatal mortality (Mori et al., 2007) and poor physiologic status of newborns (Arora et al., 2014).

In particular, I focus on the distance from a birth hospital to the closest hospital with a NICU facility. Focusing on hospitals with a NICU is a natural choice since the majority of infants near the threshold utilize NICU. To illustrate the geographical difference between New York City and the rest of the state, I compare straight-line distances. Specifically, I geocode the center point of each hospital zip code and compute the distance from a birth hospital to the nearest hospital that provides a NICU facility. As expected, the distance between hospitals is much shorter in New York City compared to other counties outside of New York City. The median distance is 1 mile in New York City and 22 miles outside of New York City.

I compare hospitals that have a NICU hospital close by with hospitals that have a NICU hospital far away relative to the median distance within New York City. Table 8 shows that the reductions in lengths of stay, hospital charges and costs and the increase in the probability of transfer are more pronounced when the distance between a birth hospital and a hospital with a NICU is shorter (panel A) even within New York City. Panel B shows the estimates for birth hospitals that have a NICU hospital relatively far away. The results shows that the estimates are much smaller and less precise.

This suggests that proximity between hospitals plays an important role in birth hospitals' decision-making process for these high-risk newborns. Given the longer

[46] For instance, Mohamed and Aly (2010), Nasr and Langer (2011) & Nasr and Langer (2012) document neonatal transfers are associated with higher mortality and more complications. However, since transfers are not randomly assigned, the resulting outcomes are confounded by selection into transfers.

Table 8: Does distance between local hospitals matter? New York City

	(1)	(2)	(3)	(4)	(5)	(6)
	MMC	Log(LOS)	Log(total charges)	Log(total costs)	Transfer	In-hospital mortality
Panel A. Below the median distance						
Above	0.228	-0.246	-0.379	-0.237	0.053	0.043
	(0.034)	(0.090)	(0.120)	(0.127)	(0.027)	(0.021)
Observations	1461	1461	1461	1085	1461	1461
Mean below cutoff	0.027	53.373	335576.576	118894.276	0.057	0.041
Panel B. Above the median distance						
Above	0.222	-0.107	-0.079	-0.226	0.038	0.008
	(0.031)	(0.071)	(0.085)	(0.094)	(0.021)	(0.018)
Observations	1749	1749	1749	1367	1749	1749
Adjusted R^2	0.139	0.032	0.209	0.109	0.028	-0.005
Mean below cutoff	0.029	48.727	203049.647	84066.460	0.075	0.039

Notes: In addition to the indicator for birth weight≥1,200 g, each regression includes a linear spline of birth weight, admission year fixed effects, admission month fixed effects, and hospital county fixed effects. Robust standard errors are reported. The means of logged outcomes are reported in levels.

driving distance between hospitals outside of New York City, transfer decisions might depend less on financial incentives but more on medical needs, which are unlikely to change discontinuously at the threshold. Hospitals engage in profit-seeking behavior in response to financial incentives associated with MMC, but only when they can expediently transfer their patients to a local hospital that can provide adequate care, emphasizing the importance of the structure of local hospital markets.

7.2 Do Hospitals with Lower Bargaining Power Respond More?

In this section, I hypothesize that lower-quality hospitals are likely to have lower bargaining power and thus receive lower payments from health plans compared to higher-quality hospitals (Gaynor et al., 2015). While the FFS payment is determined by the state based on a formula,[47] the MMC payment is determined based

[47]The formula adjusts the statewide base price by various factors such as the wage equalization factor (WEF) and the indirect medical education (IME). Refer to `https://www.health.ny.gov/facilities/hospital/reimbursement/apr-drg/`

Table 9: Testing hospital responses to financial incentives, New York City

	(1)	(2)	(3)	(4)	(5)	(6)
	MMC	Log(LOS)	Log(total charges)	Log(total costs)	Transfer	In-hospital mortality
Panel A1. Below-median market share of the hospital (N=1586)						
Above	0.261	-0.184	-0.205	-0.314	0.057	0.012
	(0.034)	(0.079)	(0.094)	(0.120)	(0.024)	(0.019)
Mean below cutoff	0.036	50.080	179430.316	84574.620	0.078	0.041
Panel A2. Above-median market share of the hospital (N=1627)						
Above	0.174	-0.127	-0.161	-0.165	0.027	0.030
	(0.030)	(0.081)	(0.100)	(0.100)	(0.023)	(0.021)
Mean below cutoff	0.020	51.434	345059.044	109056.868	0.055	0.038
Panel B1. Below-median NICU occupancy (N=1214)						
Above	0.226	-0.054	-0.077	-0.026	0.030	0.019
	(0.040)	(0.073)	(0.097)	(0.098)	(0.026)	(0.021)
Mean below cutoff	0.026	50.164	260203.647	102150.311	0.060	0.044
Panel B2. Above-median NICU occupancy (N=1797)						
Above	0.199	-0.161	-0.209	-0.215	0.045	0.023
	(0.028)	(0.074)	(0.093)	(0.094)	(0.021)	(0.020)
Mean below cutoff	0.022	51.457	274450.655	101381.711	0.061	0.040
Panel C1. Below-median NICU occupancy at typical destination (N=573)						
Above	0.145	-0.306	-0.416	-0.410	0.121	0.003
	(0.047)	(0.148)	(0.170)	(0.206)	(0.038)	(0.034)
Mean below cutoff	0.039	48.401	262906.387	102176.261	0.078	0.019
Panel C2. Above-median NICU occupancy at typical destination (N=822)						
Above	0.212	-0.132	-0.235	-0.360	0.056	0.013
	(0.048)	(0.134)	(0.160)	(0.189)	(0.036)	(0.034)
Mean below cutoff	0.021	50.674	285300.468	117168.173	0.102	0.043
Panel D1. Below-median severity (N=1487)						
Above	0.201	-0.078	-0.096	-0.119	0.017	-0.016
	(0.035)	(0.063)	(0.090)	(0.093)	(0.021)	(0.013)
Mean below cutoff	0.027	47.506	239590.633	89097.425	0.049	0.021
Panel D2. Below-median severity (N=1698)						
Above	0.230	-0.183	-0.219	-0.239	0.070	0.053
	(0.030)	(0.083)	(0.103)	(0.107)	(0.025)	(0.023)
Mean below cutoff	0.029	53.533	279936.443	106815.951	0.076	0.051

Notes: In addition to the indicator for birth weight$\geq$1,200 g, each regression includes a linear spline of birth weight, admission year fixed effects, admission month fixed effects, and hospital county fixed effects. Robust standard errors are reported. The means of logged outcomes are reported in levels.

on an individual contract between a health plan and a hospital. This suggests that under MMC, hospital payments are likely dependent on the bargaining power of the hospital relative to the bargaining power of the health plan. To test this hypothesis, I consider a proxy of the hospital's bargaining power, hospital market share in a Metropolitan Statistical Area (MSA) in Section 7.2.

Panels A1 and A2 of Table 9 compare the RD estimates at birth hospitals in New York City from 2005-2011 by hospital market share in a MSA. Panel A1 shows the results for hospitals with the below-median market share, while panel A2 shows the results for hospitals with the above-median market share. The reduction in lengths of stay, total charges, and total costs as well as the increase in the probability of transfer are much larger and statistically significant for hospitals with the below-median market share. This suggests that the response to MMC is much stronger for birth hospitals that are likely to receive lower MMC payments due to lower bargaining power.

In fact, infants in MMC born in relatively "lower-quality" hospital are more likely to be transferred to a "higher-quality" hospital. Appendix Figure B.12 compares mean characteristics of birth hospitals and receiving hospitals for low birth weight infants. Receiving hospitals on average have more beds and also have more physicians and nurses. They are more likely to have a NICU facility and more likely to be teaching hospitals. Instead of hospital market share, I consider total admissions, the number of total beds as well as the categorization of a teaching hospital as a proxy for the hospital bargaining power. I consistently find that the effects are stronger for hospitals with fewer admissions, fewer beds, and for non-teaching hospitals (Appendix Table C.8).

7.3 Do Hospitals' Capacity-Constraints Play a Role?

In this section, I examine the role of capacity constraints because the incentive to differentially treat patients based on the prospective payment is maximized when the hospital is capacity-constrained. Suppose that the number of NICU beds is fixed, and the hospital decides whether to retain a low birth weight infant at its own

---

`presentations/docs/mc_presentation.pdf` for further information.

NICU facility or to transfer the infant to another hospital following birth. Although entering the NICU market has a large fixed cost, the marginal cost of providing neonatal intensive care is relatively low. Therefore, the hospital has an incentive to utilize empty beds.[48] When the hospital is capacity-constrained, however, the hospital can benefit more from holding onto infants enrolled in FFS than those enrolled in MMC.

To examine the role of capacity constraints, I exploit variation in monthly NICU occupancy. Specifically, I define the NICU occupancy in a given month as the number of infants admitted last month and who stayed in a NICU facility for at least 20 days.[49] I use the number of infants admitted last month to avoid counting the endogenous number of NICU stays in the contemporaneous month as a measure of how crowded the NICU is.

I compare months when the NICU occupancy is below the median with months when the NICU occupancy is above the median at a given hospital in a given year. Within hospital-year comparisons ensure that the comparison is made at fixed capacity since the number of NICU beds is unlikely to change dramatically for a given hospital in a given year. The results are shown in panels B1 and B2 of Table 9. When the NICU occupancy is above the median, lengths of stay, total charges, and total costs for infants born just above the threshold decrease by about 16-22%, and the probability of transfer also increases by 4.5 percentage points. When the NICU occupancy is below the median (i.e., hospitals have sufficient beds), I find little impact of MMC on all outcomes, consistent with the capacity constraint playing an important role.

Similarly, since hospitals have a financial incentive to utilize empty beds, I examine the role of crowdedness at potential destination hospitals. I consider a "typical destination" hospital, which I define as the receiving hospital of the majority of (any) neonatal transfers from a given hospital. I find that the birth hospital is more likely to differentially treat infants across the threshold when its typical destination is relatively less crowded (panels C1 and C2 of Table 9). This also suggests that

[48] Freedman (2016) tests this hypothesis and finds that empty beds increase NICU utilization.

[49] To ensure that infants who leave the hospital soon after birth are not included in the occupancy measure, I restrict the length of stay to be at least 20 days. Given that the mean length of stay for very low birth weight infants is longer than a month, 20 days is unlikely to be a binding restriction.

MMC may have induced hospitals to engage in reallocation of at-risk infants from a crowded hospital to a less crowded hospital via transfers.

7.4 Do Hospitals Treat Infants Differently Based on Expected Costs?

In this section, I examine the profitability of infants based on the expected costs of treatment. Unless the reimbursement payments are perfectly adjusted for severity, infants with different costs of treatment can have a varying degree of profitability.[50] Therefore, profit-maximizing hospitals are more likely to respond to infants whose marginal costs are high.

As a measure of expected costs, I compute predicted list prices by regressing total charges on principal diagnosis fixed effects and principal procedure fixed effects. This measure thus predicts the total charges solely based on the severity of patients' conditions. Consistent with the hypothesis, I find that hospital responses are stronger for infants with higher predicted list prices (panels D1 and D2 of Table 9). For infants with below-median predicted list prices, MMC reimbursement payments may still exceed the marginal costs. For infants with above-median predicted list prices, the lower reimbursement payments under MMC may not cover the expected costs of treatment and birth hospitals would have an incentive to transfer out these infants, if possible.

However, for infants with above-median predicted list prices, I find that mortality during hospitalization at birth hospitals increases above the threshold and the estimate is marginally significant at the 5% level. This suggests that hospitals may shift resources towards infants under FFS with higher reimbursement payments, resulting in harming health among the highest-risk subpopulations under MMC.

[50] New York State implemented a severity-based methodology, All Patient Refined Diagnosis Related Groups (APR-DRGs) effective December 1, 2009, introducing four severity levels within a DRG. The differential treatment for infants with severe conditions weakens after the adoption of APR-DRGs.

8 Conclusion

Recognizing limitations of the FFS system, the US health care market has increasingly adopted new payment systems that promote more efficient delivery of health care. These new systems are generally designed to reward improvements in the quality of care without unnecessarily increasing costs (Hackbarth et al. 2008; Arrow et al. 2009). Notably, the Affordable Care Act introduced accountable care organizations (ACOs) for Medicare populations[51] that share similar incentives and goals as managed care organizations under Medicaid. This paper provides important implications for hospital responses to these incentives.

My findings suggest that MMC does not impact hospital practice in an average hospital market. In an extremely dense market such as New York City, MMC may influence hospitals to adjust their practice patterns, resulting in lower hospital costs. For very low birth weight infants, I find that MMC achieves savings by reducing the intensity of treatment and by encouraging inter-hospital transfers. I find no impact on hospital readmission but provide evidence that an incentive to reduce the treatment intensity may result in increased mortality during hospitalization, especially for the highest-risk newborns.

I investigate a number of mechanisms through which MMC can influence hospitals to achieve savings. First, I find that the hospital responses are pronounced in an urban area where the density of hospital market is extremely high, which allow hospitals to engage in expedient care coordination. Second, I show that hospitals respond to financial disincentives associated with MMC. The effects are stronger for hospitals with lower bargaining power, when they face capacity-constraints, and especially for patients with high expected costs.

My findings have two policy implications. First, they directly speak to the impact of expanding managed care to previously excluded high-cost and critically-ill subpopulations. My results highlight that financial disincentives under MMC may lead to cost savings but they may come at the expense of increased in-hospital mortality. Second, the structure of local health care markets might play a role in how

[51]Duggan et al. (2018) show that Medicare Advantage plans reduce hospital inpatient utilization without harming the quality of care.

health plans influence hospital behavior for these high-cost, high-risk patients. The expected outcomes may depend on the existence of nearby hospitals that can provide high-quality care as well as an efficient care coordination system among local hospitals.

References

Acemoglu, D. and A. Finkelstein (2008). Input and technology choices in regulated industries: Evidence from the health care sector. *Journal of Political Economy 116*(5), 837–880.

Aizer, A., J. Currie, and E. Moretti (2007). Does managed care hurt health? Evidence from Medicaid mothers. *The Review of Economics and Statistics 89*(3), 385–399.

Almond, D., J. J. Doyle, A. E. Kowalski, and H. Williams (2010). Estimating marginal returns to medical care: Evidence from at-risk newborns. *The Quarterly Journal of Economics 125*(2), 591–634.

Arora, P., M. Bajaj, G. Natarajan, N. P. Arora, V. K. Kalra, M. Zidan, and S. Shankaran (2014). Impact of interhospital transport on the physiologic status of very low-birth-weight infants. *American journal of perinatology 31*(03), 237–244.

Arrow, K., A. Auerbach, J. Bertko, S. Brownlee, L. P. Casalino, J. Cooper, F. J. Crosson, A. Enthoven, E. Falcone, R. C. Feldman, et al. (2009). Toward a 21st-century health care system: Recommendations for health care reform. *Annals of Internal Medicine 150*(7), 493–495.

Barreca, A. I., M. Guldi, J. M. Lindo, and G. R. Waddell (2011). Saving babies? Revisiting the effect of very low birth weight classification. *The Quarterly Journal of Economics 126*, 2117–2123.

Barreca, A. I., J. M. Lindo, and G. R. Waddell (2016). Heaping-induced bias in regression-discontinuity designs. *Economic Inquiry 54*(1), 268–293.

Bharadwaj, P., K. V. Løken, and C. Neilson (2013). Early life health interventions and academic achievement. *American Economic Review 103*(5), 1862–1891.

Brown, J., M. Duggan, I. Kuziemko, and W. Woolston (2014). How does risk selection respond to risk adjustment? new evidence from the Medicare Advantage program. *The American Economic Review 104*(10), 3335–3364.

Calonico, S., M. D. Cattaneo, and R. Titiunik (2014). Robust nonparametric confidence intervals for regression-discontinuity designs. *Econometrica 82*(6), 2295–2326.

Card, D. and D. S. Lee (2008). Regression discontinuity inference with specification error. *Journal of Econometrics 142*(2), 655–674.

Centers for Medicare & Medicaid Services (CMS) (2015a). Medicaid managed care enrollment and program characteristics, 2013.

Centers for Medicare & Medicaid Services (CMS) (2015b). Medicaid managed care trends and snapshots, 2000-2013.

Conover, C. J., P. J. Rankin, and F. A. Sloan (2001). Effects of tennessee Medicaid managed care on obstetrical care and birth outcomes. *Journal of health politics, policy and law 26*(6), 1291–1324.

Currie, J. and J. Fahr (2005). Medicaid managed care: Effects on children's Medicaid coverage and utilization. *Journal of Public Economics 89*(1), 85–108.

Cutler, D. M., M. McClellan, and J. P. Newhouse (2000). How does managed care do it? *The RAND Journal of Economics 31*(3), 526–548.

Dafny, L. (2005). How do hospitals respond to price changes? *American Economic Review 95*(5), 1525–1547.

Dafny, L. and J. Gruber (2005). Public insurance and child hospitalizations: Access and efficiency effects. *Journal of public Economics 89*(1), 109–129.

Duggan, M. (2004). Does contracting out increase the efficiency of government programs? Evidence from Medicaid HMOs. *Journal of Public Economics 88*(12), 2549–2572.

Duggan, M., J. Gruber, and B. Vabson (2018). The consequences of health care privatization: Evidence from Medicare Advantage exits. *American Economic Journal: Economic Policy*.

Duggan, M. and T. Hayford (2013). Has the shift to managed care reduced Medicaid expenditures? Evidence from state and local-level mandates. *Journal of Policy Analysis and Management 32*(3), 505–535.

Duggan, M., M. S. Kearney, and S. Rennane (2015). The Supplemental Security Income (SSI) Program. NBER Working Paper 21209.

Freedman, S. (2016). Capacity and utilization in health care: The effect of empty beds on neonatal intensive care admission. *American Economic Journal : Economic Policy 8*(2), 154–185.

Gaynor, M., K. Ho, and R. J. Town (2015). The industrial organization of health care markets. *Journal of Economic Literature 53*(2), 235–284.

Guldi, M., A. Hawkins, J. Hemmeter, and L. Schmidt (2017). Supplemental security income and child outcomes: Evidence from birth weight eligibility cutoffs. *working paper*.

Hackbarth, G., R. Reischauer, and A. Mutti (2008). Collective accountability for medical care—toward bundled Medicare payments. *New England Journal of Medicine 359*(1), 3–5.

Harman, J. S., A. G. Hall, C. H. Lemak, and R. P. Duncan (2014). Do provider service networks result in lower expenditures compared with HMOs or primary care case management in Florida's Medicaid program? *Health Services Research 49*(3), 858–877.

Healthcare Cost and Utilization Project (HCUP) (2013). Hospital stays for newborns, 2011.

Herring, B. and E. K. Adams (2011). Using HMOs to serve the Medicaid population: What are the effects on utilization and does the type of HMO matter? *Health Economics 20*(4), 446–460.

Holahan, J. and M. Schirmer (1999). Medicaid managed care payment methods and capitation rates: results of a national survey. Technical report, Urban Institute.

Howell, E. M., L. Dubay, G. Kenney, and A. S. Sommers (2004). The impact of Medicaid managed care on pregnant women in Ohio: a cohort analysis. *Health services research 39*(4p1), 825–846.

Iglehart, J. K. (2011). Desperately seeking savings: States shift more Medicaid enrollees to managed care. *Health Affairs 30*(9), 1627–1629.

Kaestner, R., L. Dubay, and G. Kenney (2005). Managed care and infant health: An evaluation of Medicaid in the US. *Social science & medicine 60*(8), 1815–1833.

Kaiser Family Foundation (KFF) (2015). Medicaid reforms to expand coverage, control costs and improve care: Results from a 50-state Medicaid budget survey for state fiscal years 2015 and 2016.

Krieger, J. W., F. A. Connell, and J. P. LoGerfo (1992). Medicaid prenatal care: A comparison of use and outcomes in fee-for-service and managed care. *American Journal of Public Health 82*(2), 185–190.

Kuziemko, I., K. Meckel, and M. Rossin-Slater (2013). Do insurers risk-select against each other? Evidence from Medicaid and implications for health reform. NBER Working Paper 19198.

Lee, D. S. and T. Lemieux (2010). Regression discontinuity designs in economics. *Journal of Economic Literature 48*(2), 281–355.

Levinson, A. and F. Ullman (1998). Medicaid managed care and infant health. *Journal of Health Economics 17*(3), 351–368.

Libersky, J., A. H. Dodd, and S. Verghese (2013). National and state trends in enrollment and spending for dual eligibles under age 65 in Medicaid managed care. *Disability and Health Journal 6*, 87–94.

Marton, J., A. Yelowitz, and J. C. Talbert (2014). A tale of two cities? The heterogeneous impact of Medicaid managed care. *Journal of health economics 36*, 47–68.

McCrary, J. (2008). Manipulation of the running variable in the regression discontinuity design: A density test. *Journal of Econometrics 142*(2), 698–714.

Mohamed, M. A. and H. Aly (2010). Transport of premature infants is associated with increased risk for intraventricular haemorrhage. *Archives of Disease in Childhood-Fetal and Neonatal Edition 95*(6), F403–F407.

Mori, R., M. Fujimura, J. Shiraishi, B. Evans, M. Corkett, H. Negishi, and P. Doyle (2007). Duration of inter-facility neonatal transport and neonatal mortality: Systematic review and cohort study. *Pediatrics International 49*(4), 452–458.

Nasr, A. and J. C. Langer (2011). Influence of location of delivery on outcome in neonates with congenital diaphragmatic hernia. *Journal of pediatric surgery 46*(5), 814–816.

Nasr, A. and J. C. Langer (2012). Influence of location of delivery on outcome in neonates with gastroschisis. *Journal of pediatric surgery 47*(11), 2022–2025.

New York State Department of Health (NYSDOH) (2000). Medicaid coverage for newborns.

New York State Department of Health (NYSDOH) (2001). Automatic Medicaid enrollment for newborns (chapter 412 of the laws of 1999).

New York State Department of Health (NYSDOH) (2016). New York State Medicaid program transportation manual policy guidelines.

New York State Office of the State Comptroller (NYS Comptroller) (2014). Overpayments to managed care organizations and hospitals for low birth weight newborns.

Parker, J. D. and K. C. Schoendorf (2000). Variation in hospital discharges for ambulatory care-sensitive conditions among children. *Pediatrics 106*(Supplement 3), 942–948.

Quinn, K. (2008). New directions in Medicaid payment for hospital care. *Health Affairs 27*(1), 269–280.

Shigeoka, H. and K. Fushimi (2014). Supplier-induced demand for newborn treatment: Evidence from Japan. *Journal of health economics 35*, 162–178.

Sparer, M. (2008). *Medicaid Managed Care Reexamined*. United Hospital Fund.

United Hospital Funds (UHF) (2000). Provider networks in Medicaid managed care plans. *Currents 5*(4).

Van Parys, J. (2015). How do managed care plans reduce healthcare costs? Job market paper, Columbia University.

Appendix

Appendix A. Hospital Payments Under MMC

A.1 State Payments to Health Plans

The state negotiates with each health plan to determine monthly capitation payments in New York State. Health plans submit data on enrollees and previous expenditures and propose new rates based on expected costs for each region they participate. The state reviews the data and offers a new set of rates that vary by age, sex, and region. These rates are applicable for a one-year period. The plans can receive a bonus up to 3 percent of the rate based on their performance on quality measures. In 2008, the state introduced a new payment system that accounts for health conditions of the enrollees by adjusting the capitation rates by Clinical Risk Groups. This new payment system was fully implemented in 2011 (Sparer, 2008).[52]

The New York State Medicaid program paid a monthly capitation rate of $138 on average for newborns younger than six months old in 1998 (Holahan and Schirmer, 1999), which is roughly $190 in 2011 values. For newborn services, however, plans receive lump-sum payments for costs related to newborn medical care in addition to monthly capitation payments. These lump-sum payments range from $2,277 to $6,651 per newborn weighing 1,200 grams or more (NYS Comptroller, 2014). Effective April 2012 following the expansion of the MMC mandate to infants with birth weight below 1,200 grams, plans receive lump-sum payments ranging from $68,355 to $105,108 per newborn for these low birth weight enrollees.

In return, health plans are responsible for providing health care services to their enrollees. Health plans offer a network of health care providers to their enrollees and reimburse the providers for their services. Health plans employ a number of payment methods to reimburse providers. I focus on reimbursement for inpatient services in this paper.

[52]It is unclear whether risk-adjusted payments can in fact reduce adverse selection and thus reduce government spending (Brown et al., 2014).

A.2 Plan Payments to Hospitals

For patients enrolled in MMC, hospitals are paid in several ways depending on contractual details between health plans and hospitals. However, plan-to-provider payment rates for MMC in New York State are classified as confidential and proprietary and thus not available. Although the exact payment methods and rates are unknown, most health plans in New York State reimburse providers through primary care capitation models (UHF, 2000). Inpatient payments associated with newborn medical care are often excluded in monthly capitation payments for primary care capitation models and are reimbursed on a fee-for-service basis using a Diagnosis-Related Group (DRG) method.[53] That is, each inpatient stay is classified into a DRG, and Medicaid pays a fixed rate to hospitals based on the DRG assigned to the patient (Quinn, 2008).

The New York State Department of Health (NYSDOH) provides inpatient payments base rates for enrollees in both the FFS system and the MMC system along with weights for each DRG.[54] The state Medicaid program uses the FFS rates for inpatient payments for patients enrolled in FFS. The MMC rates are intended to be used by health plans as base rates in negotiation with hospitals. As expected, these MMC rates are generally lower than the FFS rates that the state uses to pay hospitals directly. In 2009, for instance, the base discharge rate for FFS was $6,471.31 on average, while the base contract discharge rate for MMC was $5,284 on average.

[53] New York State implemented a severity-based methodology, All Patient Refined Diagnosis Related Groups (APR-DRGs) effective December 1, 2009. Prior to that, New York State utilized All Patient Diagnosis Related Groups (AP-DRG) for hospital payments.

[54] `http://www.health.ny.gov/facilities/hospital/reimbursement/apr-drg/rates/ffs/index.htm`

Appendix B. Figures

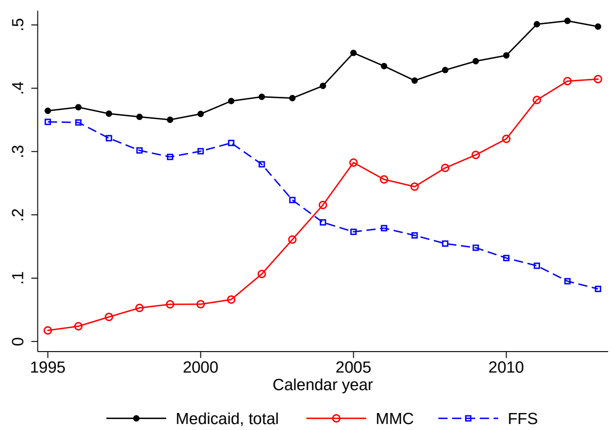


Figure B.1: Share of infants covered by Medicaid, New York State, 1995-2013

Sources: HCUP State Inpatient Databases
Notes: HMO stands for Health Maintenance Organization, a type of managed care organizations (MCOs).

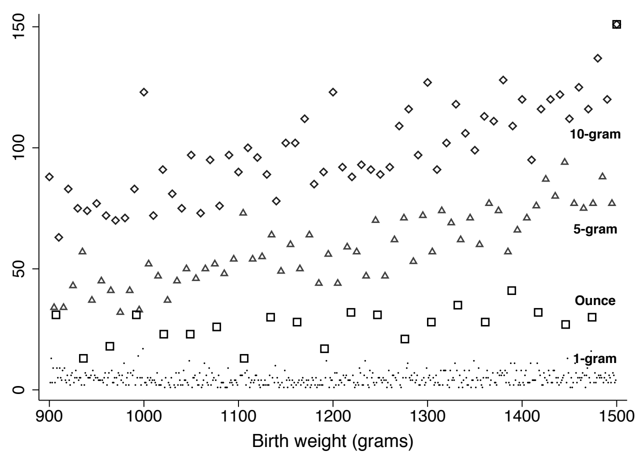
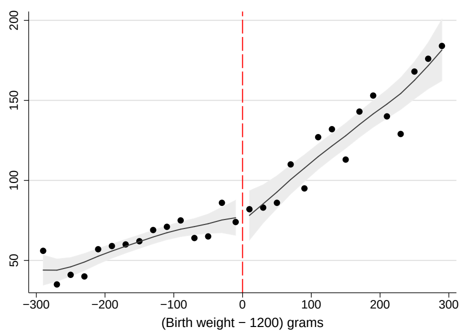
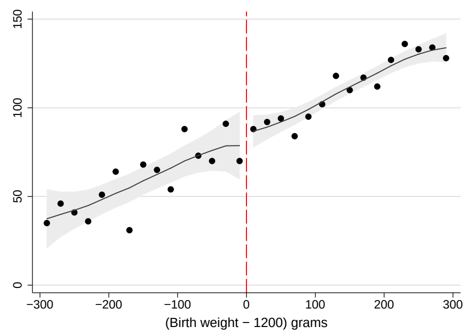


Figure B.2: Heaped data

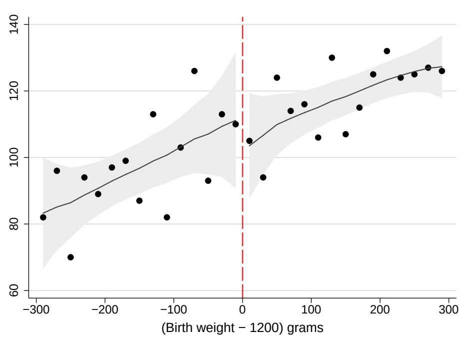
Notes: Diamonds indicate data at multiples of 10-gram. Triangles indicate data at multiples of 5-gram (but not 10-gram). Squares show data at ounce multiples.



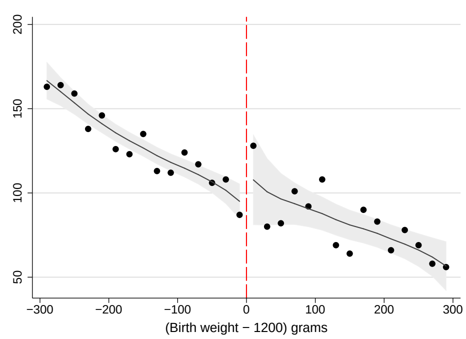
(a) Bottom quartile



(b) Q2



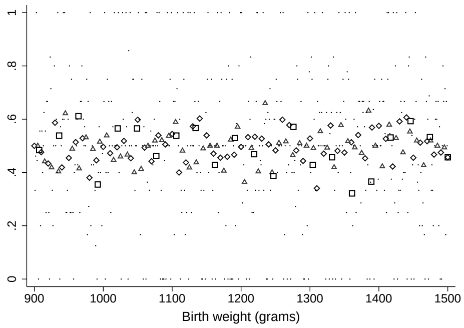
(c) Q3



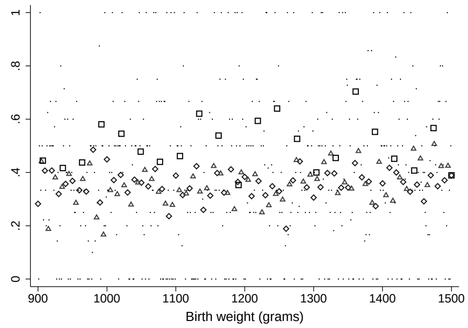
(d) Top quartile

Figure B.3: Mean frequency of the running variable by each 20-gram bin, by predicted list prices

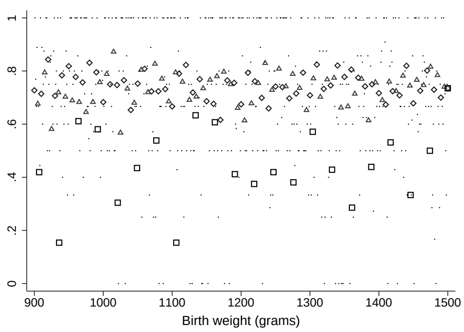
Notes: Predicted list prices are computed from a regression of total charges on principal diagnosis and principal procedure fixed effects. I divide the sample by quartiles using the predicted list prices. Each panel plots mean frequency for each 20-gram bin (dots) along with a local linear regression fitted lines (solid lines) and the 95% confidence intervals below and above the threshold for each quartile of predicted list prices. I use the triangular kernel and a bandwidth of 150 grams for local linear regressions.



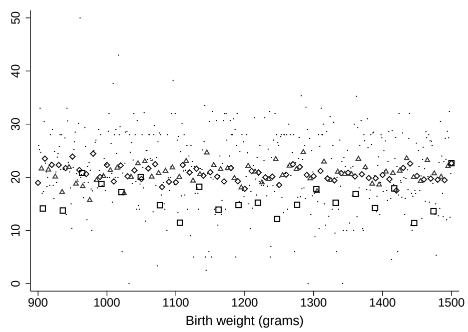
(a) Female



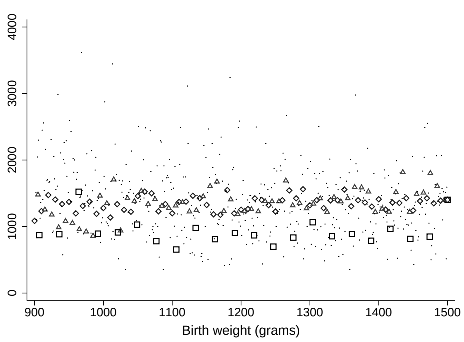
(b) White



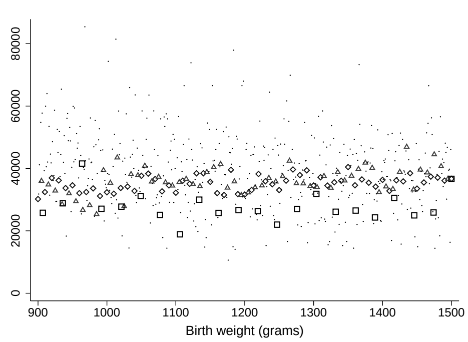
(c) Teaching hospital



(d) NICU beds



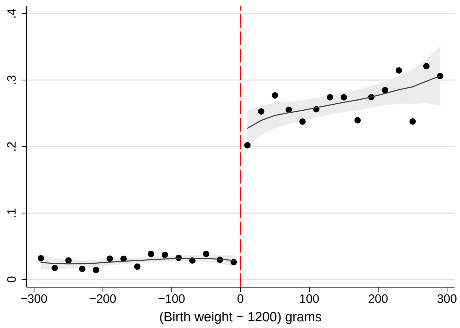
(e) Nurses



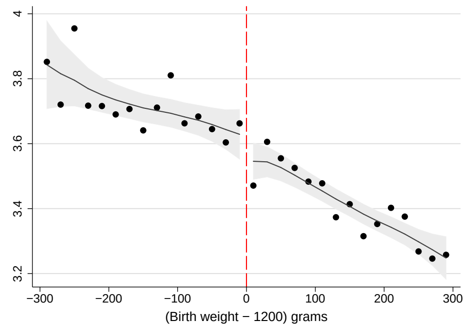
(f) Total admissions

Figure B.4: Characteristics of heaped data

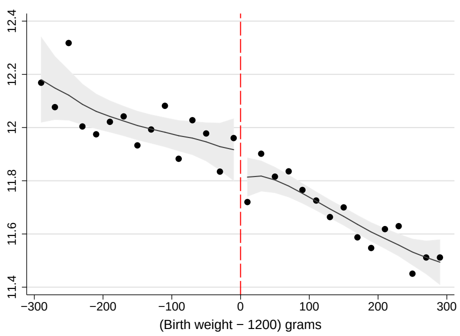
Notes: Diamonds indicate data at multiples of 10-gram. Triangles indicate data at multiples of 5-gram (but not 10-gram). Squares show data at ounce multiples.



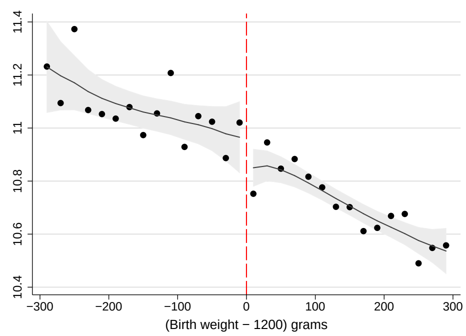
(a) MMC



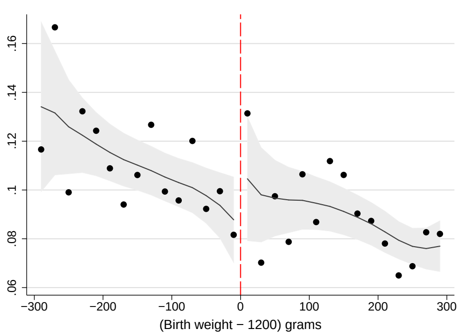
(b) Log(length of stay)



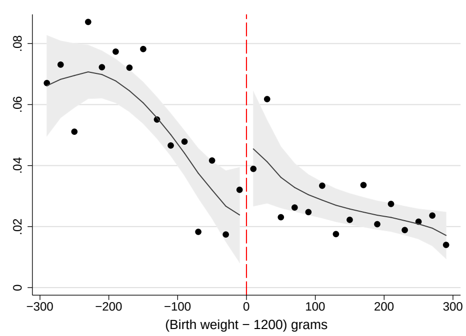
(c) Log(total charges)



(d) Log(total costs)



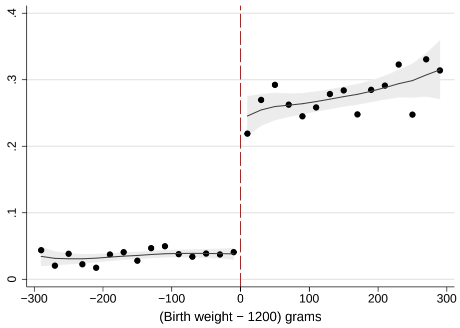
(e) Transfer



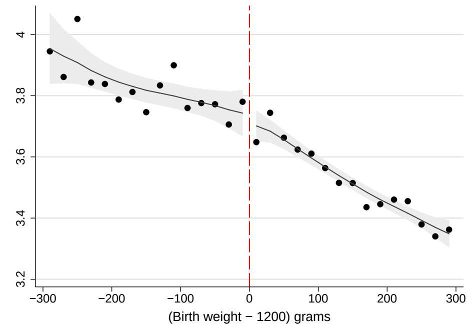
(f) Mortality during hospitalization

Figure B.5: Effects of birth weight≥1,200 grams on discharge outcomes at birth, New York State

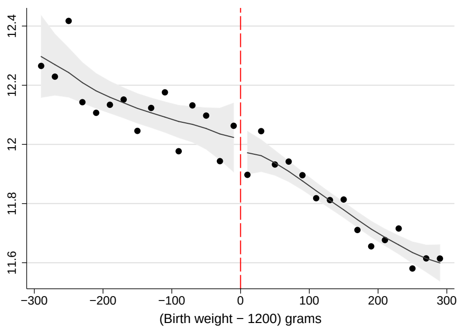
Notes: Panels (a)-(f) plot mean values of each outcome variable for each 20-gram bin (dots) along with a local linear regression fitted lines (solid lines) and the 95% confidence intervals below and above the threshold. I use the triangular kernel and a bandwidth of 150 grams for local linear regressions.



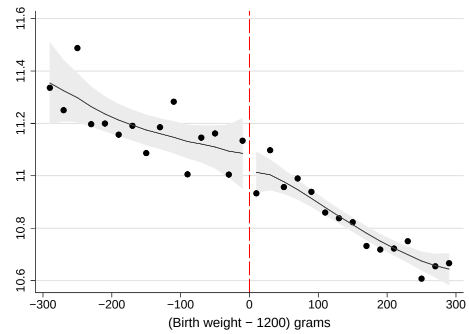
(a) MMC



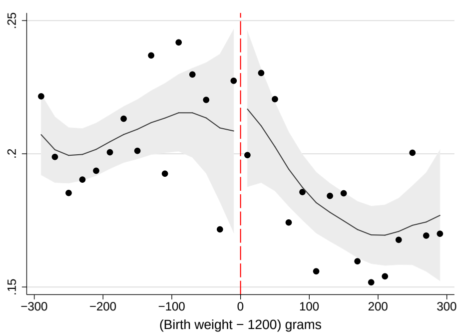
(b) Log(length of stay)



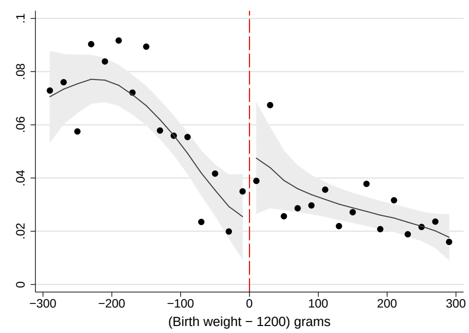
(c) Log(total charges)



(d) Log(total costs)



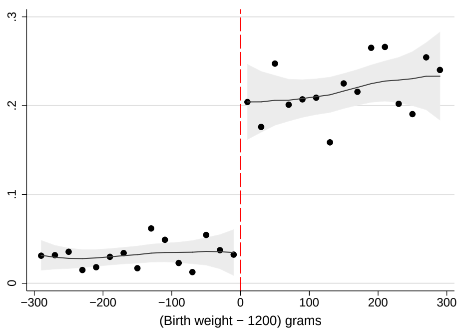
(e) Readmission



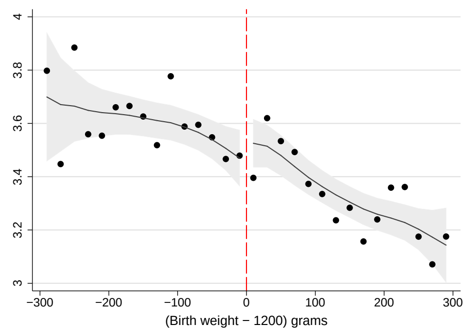
(f) 1-year mortality during hospitalization

Figure B.6: Effects of birth weight≥1,200 grams on aggregated discharge outcomes, New York State

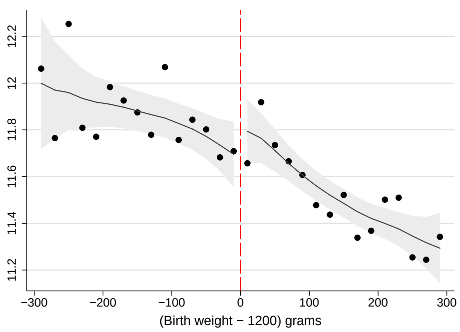
Notes: Panels (a)-(f) plot mean values of each outcome variable for each 20-gram bin (dots) along with a local linear regression fitted lines (solid lines) and the 95% confidence intervals below and above the threshold. I use the triangular kernel and a bandwidth of 150 grams for local linear regressions.



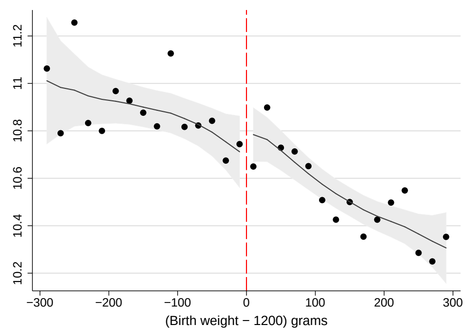
(a) MMC



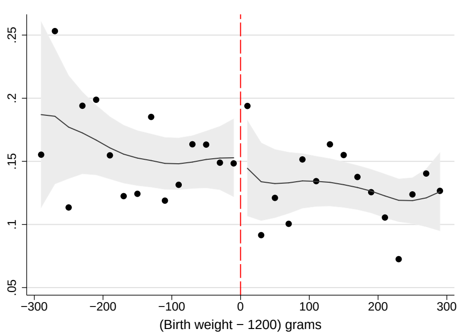
(b) Log(length of stay)



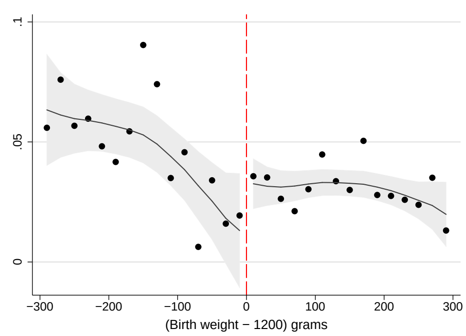
(c) Log(total charges)



(d) Log(total costs)



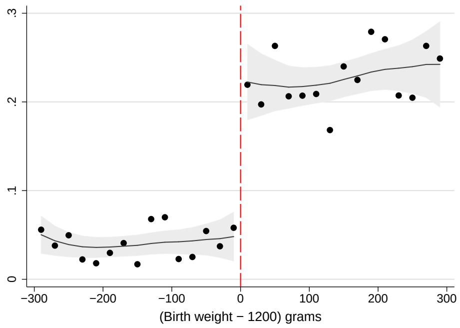
(e) Transfer



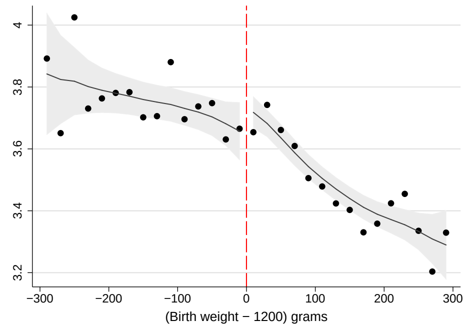
(f) Mortality during hospitalization

Figure B.7: Effects of birth weight≥1,200 grams on discharge outcomes at birth, rest of the state

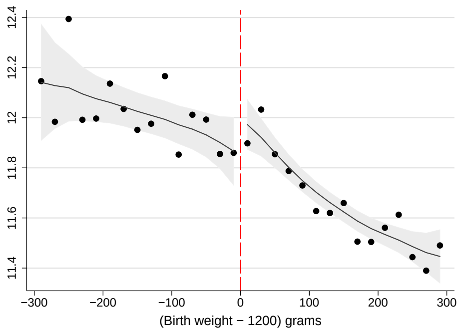
Notes: Panels (a)-(f) plot mean values of each outcome variable for each 20-gram bin (dots) along with a local linear regression fitted lines (solid lines) and the 95% confidence intervals below and above the threshold. I use the triangular kernel and a bandwidth of 150 grams for local linear regressions.



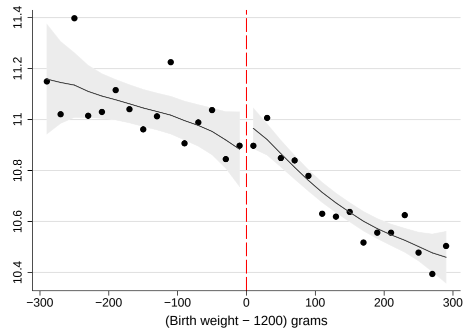
(a) MMC



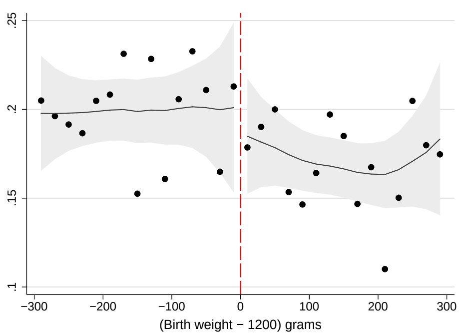
(b) Log(length of stay)



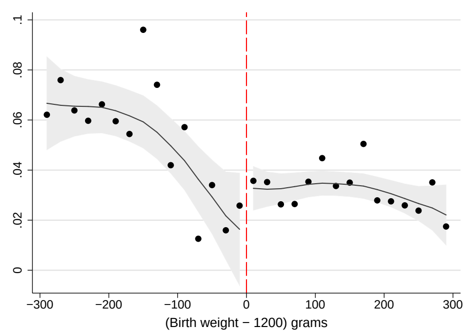
(c) Log(total charges)



(d) Log(total costs)



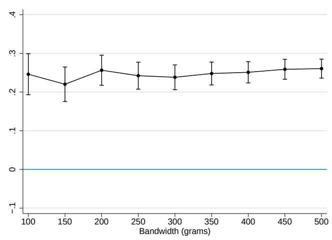
(e) Readmission



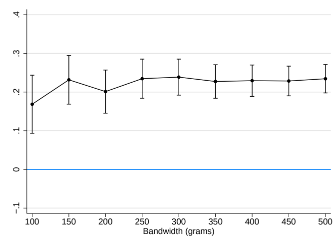
(f) 1-year mortality during hospitalization

Figure B.8: Effects of birth weight≥1,200 grams on aggregated discharge outcomes, rest of the state

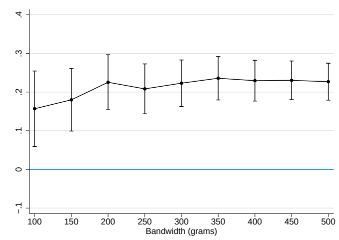
Notes: Panels (a)-(f) plot mean values of each outcome variable for each 20-gram bin (dots) along with a local linear regression fitted lines (solid lines) and the 95% confidence intervals below and above the threshold. I use the triangular kernel and a bandwidth of 150 grams for local linear regressions.



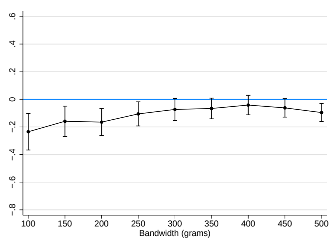
(a) MMC, linear



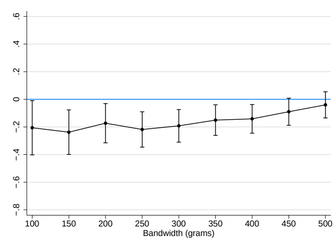
(b) MMC, quadratic



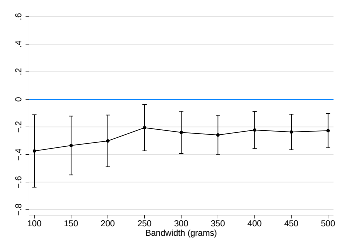
(c) MMC, cubic



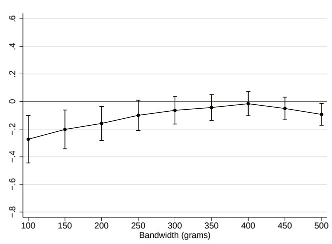
(d) Log(length of stay), linear



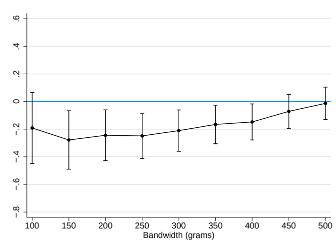
(e) Log(length of stay), quadratic



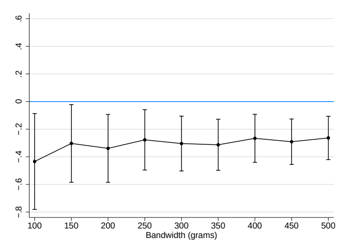
(f) Log(length of stay), cubic



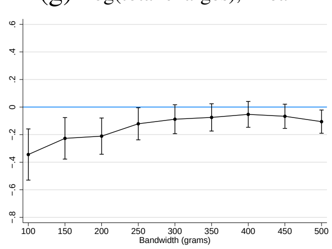
(g) Log(total charges), linear



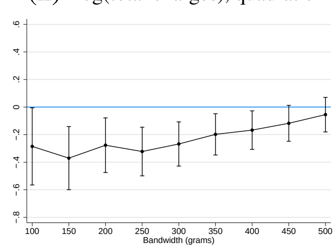
(h) Log(total charges), quadratic



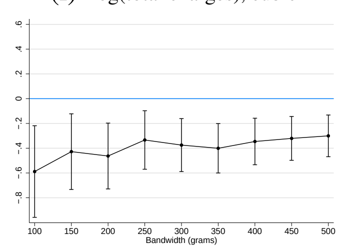
(i) Log(total charges), cubic



(j) Log(total costs), linear



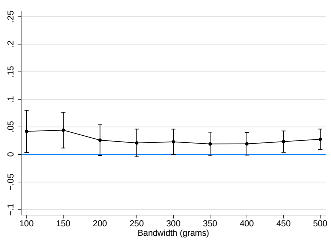
(k) Log(total costs), quadratic



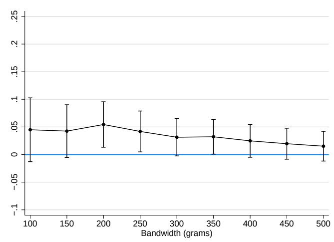
(l) Log(total costs), cubic

Figure B.9: Sensitivity to bandwidth and polynomial, New York City

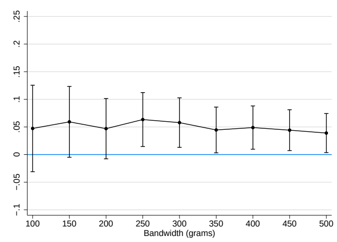
Notes: I repeat the estimation for each outcome for a different choice of bandwidth and polynomial. I use a range of bandwidths from 100 grams to 500 grams varying the degree of polynomials from degree 1 (linear), degree 2 (quadratic), to degree 3 (cubic).



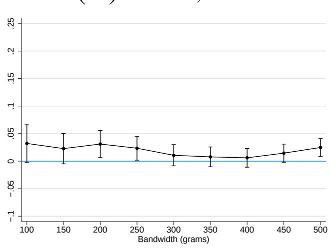
(m) Transfer, linear



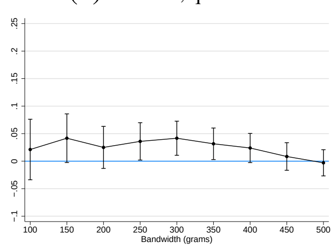
(n) Transfer, quadratic



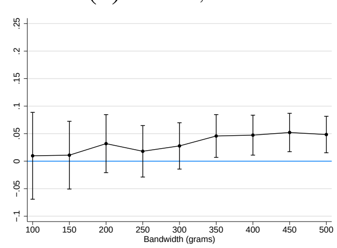
(o) Transfer, cubic



(p) In-hospital mortality, linear



(q) In-hospital mortality, quadratic



(r) In-hospital mortality, cubic

Figure B.9: Sensitivity to bandwidth and polynomial, New York City (continued)

Notes: I repeat the estimation for each outcome for a different choice of bandwidth and polynomial. I use a range of bandwidths from 100 grams to 500 grams varying the degree of polynomials from degree 1 (linear), degree 2 (quadratic), to degree 3 (cubic).

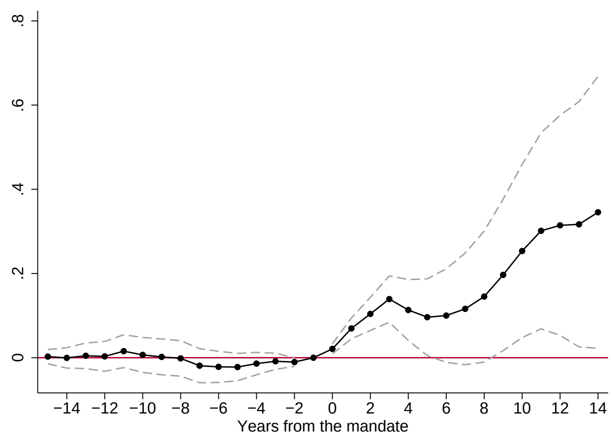
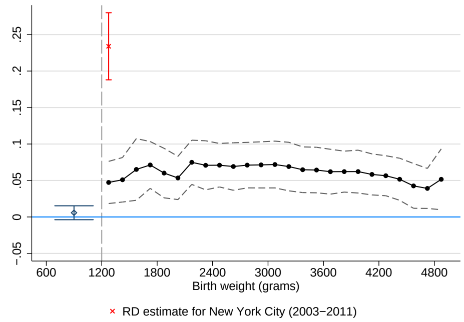
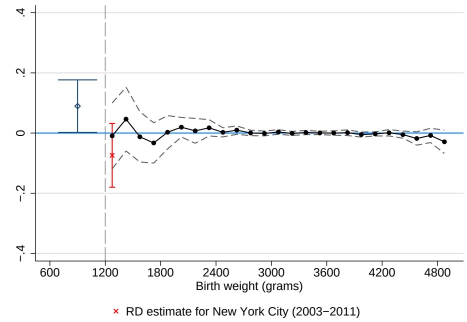


Figure B.10: MMC participation by years from the MMC mandate

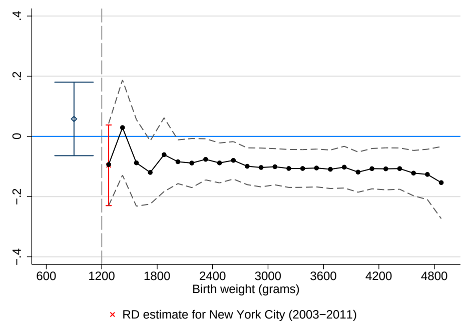
Notes: The above figure plots estimates from a regression of an indicator for MMC participation on a set of dummies that indicate years from the MMC mandate for each county. County fixed effects, year fixed effects, and county-specific time trends are also included in the regression. The dashed lines plot tge 95% confidence intervals computed based on standard errors clustered at the county level.



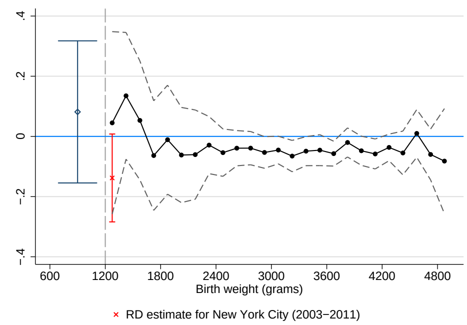
(a) MMC



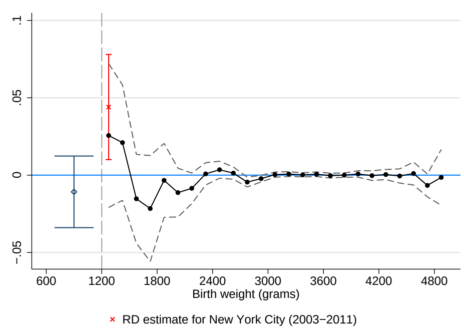
(b) Log(length of stay)



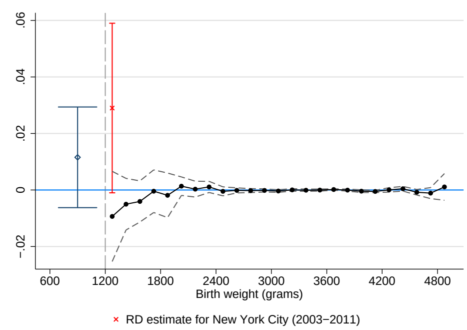
(c) Log(total charges)



(d) Log(total costs)



(e) Transfer



(f) Mortality during hospitalization

Figure B.11: Difference-in-difference estimates by birth weight

Notes: I estimate a difference-in-difference model by birth weight groups. Below the 1,200-gram threshold, I aggregate infants between 600 and 1,200 grams for precision and plot the difference-in-difference estimate with a navy bar. Above the 1,200-gram threshold, I plot the difference-in-difference estimates by birth weight groups in 150-gram increments (black). The estimates (solid lines) are plotted with the 95% confidence intervals (dotted lines). The corresponding RD estimate for the New York City sample is shown in red (x) along with its 95% confidence intervals.

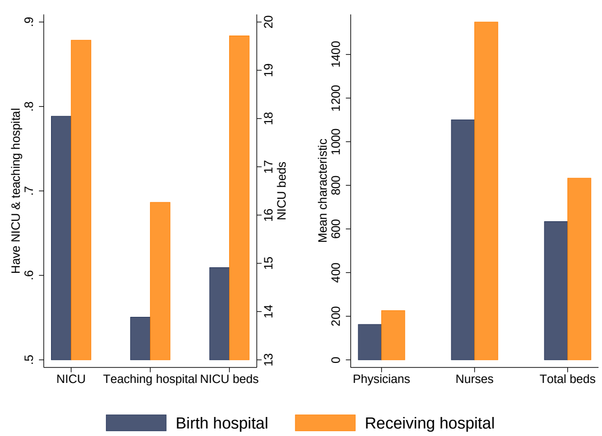


Figure B.12: Characteristics of birth hospitals and receiving hospitals

Notes: Navy bars summarize mean characteristics of birth hospitals. Orange bars describe mean characteristics of hospitals that receive transfers.

Appendix C. Tables

Table C.1: Balance of covariates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Female	White	Black	Hispanic	Asian	Poor	Scheduled	Weekend
Panel A. Patient characteristics								
Above	0.006	-0.017	0.010	0.011	0.002	-0.025	0.034	0.004
	(0.027)	(0.023)	(0.024)	(0.018)	(0.012)	(0.025)	(0.038)	(0.023)
Observations	5920	5726	5726	5726	5726	4572	1854	5920
Mean below cutoff	0.497	0.363	0.304	0.138	0.058	0.352	0.717	0.252
	NICU	Teaching	NICU beds	#Physicians	#Nurses	#Admissions	#Beds	#Births
Panel B. Hospital characteristics								
Above	0.001	-0.001	0.094	-6.860	-7.273	-275.029	-5.434	-57.445
	(0.010)	(0.019)	(0.539)	(13.398)	(40.721)	(911.325)	(19.980)	(109.420)
Observations	5002	5917	5002	5917	5917	5917	5917	5917
Mean below cutoff	0.953	0.723	20.684	192.573	1341.622	35893.862	760.999	4054.038

Notes: In addition to the indicator for birth weight$\geq$1,200 g, each regression includes a linear spline of birth weight, admission year fixed effects, admission month fixed effects, and hospital county fixed effects. Robust standard errors are reported. I define "Poor" as the patient zip code in the bottom quartile of the median income distribution.

Table C.2: Balanced of covariates, indices

	(1)	(2)	(3)	(4)
	Predicted costs	Predicted in-hospital mortality	Predicted costs	Predicted in-hospital mortality
			(replacing missing values with zero (and including dummies for missing values)	
Above	0.054	-0.003	0.008	-0.000
	(0.083)	(0.003)	(0.026)	(0.000)
Observations	748	748	5920	5920
Adjusted R^2	0.601	0.222	0.444	0.297
Mean below cutoff	10.861	0.032	10.886	0.039

Notes: I regress hospital costs and in-hospital mortality on all predetermined characteristics shown in Appendix Table C.1 to create indices. These indices have missing values due to missing predetermined characteristics (columns 1 and 2). To deal with missing values, I regress hospital costs and in-hospital mortality on all predetermined characteristics after replacing missing values with zero, including indicators for the missing values (column 3 and 4). In addition to the indicator for birth weight≥1,200 g, each regression includes a linear spline of birth weight, admission year fixed effects, admission month fixed effects, and hospital county fixed effects. Robust standard errors are reported.

Table C.3: Effects of birth weight≥1,200 grams, New York City, routine discharges

	(1)	(2)	(3)
	Log(LOS)	Log(total charges)	Log(total costs)
Panel A. Outcomes for routine discharges only			
Above	-0.080	-0.101	-0.110
	(0.033)	(0.065)	(0.064)
Observations	2023	2023	1467
Mean below cutoff	53.960	269705.878	105781.553
Panel B. Imputed outcomes for non-routine discharges			
Above	-0.048	-0.066	-0.057
	(0.021)	(0.041)	(0.035)
Observations	3213	3213	2657
Mean below cutoff	50.877	253670.036	97297.228

Notes: In addition to the indicator for birth weight≥1,200 g, each regression includes a linear spline of birth weight, admission year fixed effects, admission month fixed effects, and hospital county fixed effects. Robust standard errors are reported. The means of logged outcomes are reported in levels.

Table C.4: Effects of birth weight≥1,200 grams on other health/quality outcomes, rest of the state

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Avoidable readmission	Level IV NICU stay	Any NICU stay	Chest X-ray	Ultrasound	Implant	Physical therapy	Respiratory therapy	Speech therapy
Above	-0.014	-0.005	0.003	0.050	0.005	-0.008	0.050	0.021	0.016
	(0.020)	(0.024)	(0.017)	(0.030)	(0.020)	(0.011)	(0.031)	(0.023)	(0.017)
Observations	2707	2707	2707	2707	2707	2707	2707	2707	2707
Mean below cutoff	0.079	0.855	0.922	0.694	0.904	0.022	0.404	0.915	0.059

Notes: Column 1 shows the RD estimate for hospital readmission due to preventable conditions. Columns 2-9 show the RD estimates for utilization of various inpatient services at the individual level. In addition to the indicator for birth weight≥1,200 g, each regression includes a linear spline of birth weight, admission year fixed effects, admission month fixed effects, and hospital county fixed effects. Robust standard errors are reported.

Table C.5: Robustness to the inclusion of hospital fixed effects, New York City

	(1)	(2)	(3)	(4)	(5)	(6)
	MMC	Log(LOS)	Log(total charges)	Log(total costs)	Transfer	In-hospital mortality
Discharge outcomes at birth hospitals with hospital fixed effects						
Above	0.209	-0.100	-0.122	-0.124	0.026	0.023
	(0.023)	(0.049)	(0.053)	(0.061)	(0.015)	(0.014)
Observations	3213	3213	3213	2452	3213	3213
Mean below cutoff	0.028	50.753	261746.798	98855.931	0.067	0.039

Notes: The table shows the RD estimates for each outcome from discharge records at birth hospitals. In addition to the indicator for birth weight≥1,200 g, each regression includes a linear spline of birth weight, admission year fixed effects, admission month fixed effects, hospital county fixed effects, and hospital fixed effects. Robust standard errors are reported. The means of logged outcomes are reported in levels.

Table C.6: Robustness to non-random heaping, New York City

	(1) MMC	(2) Log(LOS)	(3) Log(total charges)	(4) Log(total costs)	(5) Transfer	(6) In-hospital mortality
Panel A. Dropping ounce heaps						
Above	0.225	-0.162	-0.209	-0.233	0.042	0.025
	(0.023)	(0.057)	(0.073)	(0.079)	(0.017)	(0.015)
Observations	3087	3087	3087	2352	3087	3087
Mean below cutoff	0.027	51.001	262813.173	100209.948	0.069	0.040
Panel B. Using only heaps (multiples of 10-gram, 5-gram, and ounce)						
Above	0.222	-0.143	-0.164	-0.204	0.047	0.021
	(0.024)	(0.060)	(0.077)	(0.085)	(0.017)	(0.015)
Observations	2825	2825	2825	2111	2825	2825
Mean below cutoff	0.027	51.264	263888.405	101442.280	0.061	0.041
Panel C. A donut RD (dropping observations at 1,200 grams)						
Above	0.232	-0.141	-0.171	-0.183	0.039	0.019
	(0.025)	(0.056)	(0.072)	(0.076)	(0.017)	(0.014)
Observations	3149	3149	3149	2405	3149	3149
Mean below cutoff	0.028	50.753	261746.798	98855.931	0.067	0.039

Notes: The table shows the RD estimates for each outcome from discharge records at birth hospitals. In addition to the indicator for birth weight≥1,200 g, each regression includes a linear spline of birth weight, admission year fixed effects, admission month fixed effects, hospital county fixed effects, and hospital fixed effects. Robust standard errors are reported. The means of logged outcomes are reported in levels.

Table C.7: Difference-in-difference estimates, other health/quality outcomes

	(1) Any NICU stay	(2) Chest X-ray	(3) Ultrasound	(4) Implant	(5) Physical therapy	(6) Respiratory therapy	(7) Speech therapy
Panel A. Without county-specific time trends							
MMC mandate	0.005	-0.009	-0.008	-0.002	0.000	-0.010	-0.006
	(0.005)	(0.006)	(0.004)	(0.001)	(0.006)	(0.008)	(0.008)
Observations	1814623	1814623	1814623	1814623	1814623	1814623	1814623
Mean	0.127	0.090	0.063	0.005	0.013	0.086	0.007
Panel B. With county-specific time trends							
MMC mandate	0.005	-0.011	-0.007	-0.001	-0.000	-0.016	-0.006
	(0.007)	(0.007)	(0.004)	(0.001)	(0.003)	(0.005)	(0.003)
Observations	1814623	1814623	1814623	1814623	1814623	1814623	1814623
Mean	0.127	0.090	0.063	0.005	0.013	0.086	0.007

Notes: Panel A presents difference-in-difference estimates for each outcome without including the county-specific trends. Panel B shows the estimates including the county-specific trends. The means of logged outcomes are reported in levels.

Table C.8: Heterogeneity by other measures of bargaining power, New York City

	(1)	(2)	(3)	(4)	(5)	(6)
	MMC	Log(LOS)	Log(total charges)	Log(total costs)	Transfer	In-hospital mortality
Panel A. Below-median total admissions						
Above	0.275	-0.197	-0.193	-0.311	0.059	0.015
	(0.033)	(0.087)	(0.102)	(0.140)	(0.026)	(0.019)
Observations	1601	1601	1601	971	1601	1601
Mean below cutoff	0.031	49.471	152218.547	78665.897	0.095	0.043
Panel B. Above-median total admissions						
Above	0.158	-0.090	-0.139	-0.114	0.023	0.026
	(0.031)	(0.072)	(0.086)	(0.084)	(0.020)	(0.021)
Observations	1609	1609	1609	1481	1609	1609
Mean below cutoff	0.025	52.115	372044.788	111913.136	0.039	0.036
Panel C. Below-median number of beds						
Above	0.257	-0.231	-0.271	-0.365	0.090	0.006
	(0.032)	(0.089)	(0.108)	(0.131)	(0.026)	(0.020)
Observations	1572	1572	1572	1079	1572	1572
Mean below cutoff	0.029	48.853	186328.307	83225.141	0.094	0.042
Panel D. Above-median number of beds						
Above	0.190	-0.052	-0.069	-0.045	-0.004	0.032
	(0.033)	(0.069)	(0.087)	(0.088)	(0.020)	(0.020)
Observations	1638	1638	1638	1373	1638	1638
Mean below cutoff	0.027	52.562	331009.849	110392.369	0.042	0.037
Panel E. Not a teaching hospital						
Above	0.241	-0.351	-0.398	-0.569	0.107	0.023
	(0.062)	(0.158)	(0.170)	(0.182)	(0.045)	(0.025)
Observations	585	585	585	497	585	585
Mean below cutoff	0.062	45.777	145543.524	57090.540	0.106	0.036
Panel F. Teaching hospital						
Above	0.208	-0.103	-0.132	-0.100	0.026	0.025
	(0.024)	(0.058)	(0.076)	(0.078)	(0.018)	(0.016)
Observations	2625	2625	2625	1955	2625	2625
Mean below cutoff	0.020	51.916	288024.716	109728.933	0.058	0.040

Notes: In addition to the indicator for birth weight$\geq$1,200 g, each regression includes a linear spline of birth weight, admission year fixed effects, admission month fixed effects, and hospital county fixed effects. Robust standard errors are reported. The means of logged outcomes are reported in levels.