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

Ajin Lee†

July 2017

Abstract

Medicaid, the largest public health insurance program in the US, has transitioned from a fee-for-service system (FFS) primarily administered by the government to a managed care system (MMC) administered by private insurers over the last few decades. I examine how hospitals' responses to financial incentives under these two systems affect hospital costs and newborn health outcomes. I analyze the universe of inpatient discharge records across New York State from 1995-2013, totaling 4.5 million births. First, 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. Using a regression discontinuity design, I find that newborns enrolled in MMC stayed fewer days in hospitals and thus had less expensive visits relative to newborns enrolled in FFS. The cost difference is driven by birth hospitals retaining more newborns enrolled in FFS while transferring away those enrolled in MMC. Despite the cost difference at the threshold, I do not detect statistically significant impacts of MMC on average newborn health, measured by in-hospital mortality and hospital readmission. Hospitals tended to transfer out MMC newborns only when a high-quality hospital was nearby, suggesting that these newborns were able to receive adequate care at the transferred hospital. Second, I exploit county-level rollout of the MMC mandate to examine impacts on the full population of infants using a difference-in-difference design. I find that hospitals achieved a similar rate of cost savings as for infants over the 1,200-gram threshold, while length of stay, the probability of transfer, and mortality did not change following the mandate. This finding suggests that there are alternative, successful methods by which hospitals reduce costs under MMC, including for high-risk deliveries.

*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 Hyuncheol Bryant Kim, Yogita Shamdasani, Boris Vabson, and 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.

†Columbia University: al3045@columbia.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. 40% of US children are covered by Medicaid, the means-tested health insurance program funded by states and the federal government. To reduce wasteful spending and improve quality, Medicaid has transitioned from the traditional fee-for-service (FFS) system administered by the government to the Medicaid managed care (MMC) system administered by capitated 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 nearly half of total Medicaid expenditures today.[1]

Despite the systematic transition to MMC, the existing literature finds mixed impacts of MMC on both cost and health outcomes. A priori, MMC's incentive structure might restrain the excesses of FFS. While the per-service reimbursement for health care providers (such as physicians and hospitals) under FFS has been criticized for encouraging over-provision of care with dubious health benefits (Hackbarth et al. 2008; Arrow et al. 2009), the capitation payment (a set fee per month per enrollee) for health plans under MMC has been considered as a means to reduce the over-provision and manage quality. However, the incentive structure under MMC does not directly regulate payments of health care providers, making it unclear how the actual providers of care would respond to MMC. Ultimately, the success of MMC is contingent upon *provider responses*. Yet little evidence exists on whether providers alter their practice patterns based on the payment system, limiting our understanding of MMC.

This paper focuses on how hospitals respond to MMC in comparison to FFS. Do hospitals treat patients differentially based on the payment system? Does MMC incentivize hospitals to reduce costs without compromising patient health? Specifically, I focus on hospital care for high-risk newborns in New York State to exploit variation in the probability of MMC enrollment at a birth weight cutoff: infants weighing less than 1,200 grams (2 pounds, 10 ounces) were excluded from mandatory enrollment in MMC in New York State and were instead served through the traditional FFS system for the first six months of their lives (NYSDOH, 2000, 2001). I compare infants whose birth weight falls just below the threshold and thus enroll in FFS with infants whose birth weight falls just above the threshold and thus enroll in MMC in a regression discontinuity (RD) design. While local, my estimates are important because they focus on the most expensive newborn deliveries. Infants that weigh below 1,200 grams account for one percent of the total newborn population but incur approximately <u>one-third</u> of total newborn hospital costs. This suggests that potential cost savings

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

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. 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.

Consistent with the exclusion from the MMC mandate, I find that infants above the 1,200-gram threshold are more likely to participate in MMC compared to infants below the threshold by 23 percentage points. Focusing on hospital discharge records from New York City, I find that infants above the threshold also have shorter length of stay and thus have lower hospital costs in the first six months of their lives. I find that the cost difference is driven by birth hospitals' transfer behavior. Birth hospitals tend to transfer more infants above the threshold to other short-term hospitals while holding onto infants below the threshold. Hospitals that receive the transferred infants are on average bigger and better-equipped than birth hospitals, suggesting that MMC steers high-risk infants towards "high-quality" hospitals that can provide better-suited care to these infants.

To investigate whether the reduction in length of stay results in worse health outcomes, I examine mortality during hospitalization and the incidence of hospital readmission following the birth episode. Although costs and care change, I find no clear evidence of adverse effects on average newborn health, at least to the extent that newborn health can be measured. This may not be surprising given that infants enrolled in MMC are more likely to be transferred to higher-quality hospitals, mitigating potential harm to health during the transfer or at birth hospitals. These results suggest that MMC may be able to efficiently manage care of at-risk newborns by reallocating them to higher-quality hospitals.

These hospital responses to different payment systems suggest that hospitals internalize financial incentives to reduce costs for MMC infants. I provide additional evidence that financial incentives do indeed drive these hospital responses. Consistent with a profit maximization problem of hospitals, effects are stronger when hospitals' spatial constraints bind (i.e., when they have few Neonatal Intensive Care Unit (NICU) beds available) and when potential receiving hospitals have spare capacity. In addition, the effects are stronger for infants with high expected costs of treatment.

I propose a mechanism through which hospitals might engage in such behavior in response to MMC: expedient coordination of care between local hospitals. In contrast to the above findings in New York City, I show that there are no differences between MMC and FFS in counties outside of New York City. This suggests that the structure of local health care markets may impact how hospitals respond to MMC. In particular, I consider distance from a birth hospital to a hospital with a NICU facility (which I consider as a sign of high-quality) as one possible factor driving the differences between New York City and upstate counties. I find that hospitals are in fact more responsive to MMC when they have a high-quality hospital nearby, even within New York City. This suggests that even if MMC motivates hospitals to selectively transfer infants to maximize their profits, the cost of timely transfers may outweigh the financial benefit for some hospitals due to the lack of an efficient coordination system.

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. To address this, I exploit the rollout of the MMC mandate across counties in New York State in a difference-in-difference (DD) framework. I find that the DD estimates are comparable to my RD estimates for low birth weight infants. For infants with higher birth weight, I also find that hospitals achieve a similar level of cost reductions without affecting mortality. However, length of stay and the probability of transfer do not change for this group following the MMC mandate, suggesting that hospitals adjust the amount of care conditional on retaining these infants.

I also consider the average characteristics of "compliers" for both RD and DD models. Compliers for the RD model are infants who are induced to enroll in MMC due to exceeding the birth weight threshold at 1,200 grams. Compliers for the DD model are infants who are induced to enroll in MMC due to living in a county at the time of the MMC mandate rollout. I find that two groups of compliers are quite different. For example, compliers in the RD model stay in hospitals that have more beds, staff, and equipment compared to compliers in the DD model, who also have much higher birth weight. This suggests that treatment effects for these two models could differ since hospitals with varying observable characteristics may respond differently to incentives associated with MMC. Indeed, the means by which cost reductions are achieved differ. Nevertheless, the overarching finding of lower cost but similar health outcomes under MMC persists.

The remainder of the paper is organized as follows. Section 2 discusses my contributions to the related literature. 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 main RD estimates and discusses the mechanism. To further understand hospitals' financial incentives, Section 7 explores three sources of heterogeneity: capacity at birth hospitals, capacity at potential receiving hospitals, and expected costs of treatment. Section 8 discusses several specification and robustness checks of the main results. Section 9 presents the DD estimates and compares complier characteristics between the DD and RD estimates. Section 10 discusses cost implications. Section 11 concludes.

2 Contributions to the Relevant Literature

This section summarizes the relevant literature and discusses my contributions. The current literature on MMC has three limitations. First, there is no consensus on the effects of MMC as the findings in the literature are mixed. Second, few papers focus directly on provider-level responses, thus limiting our understanding of the mechanisms. Third, most papers focus on relatively healthier subpopulations who might have little room for cost reductions and health improvements. This paper attempts to address each of these three points.

First, I utilize a type of variation that has not been previously explored to identify the effects of MMC. I exploit a discontinuous exclusion from MMC enrollment based on birth weight in an RD framework. To complement my RD strategy, I also estimate a DD model using county-level rollout of the MMC mandate in New York State. Moreover, I compute mean characteristics of compliers for both RD and DD models to further understand the differences between these two models.

Several papers use local MMC mandates as an exogenous source of variation in a DD framework, but the findings are mixed. For instance, Duggan (2004) focuses on the impact on Medicaid expenditures using a local MMC mandate in California as a source of variation. He finds that an MMC mandate in California led to an *increase* in government spending with no health improvement, suggesting that while states implemented MMC in search of greater cost-savings, such savings may not have been realized. His findings, however, do not always apply to a similar study in other states. For example, Harman et al. (2014) show that the MMC mandate in Florida led to a *reduction* in Medicaid expenditures. On the other hand, using datasets that represent a national sample, Herring and Adams (2011) and Duggan and Hayford (2013) find no overall effects on expenditures.

Similarly, the findings on the effects of MMC on health outcomes are also inconclusive. Several papers focus on pregnant women and infants as they account for a large share of Medicaid beneficiaries. 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.[2] Their findings suggest that providers can respond to MMC by limiting care for certain subpopulations, resulting in adverse effects on health.[3] 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).

Second, I focus on hospital responses to MMC and propose a hospital-level mechanism through which MMC can achieve its goals. Few papers in the literature directly discuss mechanisms and most focus on health plans' incentives. 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.[4] In addition, Van Parys (2015) examines

[2] 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.

[3] Kuziemko et al. (2013) provide evidence on 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.

[4] 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

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. Although it is useful to understand plan-level incentives, the lack of attention on provider-level incentives limits our understanding of how MMC can influence actual provider practice.[5]

Third, I focus on a high-cost subpopulation - low birth weight infants. 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 literature focuses on relatively healthier subpopulations because most of the local MMC mandates exclude disabled subpopulations and high-cost procedures are often carved out of benefit packages.[6] As a number of states have begun to expand MMC to those with critical conditions (Iglehart 2011; Libersky et al. 2013; KFF 2015), however, it is timely and policy-relevant to understand whether MMC can successfully deliver medical care to these populations.

This paper is also related to the literature on hospital responses to a change in prices.[7] Dafny (2005) shows that hospitals "upcode" patients to take advantage of large price increases for certain diagnoses.[8] Acemoglu and Finkelstein (2008) find a large increase in capital-labor ratios following a reform that decreased reimbursement for labor input. Shigeoka and Fushimi (2014) find an increase in NICU utilization following a reform that made it more profitable in Japan. I contribute to this literature by examining how hospitals respond to a change in reimbursement rates for severely ill patients.

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.

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traditional indemnity insurance, while they find relative modest differences in quantity (i.e., treatment patterns) and health outcomes.

[5]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.

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

[7]Some papers focus on physicians' financial incentives. For example, see Clemens and Gottlieb (2014).

[8]See also Sacarny (2014) & Geruso and Layton (2015).

3 Background

In this section, I provide institutional details on MMC in New York State focusing on newborns. Section 3.1 describes mandatory enrollment in MMC in New York State and discusses imperfect compliance with the mandate. Section 3.2 describes the exclusion of newborns from mandatory enrollment in MMC based on birth weight. Section 3.3 discusses hospital payments under FFS versus MMC in treating low birth weight infants.

3.1 Mandatory MMC Enrollment in New York State

Medicaid beneficiaries in New York State are generally required to enroll in a managed care plan.[9] The mandatory enrollment in MMC was phased in starting 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.[10] However, the actual share of Medicaid recipients enrolled in MMC falls short of 100%. In July 2015, two and a half years after the full implementation, only 78% of the New York State Medicaid population were enrolled in MMC while the rest were still enrolled in FFS.[11]

Figure 2 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 study period. In 1995, only about 5% of total Medicaid infants were covered by Health Maintenance Organizations (HMOs), a type of managed care organizations (MCOs), while the rest 95% were covered by non-HMO. By 2013, 83% of total Medicaid infants were enrolled in HMOs, and the rest 17% were served through non-HMO. 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.[12]

The share covered by HMO is not 100% even after the statewide implementation of the mandate due to three reasons. First and foremost, there are a few infants who are still covered by Medicaid FFS due to

[9] Prior to the mandate, Medicaid beneficiaries had an option to enroll in MMC voluntarily, but the participation rate was low.

[10] Medicaid beneficiaries under the Supplemental Security Income (SSI) program were excluded from the MMC mandates prior to 2006. In 2006, a separate set of mandates was rolled out for SSI population only. Due to data limitation, I am unable to identify newborns who participate in SSI. However, less than 5% of newborns are covered by SSI.

[11] `http://kff.org/medicaid/state-indicator/share-of-medicaid-population-covered-under-different-delivery-systems/`

[12] 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.

exclusions and exemptions from the MMC enrollment. I exploit one of the exclusions for my identification strategy, which I describe further in the following section. Second, some infants who are newly enrolled in Medicaid might show up as having the FFS coverage in the discharge records at birth, in case their parents fail to enroll their child in a managed care plan in a timely manner.[13] 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 Grams Birth Weight Threshold

Infants born to pregnant 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. When the infant weighs less than 1,200 grams, however, the 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. They are instead served 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.

These infants with very low birth weight were excluded from MMC enrollment along with other subpopulations that are medically complicated and expensive to treat. For example, nursing home residents and people residing in state psychiatric facilities were also excluded from MMC enrollment during the study period (Sparer, 2008). Given the high costs of treatment and clinical complications, these groups were excluded initially 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, the state has been gradually phasing in mandatory enrollment into MMC for these subpopulations, mainly for greater cost savings. As part of the Medicaid Redesign Team (MRT) initiatives, infants weighing less than 1,200 grams at birth have been no longer excluded from MMC enrollment since April 2012.[14] Therefore, this paper has direct policy implications on whether MMC can achieve cost reductions without harming health outcomes of critically ill newborns.

3.3 Hospital Payments Under FFS Versus MMC

Under FFS, hospitals are directly reimbursed by Medicaid in a uniform manner. In New York State, the Medicaid program uses a Diagnosis Related Group (DRG) to reimburse health care providers for inpatient

[13] Newly enrolled Medicaid beneficiaries are given 90 days to choose a health plan.
[14] `http://www.health.ny.gov/health_care/medicaid/program/update/2012/2012-02.htm#infants`

services they provide to FFS enrollees. 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).

Under MMC, Medicaid pays health plans a flat fee per month per enrollee (i.e., capitation) and health plans are responsible for reimbursing hospitals for inpatient services. Hospital payments under MMC vary depending on contractual details between health plans and hospitals. Health plans choose a wide range of methods in reimbursing providers, from a fee-for-service method to capitation. For inpatient services associated with newborn medical care, however, most health plans in New York State use a fee-for-service method using DRGs.

Unfortunately, plan-to-provider payment rates for MMC in New York State are classified as confidential and proprietary and thus not available. However, since health plans have an incentive to reduce costs given the fixed revenue structure, the fee-for-service payments to hospitals under MMC may be lower than the hospital payments under FFS. According to the New York State Department of Health (NYSDOH), the actual hospital payments under FFS are in fact higher than the *suggested* hospital payments under MMC.[15] This suggests that hospitals may benefit more from treating infants enrolled in FFS than infants enrolled in MMC who would bring in smaller profits. Refer to Appendix Section A for further details on hospital payments. I discuss a conceptual framework of hospital responses to different levels of prospective payment in Appendix Section A.3.

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 1995-2013.[16] 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 primary expected payer. I examine the effects of MMC on various measures of inpatient care including total charges, length of stay (LOS), transfer, and mortality during hospitalization. Starting 2003, New York State Inpatient Databases include encrypted person identifiers that enable researchers to identify multiple hospital visits of the same patient over time. This allows me to distinguish births, transfers, and subsequent visits.

In addition, I use American Hospital Association (AHA) Annual Survey of Hospitals from 1995-2013.[17]

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

[16]Data access to HCUP was provided by the National Bureau of Economic Research (NBER).

[17]Access to AHA was also granted by NBER.

This dataset contains detailed information on hospitals such as hospital names, location, staff, and facilities. I use these various hospital characteristics to understand the mechanism through which MMC affects hospital practice.

Table 1 provides summary statistics of my main analysis sample, infants in New York State from 2003-2011. I focus on periods between 2003 and 2011 to exploit encrypted person identifiers to track patients over time and to exclude the periods when the exclusion was no longer valid. I also restrict my sample to records after the mandate was in place. Moreover, my sample restrictions include dropping newborns that I cannot consistently track over time and dropping newborns with missing birth weight or initial record at birth. Among the full sample of newborns in the first column, 43% of the total 2 million discharge records are financed by Medicaid. Within Medicaid, 62% of infants are covered by HMO.

Total charges are list prices for all services provided at the facility to each discharge record. 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 hospital-year-specific cost-to-charge ratios. This measure is considered to better reflect how much hospital services actually cost. Total costs are considerably lower than total charges, \$3,500 compared to \$9,609 on average.[18] In the full sample, infants stay on average four days in the hospital. Death 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, 95% 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 and \$145,000 above the threshold. Total costs are also high, \$75,758 below and \$52,670 above the threshold. These infants stay hospitalized for more than a month on average. Mortality is also greater than the full sample, which is around 5% below the threshold and 2% above the threshold. Transfers occur for more than 10% of these infants, and the majority of them utilize NICU (74-75%).

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 falls just below the 1,200-gram threshold and thus are served through Medicaid FFS to infants whose birth weight falls just above the threshold and

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

thus are enrolled in MMC. I estimate the following regression to examine the first stage effect of exceeding the threshold on MMC participation. Then, I proceed to examine the reduced-form effects on several discharge outcomes Y_i:

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

where i denotes a discharge record. D_i is a binary variable that takes one if the 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 (ϕ_m), and hospital county fixed effects (ψ_c). Excluding these additional controls has little impact on the results.

For bandwidth selection, I employ a bandwidth selection method proposed by Calonico et al. (2014) for each outcome. This method suggests a bandwidth ranging from 100 to 200 grams for my main outcome variables. I estimate these models with Ordinary Least Squares (i.e., local linear regressions with a uniform kernel). In the tables, I specify the bandwidth used for each estimation and report the RD estimate β with robust standard errors.[19] As a robustness check, I additionally examine whether the estimates are sensitive to a range of bandwidth choices and functional forms of $f(X_i)$.

The main identifying assumption of my RD design is that control over birth weight is imprecise (Lee and Lemieux, 2010). Figure 3 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. 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 frequency is smooth across the threshold. McCrary (2008) test also indicates that the discontinuity estimate is not statistically significant at the 5% level.

In addition, I test whether birth weight is manipulated for infants with high expected costs. 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 C.1). Taken together, I find no evidence of manipulation around the 1,200-gram threshold.

Additionally, I repeat the estimations dropping infants at 1,200 grams ("donut RD") to test whether the tendency to round to 1,200 grams is correlated with other characteristics that are also correlated with my

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

outcomes (Barreca et al., 2011). I find that my results are robust to this restriction, suggesting that the observed heaps are likely random and thus do not interfere with identification.[20]

To further test the validity of the RD design, I examine whether observed 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. Table 2 summarizes the RD estimates for these baseline characteristics. As expected, none of the estimates are statistically significant, indicating that the exclusion in fact created random variation in enrollment into MMC. In addition, this suggests that there is no evidence of selection into different hospitals at the threshold at the time of birth.

6 Main Results

In this section, I present main results separately for New York City in Section 6.1 and for counties outside of New York City in Section 6.2. Section 6.3 considers proximity to a high-quality hospital as a potential mechanism behind the main findings.

6.1 New York City

6.1.1 Provider Practice Outcomes

Since treatment at birth can change the course of subsequent hospital care, I distinguish visits at birth from subsequent visits. Panel A of Table 3 shows the RD estimates at birth hospitals and Figure 4 presents the corresponding figures. Consistent with the policy, panel (a) of Figure 4 shows that the MMC participation rate discontinuously increases above the threshold. This corresponds to an increase of 23 percentage points, which constructs a fuzzy RD design.[21] The MMC participation rate below the threshold is close to zero, which indicates that the exclusion from MMC enrollment based on birth weight is strictly implemented.

I show that the higher MMC rate is associated with shorter length of stay, lower charges and costs, consistent with hospitals' incentives to reduce the amount of care for infants enrolled in MMC. Column 2 of Table 3 shows that length of stay drops by 12% above the threshold.[22] The large reduction in length of stay

[20]My results are also robust to excluding other large heaps and to restricting the estimations to large heaps only.

[21]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). In addition, given that families covered by MMC are given time to choose a health plan, timing of Medicaid enrollment might vary at the threshold. To minimize selection, I do not restrict my estimation to Medicaid participants. In the RD estimation window 52% of the sample have Medicaid, 43% have private insurance, 5% are uninsured.

[22]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.

results in lower charges and lower costs by similar magnitudes.

The reduction in length of stay could be driven by (1) faster routine discharges from a birth hospital; (2) transfers from a birth hospital to another facility for additional care; or (3) (earlier) deaths. I first examine the transfer decision. An inter-hospital transfer is an option for infants who require specialized or intensive care if they are born in inadequately-equipped facilities. For infants below the threshold, hospitals may have an incentive to retain them to extract higher payments. However, since the risk of treating the infants at relatively inadequate facilities may be too great further below the threshold, hospitals would keep the healthiest among the infants enrolled in FFS, those right below the threshold. For infants above the threshold, this incentive essentially disappears, and hospitals would rather have an incentive to transfer them. I find that the probability of transfer to another short-term hospital in fact increases by 2.4 percentage points above the threshold. In addition, panel (e) of Figure 4 shows that the effect is driven by the lower likelihood of transfer right below the threshold.[23]

I examine whether the shorter length of stay is driven by faster routine discharges by focusing on infants who are routinely discharged from birth hospitals. I find no effects on length of stay or cost measures for this group of infants (e.g., RD estimate for log(length of stay): -0.017; standard error: 0.026). Note that infants who are routinely discharged below the threshold are not comparable to those above the threshold due to the differential probability of transfer across the threshold. Nevertheless, a smooth linear fit around the threshold (Appendix Figures C.2) suggests that transfers are likely the main driver of the reduction in length of stay at birth hospitals.

The majority of transfers occur soon after birth. In my sample, 70% of transfers occur within the first three days after birth (Figure 6).[24] Moreover, hospitals that receive transferred infants in my sample are "higher-quality" hospitals. Figure 7 compares mean characteristics of birth hospitals and receiving hospitals. Receiving hospitals on average have more beds, physicians, and nurses. They are more likely to be teaching hospitals and more likely to have a NICU facility. These hospital characteristics suggest that infants in my sample are generally transferred to higher-quality hospitals that are bigger and better-equipped.

Exploiting the encrypted person identifiers, I further examine how MMC affects subsequent care provided to infants around the birth weight threshold for the first six months.[25] 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 5.

[23] I examine other dispositions such as transfer to other facilities (e.g., skilled nursing facility, intermediate care facility) and home health care, but I find no effects on these measures.

[24] Hospitals have an incentive to transfer them shortly after birth since hospitals can be paid per diem instead of prospective payments for short stays.

[25] 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 in theory. Nevertheless, even when I follow these infants for as long as I can (mostly 1 year and 2 years for some), I still find the same results.

I find that the magnitudes of the shorter length of stay, lower charges, and costs are smaller when aggregating the amount of care provided at subsequent visits. However, length of stay is still shorter above the threshold by 9% and the estimate is marginally significant at the 10% level. When including birth hospital fixed effects (panel C of Table 3), the point estimates barely change but precision increases. This suggests that the effects are in fact driven by within-hospital differences in treatment depending on the infant's insurance status. With hospital fixed effects, the 9% reduction in total costs becomes marginally significant.

6.1.2 Health Outcomes

In this section, I test whether the reduced amount of care provided to infants above the threshold results in worse health outcomes. First, I examine mortality at birth hospitals. If FFS infants receive more resources than MMC infants even among those who remain at birth hospitals, there may be negative health consequences for infants enrolled in MMC at birth hospitals. I find that the point estimate is positive but insignificant (RD estimate: 0.019; robust standard error: 0.016). However, since the probability of transfer changes at the threshold, there may be selection into who remains at birth hospitals, which can differentially affect the probability of death across the threshold.

Subsequently, I track the infants over time and estimate the probability of hospital readmission following the birth episode and individual-level mortality during hospitalization within one-year (columns 5 and 6 of Table 3 panel B). 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. I find no evidence of that: the point estimate on hospital readmission is zero and statistically insignificant (RD estimate: -0.000; robust standard error: 0.021). This suggests that the reduction in total length of stay at birth may have improved efficiency by cutting down unnecessarily long stays.

The point estimate on individual-level mortality, however, is positive and large although statistically insignificant (RD estimate: 0.015; robust standard error: 0.016). In addition, it is only slightly lower than the estimate at birth hospitals, suggesting that the difference in mortality at birth hospitals are unlikely driven by selection. This is not surprising since more than half of all deaths I observe occur within the first three days following birth. This result suggests a potential shift in resources at birth hospitals from infants above the threshold towards infants below the threshold. Nevertheless, given limited precision, it is hard to conclude that MMC had significant impacts on health outcomes.[26]

Additionally, I examine various outcomes associated with the quality of care and patient health, including

[26] Adding various controls (e.g., diagnosis fixed effects) does not reduce standard errors of my mortality outcomes.

hospital readmission due to preventable conditions,[27] level IV NICU stays, any NICU stays, utilization of chest X-rays, ultrasounds, and implants, as well as various therapy services (Appendix Table D.1). I do not detect any statistically significant effect on these measures except for one outcome. For utilization of physical therapy services, I find an increase of 4 percentage points above the threshold, suggesting that if anything MMC may be associated the higher quality of care.

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 C.3 and C.4 show the corresponding figures.

In counties outside of New York City, I find few differences between MMC and FFS. The probability of MMC participation increases discontinuously at the threshold by 15 percentage points, which is slightly lower than the New York City estimate. Panel (a) of Appendix Figure C.3 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 find no effects on all other discharge outcomes in this sample. The estimates are positive and imprecise. Figures also show little evidence of discontinuous changes in outcomes across the threshold.

The lack of effects on discharge outcomes outside of New York City suggests that local health care markets may play a role in hospital responses to MMC. 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. For instance, the number of plans is much larger in New York City compared to the rest of the state, which could affect the level of competition in local health care markets and thus the strength of incentives to reduce costs and improve quality.[28] The density of local health care markets can also have an impact on hospital practice style by allowing hospitals to coordinate the provision of care to local patients. In Section 6.3, I pay particular attention to the role of proximity between hospitals in understanding this geographical heterogeneity.

6.3 Potential Mechanism

The geographical difference could be correlated with a number of factors, such as plan or patient composition. In this section, however, I consider proximity to a potential receiving hospital as one potential mechanism that drives the differences between New York City and the rest of the state. The idea is that

[27] I follow the definition of avoidable hospitalizations in Parker and Schoendorf (2000) and Dafny and Gruber (2005).

[28] 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.

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,[29] 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 a hospital with a NICU as a potential receiving hospital. 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 first measure 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. The distance between hospitals is much shorter in New York City compared to other counties outside of New York City (Appendix Figure C.5). The median distance is 1.3 miles in New York City and 18 miles outside of New York City.

To examine whether proximity predicts hospitals' practice style, I compare hospitals that have a hospital with a NICU close by with hospitals that have a hospital with a NICU far away relative to the median driving time *within* New York City. Driving time between hospitals is the relevant measure of proximity since the main mode of neonatal transport is ground ambulance (Ohning, 2015). Specifically, I compute driving time using Google Map APIs from each birth hospital to the nearest hospital with a NICU.

Table 5 shows that even within New York City, the reduction in length of stay and the increase in the probability of transfer are driven by hospitals with shorter driving time to the nearest hospital with a NICU. This suggests that proximity to a potential destination hospital plays an important role in birth hospitals' decision-making process. Given the longer 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.

This finding suggests that hospitals engage in profit-seeking behavior in response to financial incentives associated with MMC, but only when they can minimize the potential harm and costs through expedient transfer to a high-quality hospital. This finding is consistent with the growing literature that documents that health care providers respond to financial incentives but they are not willing to sacrifice the health of their patients in doing so (Ho and Pakes, 2014).

[29] For instance, Arad et al. (1999), 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.

7 Heterogeneity in New York City

To further understand how hospitals respond to MMC in New York City, I conduct three heterogeneity analyses. In Section 7.1, I examine the role of capacity at birth hospitals. Section 7.2 examines the role of capacity at potential receiving hospitals. In Section 7.3, I examine predicted list prices of newborns to evaluate whether hospitals are especially responsive to infants who are costly to treat.

7.1 Capacity at Birth Hospitals

Here, I further explore hospitals' incentives to transfer away infants with less generous payments. Suppose that the number of NICU beds is fixed, and the hospital decides whether to retain a low birth weight infant at its own NICU facility or to transfer the infant to another hospital following birth. Although entering the NICU market has a large fixed cost, marginal costs of providing neonatal intensive care is relatively low. Therefore, the hospital has an incentive to utilize empty beds.[30] That is, as long as the reimbursement payments are higher than the relatively moderate marginal costs, the hospital can increase its profits by retaining infants enrolled in both MMC and FFS. When the hospital is spatially constrained, however, the hospital can benefit more from holding onto infants enrolled in FFS than those enrolled in MMC. Therefore, incentives to transfer infants enrolled in MMC are likely pronounced when the hospital has few NICU beds available.

To test this hypothesis, I exploit variation in monthly NICU utilization. Specifically, I define the NICU occupancy in a given month as the number of infants admitted last month and stayed in a NICU facility for at least 10 days.[31] 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 NICU is. To ensure that infants who leave the hospital soon after birth are not included in the occupancy measure, I restrict length of stay to be at least 10 days. Given that the mean length of stay for very low birth weight infants is longer than a month, 10 days is unlikely to be a binding restriction.

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 A and B of Table 6. When the NICU occupancy is above the median, the reduction in length of stay, total charges, and total costs are large and significant around 20%; and the probability of transfer also increases by 4 percentage points. When the

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

[31] Appendix Figure C.6 plots this NICU occupancy measure for each month for an example hospital in a given year. It shows that there is large variation in NICU utilization across months.

NICU occupancy is below the median (i.e., hospitals have enough number of beds), I find little impact of MMC on all outcomes, consistent with the spatial constraint playing an important role. In addition, this suggests that transfer decisions are likely made by hospitals rather than health plans.

Since the NICU occupancy at the month level[32] cannot directly be compared to the number of NICU beds, high NICU occupancy may not indicate that the hospital is close to capacity. To address this issue, I create a crowdedness measure that is relative to hospital capacity. The mean length of stay for infants who stayed in a NICU facility for at least 10 days is 34 days. Thus, dividing the NICU occupancy, which is computed at the month level, by the number of beds yields a crude measure of the daily NICU occupancy rate. I compare below- and above-median months using this measure and find similar results (Appendix Table D.2). This supports the above finding that hospitals' incentives become stronger when they are spatially constrained.

7.2 Capacity at Potential Receiving Hospitals

Since hospitals have a financial incentive to utilize empty beds, I examine the role of crowdedness at potential destination hospitals. I consider two types of potential destination hospitals: (1) the nearest hospital with a NICU facility following Section 6.3; and (2) a "typical destination" hospital, which I define as the receiving hospital of the majority of (any) neonatal transfers from a given hospital.[33]

As in Section 7.1, I use the NICU occupancy to measure how crowded the potential destination hospital is. Table 7 shows that the effects are stronger in months when the nearest hospital with a NICU is relatively less crowded. Similarly, I find that the birth hospital is more likely to differentially treat infants across the threshold when its typical destination is relatively less crowded (Appendix Table D.3). This suggests that MMC may have induced hospitals to engage in reallocation of at-risk infants from a crowded hospital to a less crowded hospital via transfers.

In addition to the incentive to utilize empty beds, receiving hospitals with high-quality may have another incentive to accept the transferred infants. When health plans and hospitals negotiate over hospital payments for Medicaid patients, hospital quality plays a crucial role in determining the bargaining power of hospitals. That is, higher-quality hospitals likely have more bargaining power and thus command higher prices (Gaynor et al., 2015). In my sample, receiving hospitals are generally bigger and better-equipped, suggesting that they may face relatively modest incentives to differentially treat infants enrolled in FFS versus MMC.

[32] I observe the admission month and the discharge month but do not observe the exact date of admission or discharge. Due to this data limitation, I am unable to identify exactly how many of NICU beds are occupied on a given day.

[33] In my sample, around 32% of total transfers occur to the nearest hospital with a NICU; and around 51% of total transfers end up at typical destination hospitals.

7.3 Expected Costs of Treatment

In this section, I examine which group of infants is most affected by hospitals' financial incentives. Unless the reimbursement payments are perfectly adjusted for severity, infants with high predicted costs of treatment are especially costly to hospitals. Therefore, profit-maximizing hospitals are more likely to respond to infants whose marginal costs are high. To test this hypothesis, I create a measure of predicted costs of treatment. Specifically, I compute predicted list prices by regressing total charges on principal diagnosis fixed effects and principal procedure fixed effects. This measure thus estimates the expected 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 (Table 8). For infants with below-median predicted list prices, MMC reimbursement payments may still exceed the marginal costs and hospitals are unlikely to treat infants differentially across the threshold on the extensive margin (i.e., the retention versus transfer margin). For infants with above-median predicted list prices, the lower reimbursement payments under MMC may not cover the expected costs of treatment for these infants and thus birth hospitals are more likely transfer out infants above the threshold. Consequently, infants with severe conditions may be transferred to higher-quality hospitals, which suggests a potential improvement in the match between the patient and hospital.

For infants with above-median predicted list prices, however, I find that mortality during hospitalization at birth hospitals increases above the threshold and the estimate is marginally significant at the 10% level. This suggests that hospitals may shift resources towards infants under FFS with higher reimbursement payments, resulting in harming health among the most high-risk subpopulations under MMC. When I follow the patients over time, the individual-level mortality during hospitalization for this subgroup is still large, although insignificant (RD estimate for individual-level mortality: 0.032; robust standard error: 0.023). Albeit with limited precision, this suggests that MMC may adversely affect health for infants with the most severe conditions.

8 Specification and Robustness Checks

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 C.7 shows the RD estimates by bandwidth for different degrees of polynomials. Overall, all panels show that the RD estimates are not sensitive to the choice of bandwidth and the degree of polynomials. In particular, the estimates for log(length of stay) and the probability of transfer are stable across different choices of bandwidths and polynomials, supporting my main specification.

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

First, monthly cash payments are unlikely to affect 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 conditional on Medicaid participation. Additionally, the average monthly benefit for children was $633 in December 2014 (Duggan et al., 2015). Given the substantial amount of income transfer 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 length of stay above the threshold.

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 families and health care providers by substantially changing the cost of health care services. I examine whether the probability of receiving Medicaid discontinuously increases below the threshold. I find that the probability of Medicaid participation is in fact higher above the threshold and the estimate is not statistically significant (RD estimate: 0.024; robust standard error: 0.023). 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. This finding suggests that SSI has limited impacts on medical care of newborns around the 1,200-gram threshold.

Nevertheless, I conduct two exercises to test whether my results are robust to 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, and I find no effects on discharge outcomes for this sample (panel A of Table 9).[35] This suggests that SSI has little impact on my findings. Second, I use the inclusion of infants weighing less than 1,200 grams into mandatory MMC enrollment in April 2012 to test the robustness of my results. I repeat my estimations using the discharge records of infants born

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

[35] Additionally, I restrict the estimation to large urban areas in these two states and still find no differences below and above the threshold.

after April 2012 in New York City and I find no effects on discharge outcomes during this period (panel B of Table 9),[36] suggesting that my results are not driven by something other than the exclusion from MMC.

9 Difference-in-Difference Estimation

In this section, I employ a difference-in-difference approach using the MMC mandate rollout across counties in New York State. The mandate was phased in starting October 1997 and was fully implemented in November 2012. To compare DD estimates with my RD estimates, I restrict the estimation up to 2011 since the exclusion of low birth weight infants was lifted in April 2012. Thus, the sample consists of inpatient visits of all newborns born between 1995-2011. In a DD framework, I estimate the effects of the MMC mandate on MMC participation and various discharge outcomes.[37] I report the coefficient of interest δ from the following regression:

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

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} indicates the years after the mandate for each county. I include county-specific time trends ($\theta_c t$) in some specifications as a specification check. Standard errors are clustered at the county level.

Panel A of Table 10 shows the estimates from the baseline DD model excluding the county-specific time trends. The probability of participating in Medicaid HMO increases by 11 percentage points among infants following the mandate. This is smaller than the RD estimate which is around 23 percentage points, mainly due to heterogeneous compliance across counties. Column 2 shows that the DD estimate on length of stay is negative, but the magnitude is much smaller than my RD estimate. The DD estimates for total charges and total costs are negative and fairly close to my RD estimates. There is no change in the probability of transfer and mortality during hospitalization following the mandate in the whole sample of newborns.

As a check on the DD identification strategy, I estimate the model including the county-specific time trends. Panel B shows that including the time trends has little impact on the estimates, supporting the parallel trends assumption. Moreover, I employ an event study approach to examine pre-trends. Appendix Figure C.8 shows that there is little evidence of pre-trends in the probability of Medicaid HMO participation.

[36] I also use the periods before the mandate was introduced in New York City (prior to 1999) and find no differences at the threshold.

[37] Appendix Table D.4 examines the change in sample composition in a DD framework. It shows that Medicaid participation decreases following the MMC mandate, suggesting that the introduction of MMC negatively affected the overall Medicaid enrollment.

These results suggest that differential time trends across counties are unlikely to drive my findings.

The comparison between the two sets of estimates emphasizes how hospital responses can vary across different subpopulations, suggesting that my RD estimates may have little external validity. To further understand the differences between the two models, I take two approaches. First, I repeat the DD estimations by birth weight groups in Section 9.1. Second, I compute and compare complier characteristics in Section 9.2.

9.1 Difference-in-Difference Estimation by Birth Weight Groups

To compare the DD estimates with my RD estimates for very low birth weight infants, I repeat the DD estimations (equation (4)) 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 addition, I repeat the RD estimations using 150 grams as the bandwidth for all outcomes and compare them with the DD estimates for infants whose birth weight is between 1,200 grams and 1,350 grams. In Figure 8, I plot the DD estimates for each birth weight group along with 95% confidence intervals. I plot the RD estimates along with 95% confidence intervals from New York City in 2003-2011 in red bars for the 1,200-1,350 gram bin.

Panel (a) of Figure 8 shows that the probability of being enrolled in Medicaid HMO is not affected by the mandate for infants with birth weight below 1,200 grams, which confirms that the exclusion from the mandate is implemented well. The increase in the probability of having Medicaid HMO is around 7 percentage points for all birth weight groups above the threshold.

Panels (b)-(f) show that for infants with birth weight between 1,200 and 1,350 grams the DD estimates are similar to the RD estimates. The DD estimates are imprecise for these low birth weight infants, but the RD estimates for the 1,200-1,350 gram group 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 engage in some cost-reduction measures in response to the MMC mandate for infants across the whole range of birth weight, but potentially using different methods. Both total charges and total costs decline, while length of stay and the probability of transfer barely change following the mandate among heavier infants. 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 D.5) 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.

9.2 Complier Characteristics

To further gain insights on the differences between the RD and DD estimates, I examine hospital and patient characteristics for "compliers" who comply with each of the two instruments and compare them to the overall characteristics. Compliers in my RD context refer to those who are induced to enroll in MMC due to exceeding the 1,200-gram threshold. Compliers under the DD specification are those who are induced to enroll in MMC due to county-level rollout of the MMC mandate. It is impossible to identify compliers since counterfactual outcomes are not observable, but it is possible to describe the distribution of their characteristics (Abadie, 2003). I compute mean characteristics of the compliers following Angrist and Pischke (2009) and Almond and Doyle (2011).[38] Refer to Appendix Section B for details.

Table 11 presents the mean complier characteristics for both RD and DD samples. Panel A summarizes hospital characteristics and panel B compares patient characteristics. Column 1 shows the complier mean for the RD framework in the estimation window using the bandwidth of 150 grams, while column 2 shows the overall mean characteristics within the estimation window. Column 3 shows the complier mean for the DD specification, and column 4 shows the full sample mean of all infants.

Comparing columns 1 and 2 in panel A, compliers and the overall sample within the RD estimation window are relatively similar regarding the number of beds, staff, and admissions. A few notable differences, however, include the number of lives covered in capitated services arrangement and the share of infants covered by Medicaid. The number of lives covered in capitated services arrangement is lower for compliers than for the overall sample within the estimation window.[39] This suggests that hospitals who previously served fewer patients covered in capitation were more compliant to the birth weight exclusion, which is as expected since more patients in these hospitals were *induced* to enroll in MMC following the mandate compared to patients in hospitals with high baseline participation in some capitated services. In addition, compliers tend to stay in hospitals that serve more infants covered by Medicaid. This could be the case if hospitals with a high volume of Medicaid infants are more aware of the policy and thus more compliant to it. Moreover, assuming there is a cost associated with treating Medicaid managed care patients differently from traditional Medicaid patients (e.g., hiring a managed care manager), hospitals might do so only when there are enough number of patients affected by the adoption of MMC.

Panel B shows that compliers are likely less advantaged subgroups. They are more likely to be racial

[38] See also Kim and Lee (2016).

[39] I use the 1995 values (before the mandate was in place) for the capitated lives covered since compliers by definition have more patients covered in a capitated payment structure contemporaneously.

minorities, and they tend to live in zip codes in the bottom quartile of the median income distribution. Consistent with this finding, Appendix Table D.6 shows that the effects are driven by counties with the lowest median household income where the share of Medicaid participation is likely high.

Similar to the compliers in the RD framework, column 3 shows that hospitals that comply with the MMC mandate have fewer lives covered in capitated services arrangement and more infants covered by Medicaid compared to the full sample. The DD compliers are also more likely to be racial minorities and poor compared to the full sample. However, compliers in the DD framework are different in many dimensions from compliers in the RD framework. They have much higher birth weight and stay in hospitals that are less likely to have a NICU facility or to be a teaching hospital. They also tend to have fewer beds, staff, and patients compared to the RD compliers. This suggests that compliers in the DD framework stay in hospitals that may employ alternative methods in achieving cost savings. Consequently, the treatment effects likely vary across these two instruments, consistent with the differences between the RD and DD estimates.

10 Discussion

10.1 Cost Implications

In the New York City sample, I find that the overall costs aggregated at the individual level drop by 9% for very low birth weight infants according to my preferred specification with hospital fixed effects (panel C of Table 3). This amounts to an average reduction of \$8,764 (=0.093×\$94,237) for an infant right below the threshold in 2011 values. For average infants, I find that the overall costs aggregated at the individual level decline by 6% (panel B of Table 10). This amounts to an average reduction of \$214 (=0.062×\$3,446). Note, however, that total costs are not actual payments made by insurers. With the caveat that the reduction in total costs may not translate into actual savings in health care spending and that the cost estimates are based on a particular sample, this suggests that hospitals indeed provide less care to infants enrolled in MMC.

The effect on individual-level mortality is positive but imprecisely estimated with the 95% confidence interval [-0.014, 0.048]. Given the wide confidence interval, it is hard to draw a conclusion on the value of a statistical life. When evaluated at the mean effect, the implied cost of saving a statistical life is \$515,529 (=\$8,764/0.017), which is fairly close to the estimate of \$550,000 (in 2006 dollars) for newborns with birth weight near 1,500 grams from Almond et al. (2010).

However, the current study has a few limitations in conducting a complete cost-benefit analysis. The health measures I examine are limited and imperfect as I only observe extreme measures such as death during hospitalization. I do not observe death or other health care utilization outside of the inpatient setting (e.g., outpatient visits). In addition, there may be other forms of "costs" besides health consequences such as non-medical costs to hospitals (e.g., lawsuits) and parental disutility from separation/transfer, which I do not observe. For example, neonatal transfers can cause enormous stress and anxiety to parents (Hawthorne and Killen, 2006).

11 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 improvement 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[40] 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 hospitals respond to financial incentives stemming from different reimbursement models by adjusting their practice style. For very low birth weight infants, I provide evidence that MMC may be able to achieve a reduction in hospital-level spending by steering high-risk infants towards more efficient hospitals through inter-hospital transfers.[41] Hospital responses are particularly large when they are spatially constrained and for infants with high predicted list prices. However, I find no impact on hospital readmission and do not detect statistically significant impacts on mortality during hospitalization. Given my focus on very low birth weight infants, these findings suggest that MMC expansion to previously excluded high-cost and critically-ill subpopulations may be successful. Even for average infants, I provide evidence that MMC may be able to achieve savings at the hospital level by reducing the provision of certain types of services.

In addition, I find that the effects are driven by birth hospitals that have a hospital with a NICU nearby. This suggests that hospitals do not compromise the quality of care or patient health, by engaging in profit-seeking behavior only when they can minimize the potential harm through expedient coordination with a high-quality hospital. Notice that the *interaction* between financial incentives under MMC and short distances between local hospitals resulted in efficient delivery of MMC for high-risk infants. This suggests that the structure of local health care markets may play an important role in successful delivery of a health care system, especially for critically ill patients who require coordination of care between local hospitals.

[40] Also look at Duggan et al. (forthcoming) that examines the impact of Medicare Advantage plans.
[41] See Raval and Rosenbaum (2016).

The overall finding that MMC achieves cost reductions in ways that do not appear to compromise the quality of care is robust across the RD and DD models. This is surprising given the large differences in complier means between these two models, as shown in Table 11. There are two implications of this finding. First, my estimates are fairly representative and generalizable to the overall newborn population, as supported by the similarity between the DD complier mean and the overall sample mean. Second, even for the highest-risk infants, the RD results suggest a similar conclusion that costs go down while health does not seem to deteriorate. My finding of no adverse (postnatal) health effects, however, is in contrast to negative effects on prenatal care and worse birth outcomes found in Aizer et al. (2007). Whether there are differences between the response of prenatal versus postnatal care to MMC, both of which affect neonatal health but through distinct clinical channels, is an area for future research.

References

Abadie, A. (2003). Semiparametric instrumental variable estimation of treatment response models. *Journal of econometrics*, 113(2):231–263.

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

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

Almond, D. and Doyle, J. J. (2011). After midnight: A regression discontinuity design in length of postpartum hospital stays. *American Economic Journal: Economic Policy*, 3(3):1–34.

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

Angrist, J. D. and Pischke, J.-S. (2009). *Mostly Harmless Econometrics: An Empiricist's Companion*. Princeton University Press.

Arad, I., Gofin, R., Baras, M., Bar-Oz, B., Peleg, O., and Epstein, L. (1999). Neonatal outcome of inborn and transported very-low-birth-weight infants: Relevance of perinatal factors. *European Journal of Obstetrics, Gynecology, and Reproductive Biology*, 83(2):151–157.

Arora, P., Bajaj, M., Natarajan, G., Arora, N. P., Kalra, V. K., Zidan, M., and Shankaran, S. (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., Auerbach, A., Bertko, J., Brownlee, S., Casalino, L. P., Cooper, J., Crosson, F. J., Enthoven, A., Falcone, E., Feldman, R. C., 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., Guldi, M., Lindo, J. M., and Waddell, G. R. (2011). Saving babies? Revisiting the effect of very low birth weight classification. *The Quarterly Journal of Economics*, 126:2117–2123.

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

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

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

Card, D. and Lee, D. S. (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.

Clemens, J. and Gottlieb, J. D. (2014). Do physicians' financial incentives affect medical treatment and patient health? *American Economic Review*, 104(4):1320–1349.

Conover, C. J., Rankin, P. J., and Sloan, F. A. (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 Fahr, J. (2005). Medicaid managed care: Effects on children's Medicaid coverage and utilization. *Journal of Public Economics*, 89(1):85–108.

Cutler, D. M., McClellan, M., and Newhouse, J. P. (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 Gruber, J. (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., Gruber, J., and Vabson, B. (Forthcoming). The efficiency consequences of health care privatization: evidence from medicare advantage exits. *American Economic Journal: Economic Policy.*

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

Ellis, R. P. and McGuire, T. G. (1986). Provider behavior under prospective reimbursement: Cost sharing and supply. *Journal of health economics*, 5(2):129–151.

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

Geruso, M. and Layton, T. (2015). Upcoding: Evidence from Medicare on squishy risk adjustment. NBER Working Paper 21222.

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

Harman, J. S., Hall, A. G., Lemak, C. H., and Duncan, R. P. (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.

Hawthorne, J. and Killen, M. (2006). Transferring babies between units: Issues for parents. *Infant*, 2(2):44–46.

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

Herring, B. and Adams, E. K. (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.

Ho, K. and Pakes, A. (2014). Hospital choices, hospital prices, and financial incentives to physicians. *American Economic Review*, 104(12):3841–3884.

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

Howell, E. M., Dubay, L., Kenney, G., and Sommers, A. S. (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., Dubay, L., and Kenney, G. (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.

Kim, H. B. and Lee, S.-m. (2016). When public health intervention fails: Cost sharing, crowd-out, and selection in Korea's national cancer screening program.

Krieger, J. W., Connell, F. A., and LoGerfo, J. P. (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., Meckel, K., and Rossin-Slater, M. (2013). Do insurers risk-select against each other? Evidence from Medicaid and implications for health reform. NBER Working Paper 19198.

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

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

Libersky, J., Dodd, A. H., and Verghese, S. (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., Yelowitz, A., and Talbert, J. C. (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 Aly, H. (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., Fujimura, M., Shiraishi, J., Evans, B., Corkett, M., Negishi, H., and Doyle, P. (2007). Duration of inter-facility neonatal transport and neonatal mortality: Systematic review and cohort study. *Pediatrics International*, 49(4):452–458.

Nasr, A. and Langer, J. C. (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 Langer, J. C. (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 Office of the State Comptroller (NYS Comptroller) (2014). Overpayments to managed care organizations and hospitals for low birth weight newborns.

Ohning, B. L. (2015). Transport of the critically ill newborn. *Medscape*.

Parker, J. D. and Schoendorf, K. C. (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.

Raval, D. and Rosenbaum, T. (2016). How does steering affect patient choice? Evidence from Florida medicaid. Technical report, Federal Trade Commission.

Sacarny, A. (2014). Technological diffusion across hospitals: The case of a revenue-generating practice. Job market paper, Massachusetts Institute of Technology.

Shigeoka, H. and Fushimi, K. (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.

12 Figures

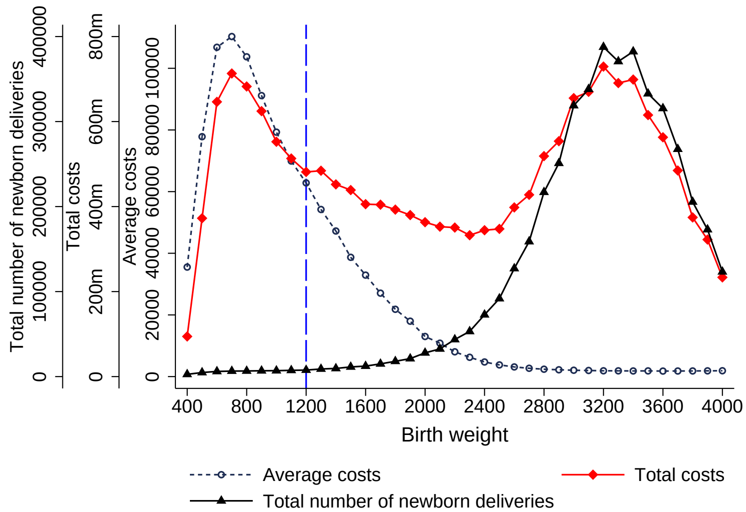


Figure 1: Average hospital costs and total discharges by birth weight, New York State, 1995-2013

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.

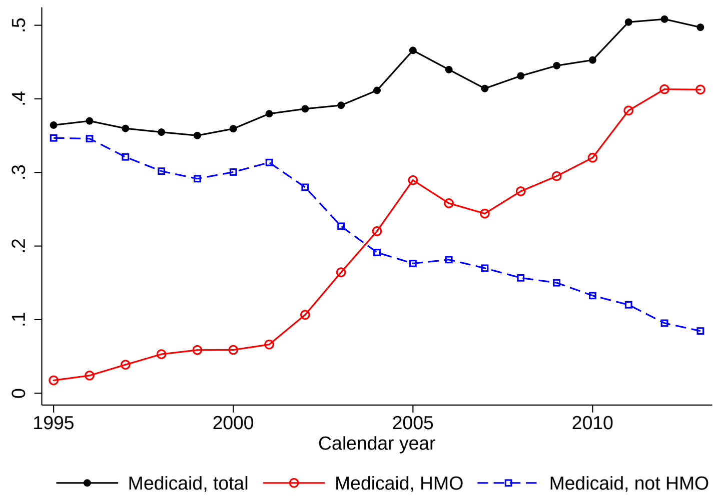
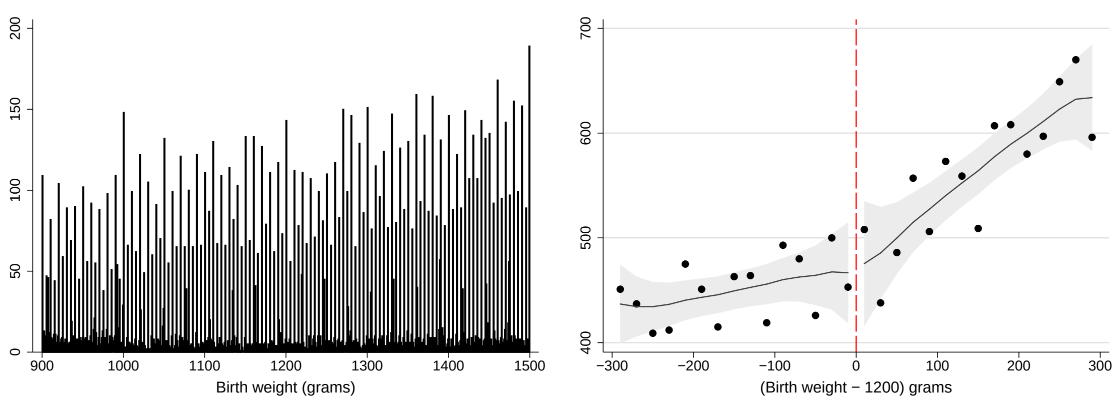


Figure 2: Share of infants covered by Medicaid, New York State, 1995-2013

Sources: HCUP State Inpatient Databases

Notes: HMO stands for Health Maintenance Organization, a type of managed care organizations (MCOs).



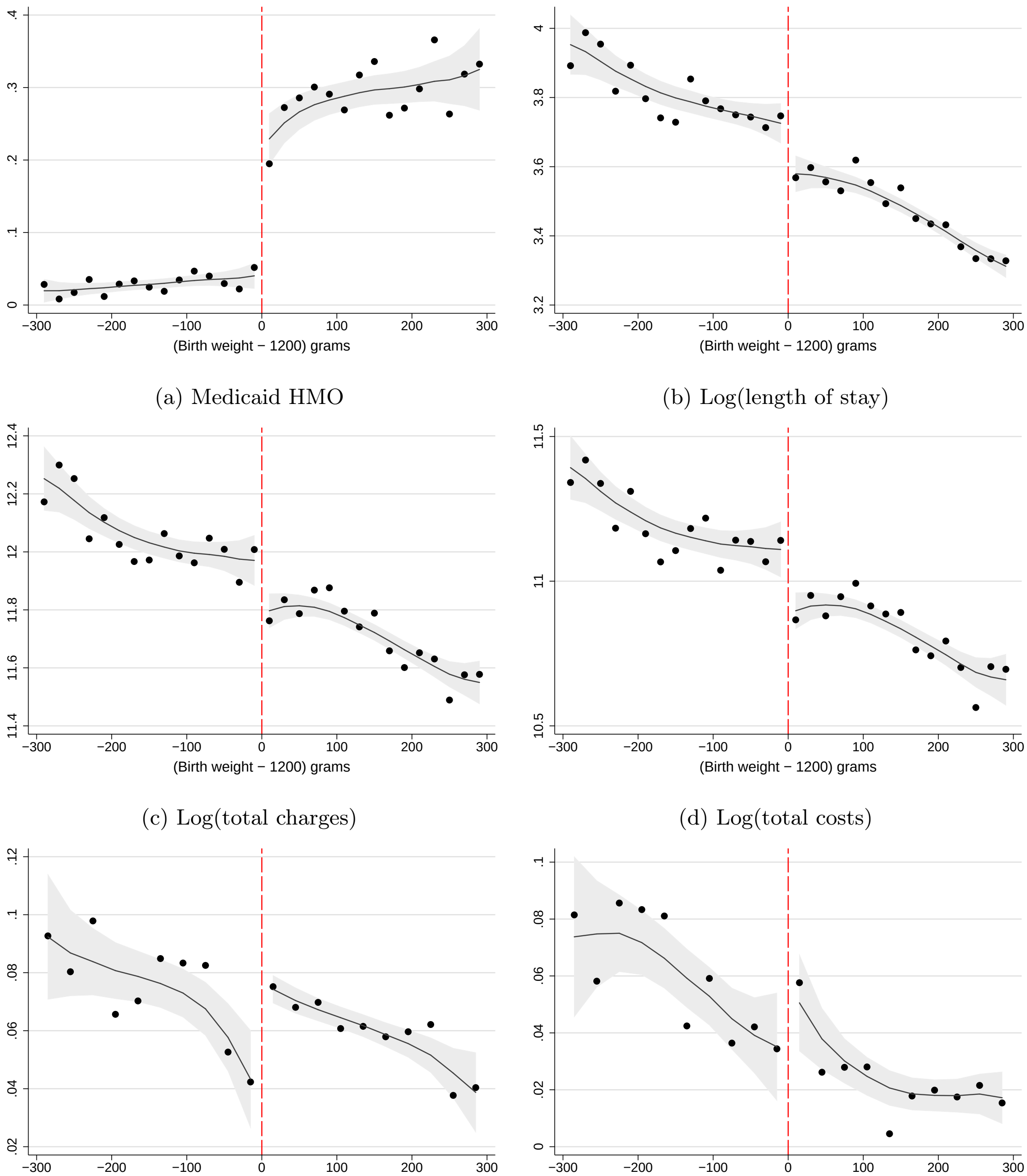
(a) Frequency for each gram

(b) Mean frequency for each 20-gram bin

Figure 3: Frequency of the running variable

Sources: HCUP State Inpatient Databases

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 95% confidence intervals below and above the threshold. I use the triangular kernel and a bandwidth of 150 grams for local linear regressions.



(a) Medicaid HMO

(b) Log(length of stay)

(c) Log(total charges)

(d) Log(total costs)

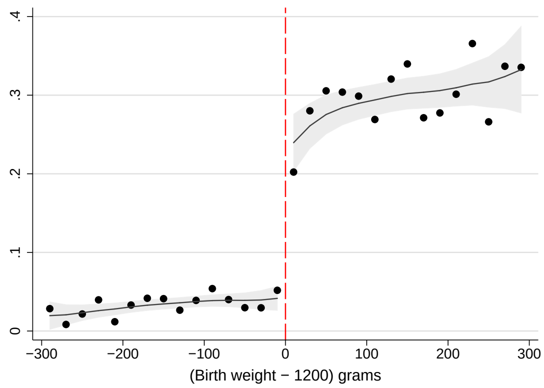
(e) Transfer

(f) Mortality during hospitalization

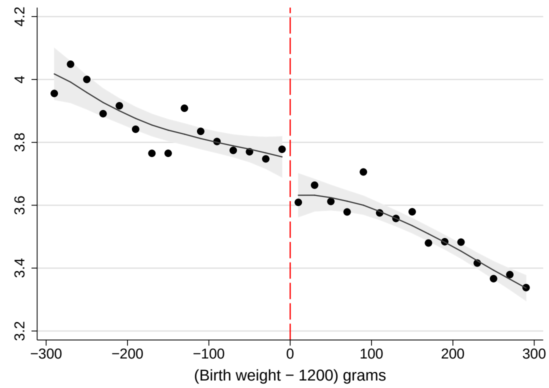
Figure 4: Effects of birth weight≥1,200 grams on discharge outcomes at birth, New York City

Sources: HCUP State Inpatient Databases

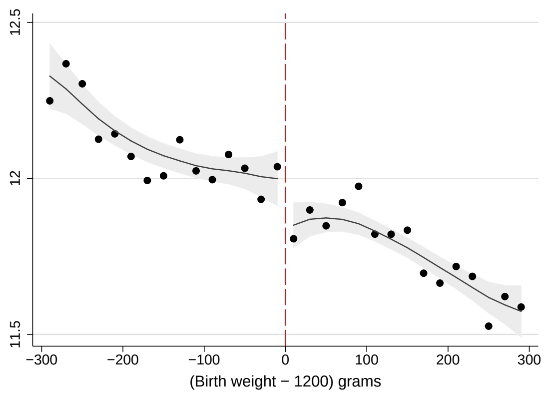
Notes: Panels (a)-(d) plot mean values of each outcome variable for each 20-gram bin (dots) along with a local linear regression fitted lines (solid lines) and 95% confidence intervals below and above the threshold. Each 20-gram bin contains roughly 250 discharge records. For panels (e) and (f) I use a bigger 30-gram bin for better visibility since transfer and death are both rare events and thus noisy. Each 30-gram bin contains around 420 discharge records. I test whether using wider bins over-smooths the data following Lee and Lemieux (2010) but find no evidence of it. I use the triangular kernel and a bandwidth of 150 grams for local linear regressions.



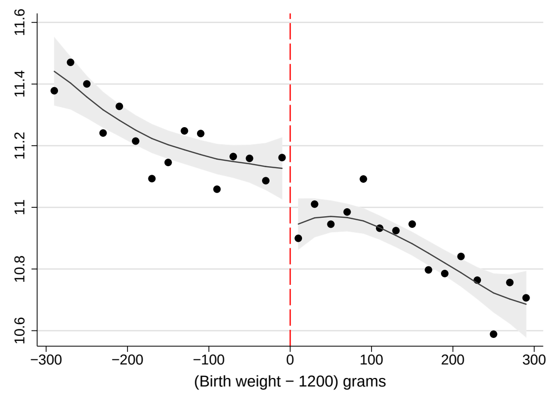
(a) Medicaid HMO



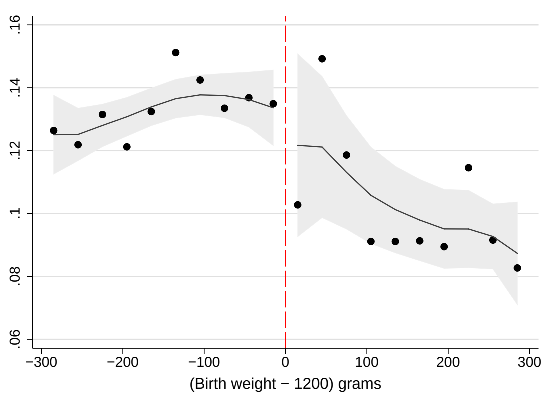
(b) Log(length of stay)



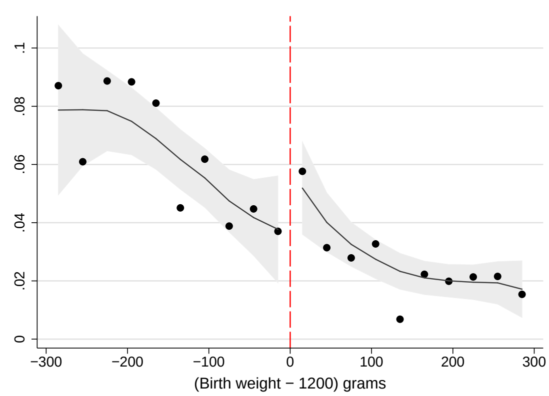
(c) Log(total charges)



(d) Log(total costs)



(e) Readmission



(f) 1-year mortality during hospitalization

Figure 5: Effects of birth weight≥1,200 grams on cumulative discharge outcomes, New York City

Sources: HCUP State Inpatient Databases

Notes: Panels (a)-(d) plot mean values of each outcome variable for each 20-gram bin (dots) along with a local linear regression fitted lines (solid lines) and 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). Each 20-gram bin contains roughly 250 discharge records. For panels (e) and (f) I use a bigger 30-gram bin for better visibility since readmission and death are both rare events and thus noisy. Each 30-gram bin contains around 420 discharge records. I test whether using wider bins over-smooths the data following Lee and Lemieux (2010) but find no evidence of it. I use the triangular kernel and a bandwidth of 150 grams for local linear regressions.

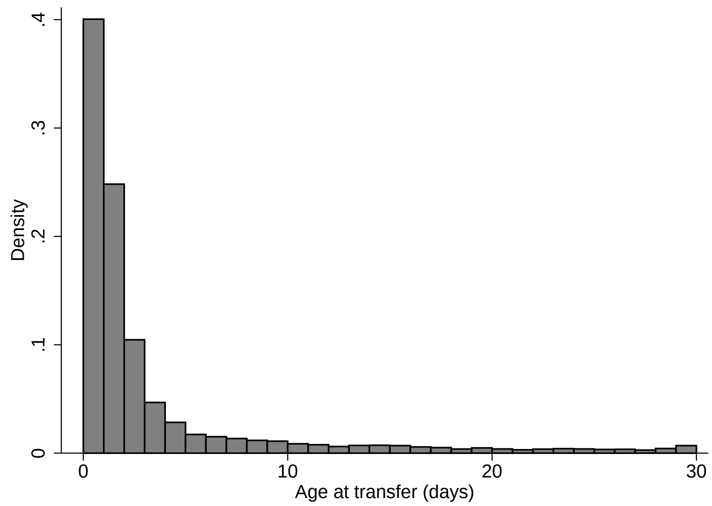


Figure 6: Age at transfer in the first month

Sources: HCUP State Inpatient Databases
Notes: 90% of neonatal transfers occur within the first month following birth. In particular, 70% of transfers occur within the first three days after birth.

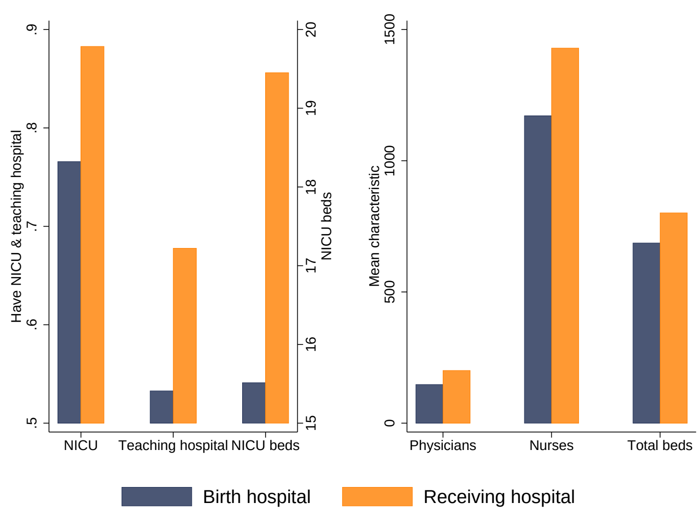
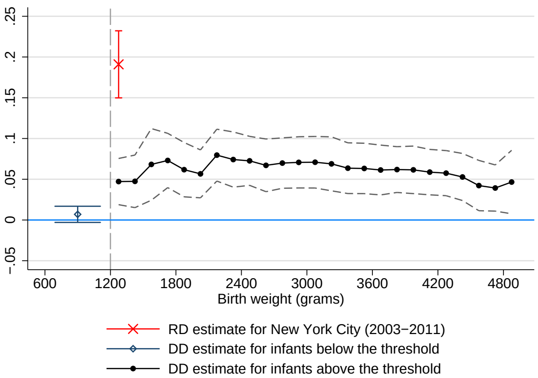
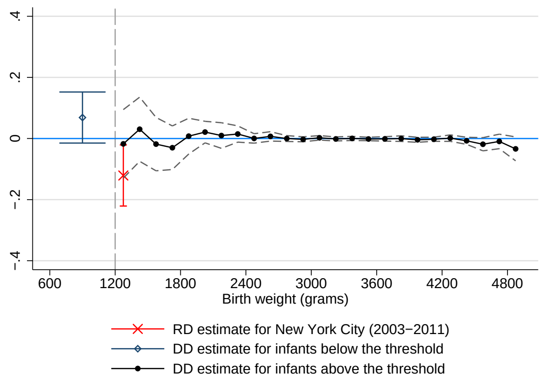


Figure 7: Characteristics of birth hospitals and receiving hospitals

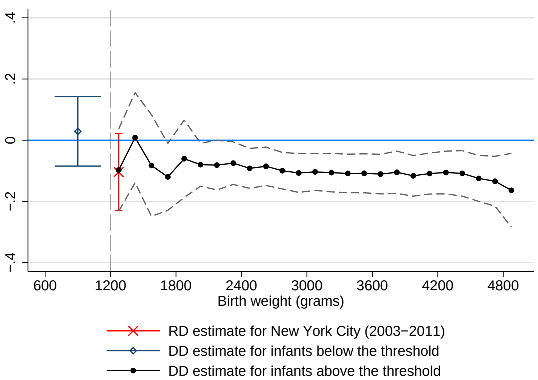
Sources: HCUP State Inpatient Databases and AHA Annual Survey of Hospitals
Notes: Navy bars summarize mean characteristics of birth hospitals. Orange bars describe mean characteristics of hospitals that receive transfers.



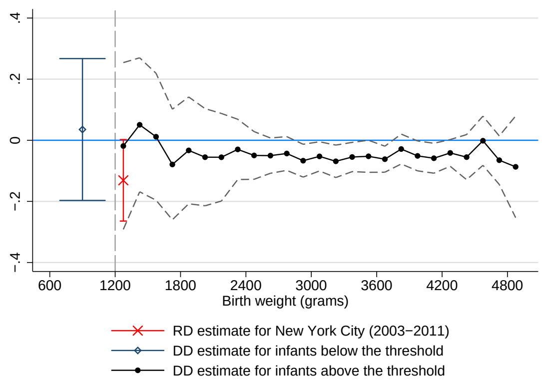
(a) Medicaid HMO



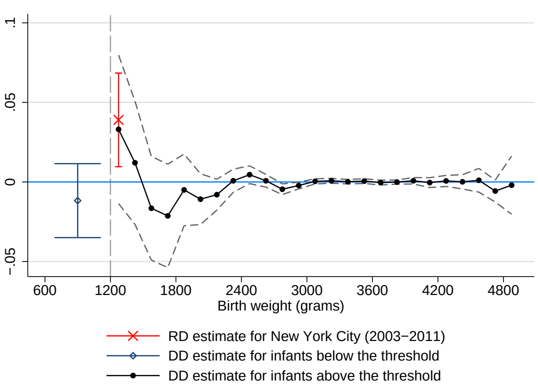
(b) Log(length of stay)



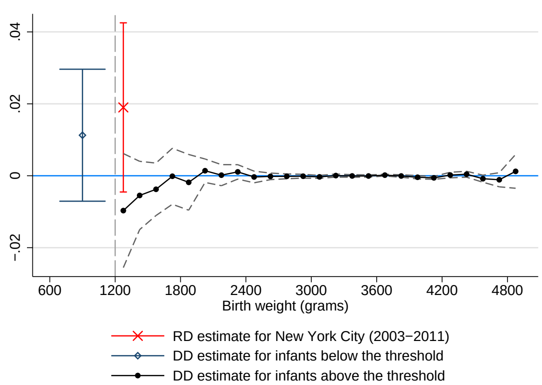
(c) Log(total charges)



(d) Log(total costs)



(e) Transfer



(f) Mortality during hospitalization

Figure 8: Difference-in-difference estimates by birth weight

Sources: HCUP State Inpatient Databases

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 in 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 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.

13 Tables

Table 1: Summary statistics, infants in New York State from 2003-2011

	(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)	3,273	1,050	1,357
Medicaid	0.427	0.544	0.508
Non-HMO	0.380	0.945	0.519
HMO	0.620	0.055	0.481
Total charges (USD)	$9,609	$204,796	$145,434
Total costs (USD)	$3,500	$75,758	$52,670
Length of stay (days)	3.710	46.370	33.016
Died during hospitalization	0.003	0.049	0.024
Subsequent visits	0.039	0.167	0.129
Transfers	0.010	0.127	0.107
NICU utilization	0.100	0.741	0.746
Observations	2001577	9076	11021

Sources: HCUP State Inpatient Databases

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.

Table 2: Balance of covariates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Female	White	Black	Hispanic	Asian	Median income	Scheduled	Weekend
Panel A. Patient characteristics								
Birth weight≥1,200 g	-0.013	-0.023	0.026	0.015	-0.012	0.032	0.034	-0.007
	(0.018)	(0.021)	(0.018)	(0.016)	(0.009)	(0.059)	(0.028)	(0.018)
Observations	12701	7177	9636	7177	9636	4617	3357	10061
Mean below cutoff	0.497	0.355	0.316	0.145	0.054	2.353	0.713	0.261
Mean above cutoff	0.493	0.374	0.309	0.135	0.047	2.420	0.731	0.260
Bandwidth (grams)	250	150	200	150	200	150	150	200
	NICU	Teaching hospital	NICU beds	Physicians	Nurses	Total admissions	Total beds	Births
Panel B. Hospital characteristics								
Birth weight≥1,200 g	-0.002	0.009	-0.438	-7.346	-14.516	-560.159	-11.567	-97.628
	(0.009)	(0.014)	(0.586)	(11.330)	(35.162)	(814.747)	(18.180)	(98.570)
Observations	6278	10057	4184	7477	7477	7477	7477	7477
Mean below cutoff	0.955	0.715	20.7	180.1	1287.3	35357.2	753.1	4044.2
Mean above cutoff	0.945	0.698	20.4	187.4	1279.3	34946.2	732.3	3994.7
Bandwidth (grams)	150	200	100	150	150	150	150	150

Sources: HCUP State Inpatient Databases and AHA Annual Survey of Hospitals

Notes: Panel A shows the RD estimates for patient characteristics. Panel B shows the RD estimates for hospital characteristics. 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.

* Significant at 10%, ** significant at 5%, *** significant at 1%.

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

	(1)	(2)	(3)	(4)	(5)	(6)
	Medicaid HMO	Log(LOS)	Log(total charges)	Log(total costs)	Transfer	Mortality
Panel A. Discharge outcomes at birth hospitals						
Birth weight≥1,200 g	0.228***	-0.124**	-0.109*	-0.140**	0.024*	0.019
	(0.018)	(0.051)	(0.064)	(0.069)	(0.013)	(0.016)
Observations	5490	4065	4049	3096	5490	2735
Mean below cutoff	0.033	51.7	$244,943	$93,838	0.070	0.038
Mean above cutoff	0.277	42.0	$208,055	$77,391	0.065	0.037
Bandwidth (grams)	200	150	150	150	200	100
	Medicaid HMO	Log(LOS)	Log(total charges)	Log(total costs)	Readmission	1-yr Mortality
Panel B. Aggregating at the individual level						
Birth weight≥1,200 g	0.236***	-0.089*	-0.072	-0.100	-0.000	0.015
	(0.018)	(0.049)	(0.062)	(0.067)	(0.021)	(0.016)
Observations	5490	4065	4047	3074	4065	2735
Mean below cutoff	0.039	53.2	$250,584	$95,366	0.140	0.040
Mean above cutoff	0.284	43.5	$215,080	$79,707	0.110	0.039
Bandwidth (grams)	200	150	150	150	200	100
	Medicaid HMO	Log(LOS)	Log(total charges)	Log(total costs)	Readmission	1-yr Mortality
Panel C. Aggregating at the individual level, with hospital fixed effects						
Birth weight≥1,200 g	0.237***	-0.080*	-0.057	-0.090*	0.003	0.017
	(0.018)	(0.044)	(0.046)	(0.054)	(0.021)	(0.016)
Observations	5490	4065	4047	3074	4065	2735
Mean below cutoff	0.039	53.2	$250,584	$95,366	0.140	0.040
Mean above cutoff	0.284	43.5	$215,080	$79,707	0.110	0.039
Bandwidth (grams)	200	150	150	150	200	100

Sources: HCUP State Inpatient Databases

Notes: Panel A shows the RD estimates for each outcome from discharge records at birth hospitals. Panels B and C show the RD estimates for outcome aggregated at the individual level for six months in columns (1)-(4). Readmission indicates reappearing in the inpatient database following the birth episode. Mortality in panels B and C indicates death during hospitalization within one-year following birth. 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. Panel C additionally includes hospital fixed effects. Robust standard errors are reported. The means of logged outcomes are reported in levels.

* Significant at 10%, ** significant at 5%, *** significant at 1%.

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

	(1)	(2)	(3)	(4)	(5)	(6)
	Medicaid HMO	Log(LOS)	Log(total charges)	Log(total costs)	Transfer	Mortality
Panel A. Discharge outcomes at birth hospitals						
Birth weight≥1,200 g	0.147***	0.021	0.039	0.051	0.011	0.021
	(0.018)	(0.065)	(0.073)	(0.074)	(0.019)	(0.014)
Observations	4571	3414	3407	3191	4571	2263
Mean below cutoff	0.032	49.1	$204,180	$75,151	0.149	0.030
Mean above cutoff	0.194	40.5	$167,210	$60,307	0.140	0.029
Bandwidth (grams)	200	150	150	150	200	100
	Medicaid HMO	Log(LOS)	Log(total charges)	Log(total costs)	Readmission	1-yr Mortality
Panel B. Aggregating at the individual level						
Birth weight≥1,200 g	0.151***	0.041	0.057	0.072	-0.002	0.018
	(0.018)	(0.062)	(0.070)	(0.071)	(0.021)	(0.015)
Observations	4571	3414	3407	3174	3415	2263
Mean below cutoff	0.036	51.6	$212,942	$78,495	0.113	0.034
Mean above cutoff	0.204	42.4	$173,966	$63,014	0.093	0.030
Bandwidth (grams)	200	150	150	150	200	100

Sources: HCUP State Inpatient Databases

Notes: Panel A shows the RD estimates for each outcome from discharge records at birth hospitals. Panel B shows the RD estimates for outcome aggregated at the individual level for six months in columns (1)-(4). Readmission indicates reappearing in the inpatient database following the birth episode. Mortality in panel B indicates death during hospitalization within one-year following birth. 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.

* Significant at 10%, ** significant at 5%, *** significant at 1%.

Table 5: Heterogeneity by driving time to the nearest hospital with a NICU, New York City

	(1)	(2)	(3)	(4)	(5)	(6)
	Medicaid HMO	Log(LOS)	Log(total charges)	Log(total costs)	Transfer	Mortality
Panel A. Below the median driving time						
Birth weight≥1,200 g	0.272***	-0.136*	-0.141	-0.109	0.041**	0.023
	(0.030)	(0.079)	(0.108)	(0.119)	(0.020)	(0.020)
Observations	2321	1713	1700	1230	2321	1158
Mean below cutoff	0.043	53.4	$287,628	$107,557	0.069	0.031
Mean above cutoff	0.324	43.3	$246,442	$87,755	0.079	0.028
Bandwidth (grams)	200	150	150	150	200	100
Panel B. Above the median driving time						
Birth weight≥1,200 g	0.218***	-0.083	-0.077	-0.128	0.019	0.023
	(0.025)	(0.072)	(0.080)	(0.087)	(0.018)	(0.024)
Observations	2648	1962	1959	1486	2648	1312
Mean below cutoff	0.026	51.1	$200,293	$84,847	0.066	0.044
Mean above cutoff	0.258	41.5	$167,791	$70,934	0.055	0.040
Bandwidth (grams)	200	150	150	150	200	100

Sources: HCUP State Inpatient Databases and AHA Annual Survey of Hospitals

Notes: Panel A shows the RD estimates for hospitals whose driving time to the nearest hospital with a NICU is below the median, while panel B shows the RD estimates whose driving time is above the median. 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.

* Significant at 10%, ** significant at 5%, *** significant at 1%.

Table 6: Heterogeneity by NICU crowdedness, New York City

	(1)	(2)	(3)	(4)	(5)	(6)
	Medicaid HMO	Log(LOS)	Log(total charges)	Log(total costs)	Transfer	Mortality
Panel A. Below the median NICU occupancy						
Birth weight≥1,200 g	0.246***	-0.055	-0.043	-0.029	0.007	0.030
	(0.033)	(0.081)	(0.100)	(0.103)	(0.025)	(0.029)
Observations	1442	1063	1058	808	1442	724
Mean below cutoff	0.019	52.3	$268,717	$104,320	0.063	0.035
Mean above cutoff	0.255	43.4	$244,479	$89,590	0.052	0.032
Bandwidth (grams)	200	150	150	150	200	100
Panel B. Above the median NICU occupancy						
Birth weight≥1,200 g	0.236***	-0.191**	-0.226**	-0.234**	0.037**	0.028
	(0.028)	(0.075)	(0.092)	(0.099)	(0.018)	(0.028)
Observations	2040	1513	1509	1121	2040	1010
Mean below cutoff	0.019	52.8	$275,354	$103,933	0.050	0.046
Mean above cutoff	0.285	42.5	$223,628	$84,551	0.053	0.038
Bandwidth (grams)	200	150	150	150	200	100

Sources: HCUP State Inpatient Databases and AHA Annual Survey of Hospitals

Notes: Panel A shows the RD estimates for months when the NICU occupancy is below the median for a given hospital in a given year. Panel B shows the RD estimates for relatively more crowded months when the NICU occupancy is above the median for a given hospital-year. 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.

* Significant at 10%, ** significant at 5%, *** significant at 1%.

Table 7: Heterogeneity by crowdedness at the nearest hospital with a NICU, New York City

	(1)	(2)	(3)	(4)	(5)	(6)
	Medicaid HMO	Log(LOS)	Log(total charges)	Log(total costs)	Transfer	Mortality
Panel A. Below the median NICU occupancy at the nearest hospital						
Birth weight≥1,200 g	0.232***	-0.180**	-0.227**	-0.300**	0.044**	0.029
	(0.030)	(0.084)	(0.104)	(0.119)	(0.021)	(0.027)
Observations	1846	1379	1373	995	1846	938
Mean below cutoff	0.023	52.0	$275,300	$111,706	0.062	0.046
Mean above cutoff	0.271	43.3	$237,916	$90,772	0.062	0.032
Bandwidth (grams)	200	150	150	150	200	100
Panel B. Above the median NICU occupancy at the nearest hospital						
Birth weight≥1,200 g	0.286***	-0.151*	-0.099	-0.074	-0.019	0.022
	(0.038)	(0.079)	(0.107)	(0.114)	(0.024)	(0.037)
Observations	1284	932	928	668	1284	624
Mean below cutoff	0.024	54.0	$280,850	$108,544	0.074	0.034
Mean above cutoff	0.295	41.9	$225,560	$87,478	0.054	0.049
Bandwidth (grams)	200	150	150	150	200	100

Sources: HCUP State Inpatient Databases and AHA Annual Survey of Hospitals

Notes: Panel A shows the RD estimates for months when the NICU occupancy at the nearest hospital with a NICU is below the median, while panel B shows the RD estimates for months when the NICU occupancy at the nearest hospital with a NICU is above the median. 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.

* Significant at 10%, ** significant at 5%, *** significant at 1%.

Table 8: Heterogeneity by predicted list prices, New York City

	(1)	(2)	(3)	(4)	(5)	(6)
	Medicaid HMO	Log(LOS)	Log(total charges)	Log(total costs)	Transfer	Mortality
Panel A. Below the median predicted list prices						
Birth weight≥1,200 g	0.231***	-0.025	0.050	-0.095	0.016	-0.002
	(0.029)	(0.063)	(0.085)	(0.084)	(0.017)	(0.017)
Observations	2226	1619	1619	1233	2226	1078
Mean below cutoff	0.034	47.9	$218,768	$86,188	0.054	0.019
Mean above cutoff	0.274	37.9	$174,036	$67,170	0.050	0.010
Bandwidth (grams)	200	150	150	150	200	100
Panel B. Above the median predicted list prices						
Birth weight≥1,200 g	0.227***	-0.167**	-0.174**	-0.111	0.035*	0.038*
	(0.023)	(0.070)	(0.086)	(0.092)	(0.019)	(0.022)
Observations	3202	2409	2393	1831	3202	1632
Mean below cutoff	0.031	54.1	$261,268	$98,819	0.076	0.048
Mean above cutoff	0.282	45.8	$237,610	$86,562	0.071	0.050
Bandwidth (grams)	200	150	150	150	200	100

Sources: HCUP State Inpatient Databases
Notes: Panel A shows the RD estimates for infants whose predicted list charges are below the median, while panel B shows the RD estimates for infants whose predicted list charges are above the median. 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.
* Significant at 10%, ** significant at 5%, *** significant at 1%.

Table 9: Effects of birth weight≥1,200 grams on discharge outcomes, robustness checks

	(1)	(2)	(3)	(4)	(5)	(6)
	Medicaid HMO	Log(LOS)	Log(total charges)	Log(total costs)	Transfer	Mortality
Panel A. Hospitals in New Jersey and Maryland						
Birth weight≥1,200 g	0.030	0.018	0.032	0.071	0.001	0.008
	(0.023)	(0.081)	(0.088)	(0.095)	(0.021)	(0.015)
Observations	4755	3548	3542	3144	4755	2372
Mean below cutoff	0.206	43.0	$215,660	$58,100	0.151	0.031
Mean above cutoff	0.197	35.8	$177,229	$45,062	0.124	0.023
Bandwidth (grams)	200	150	150	150	200	100
Panel B. Infants born after April 2012						
Birth weight≥1,200 g	0.109	0.022	0.018	0.209	-0.029	0.026
	(0.069)	(0.180)	(0.214)	(0.230)	(0.042)	(0.048)
Observations	900	669	669	554	900	438
Mean below cutoff	0.437	53.5	$427,550	$134,895	0.101	0.056
Mean above cutoff	0.503	42.3	$330,527	$109,927	0.055	0.042
Bandwidth (grams)	200	150	150	150	200	100

Sources: HCUP State Inpatient Databases
Notes: Panel A shows the RD estimates for each outcome at birth hospitals in New Jersey and Maryland from 2003-2011. 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 state dummy for New Jersey. Panel B shows the RD estimates for each outcome at birth hospitals for infants admitted after April 2012. Robust standard errors are reported. The means of logged outcomes are reported in levels.
* Significant at 10%, ** significant at 5%, *** significant at 1%.

Table 10: Difference-in-difference estimates

	(1)	(2)	(3)	(4)	(5)	(6)
	Medicaid HMO	Log(LOS)	Log(total charges)	Log(total costs)	Transfer	Mortality
Panel A. Without county-specific time trends						
MMC mandate	0.111***	-0.009**	-0.075**	-0.095***	-0.000	-0.000
	(0.022)	(0.004)	(0.037)	(0.022)	(0.001)	(0.000)
Observations	4173544	4169319	4168406	2311157	3448242	4173535
Mean	0.170	3.8	$7,132	$3,446	0.011	0.004
Panel B. With county-specific time trends						
MMC mandate	0.065***	-0.000	-0.106***	-0.062**	-0.001	0.000
	(0.015)	(0.003)	(0.031)	(0.025)	(0.001)	(0.000)
Observations	4173544	4169319	4168406	2311157	3448242	4173535
Mean	0.170	3.8	$7,132	$3,446	0.011	0.004

Sources: HCUP State Inpatient Databases

Notes: Panel A presents a difference-in-difference estimate 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.

* Significant at 10%, ** significant at 5%, *** significant at 1%.

Table 11: Mean complier characteristics

	(1)	(2)	(3)	(4)
	RD estimation window [1050 g,1350 g]		DD	Full sample
	Complier mean	Overall mean	Complier mean	Overall mean
Panel A. Hospital characteristics				
Total beds	756.8	750.4	634.7	581.5
NICU beds	20.5	20.3	14.4	13.5
Number of physicians	188.7	184.6	148.5	127.9
Number of nurses	1286.7	1295.9	1093.0	845.0
Total admissions	35181.4	35480.7	31757.9	25590.2
Total births	3872.6	4028.5	3716.6	3145.5
NICU	0.92	0.94	0.81	0.72
Teaching hospital	0.70	0.70	0.55	0.49
Indigent care	0.72	0.71	0.77	0.63
Lives covered, capitated (*1995 values*)	7008.3	7177.0	5782.7	7413.5
Share covered by Medicaid, infants	0.57	0.47	0.59	0.40
Share covered by Medicaid, all patients	0.37	0.31	0.35	0.26
Share covered by HMO, infants	0.18	0.21	0.17	0.24
Share covered by HMO, all patients	0.21	0.22	0.21	0.20
Panel B. Patient characteristics				
Birth weight (grams)	1305.5	1204.5	3263.3	3287.4
Fraction low birth weight (<2,500 grams)	1.00	1.00	0.07	0.08
Female	0.50	0.48	0.48	0.48
White	0.21	0.36	0.26	0.51
Black	0.37	0.31	0.20	0.17
Hispanic	0.22	0.15	0.29	0.15
Asian	0.07	0.05	0.11	0.06
Median income for patient zip code, quartile 1	0.56	0.36	0.53	0.30
Median income for patient zip code, quartile 2	0.18	0.20	0.20	0.22
Median income for patient zip code, quartile 3	0.17	0.19	0.12	0.21
Median income for patient zip code, quartile 4	0.09	0.25	0.15	0.28
Admission scheduled	0.61	0.64	0.86	0.78
Admission on the weekend	0.24	0.25	0.23	0.22
Observations		8848		4173544

Sources: HCUP State Inpatient Databases and AHA Annual Survey of Hospitals

Notes: Column 1 presents mean characteristics of compliers within the RD estimation window. Column 2 shows the overall mean characteristics within the RD estimation window. Column 3 describes the complier mean for the DD specification. Column 4 shows the full sample mean. I follow Angrist and Pischke (2009) and Almond and Doyle (2011) to compute complier characteristics. Refer to Appendix Section B for further details.

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).[42]

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.

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.[43] 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.[44] 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.

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

[43]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.

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

A.3 Conceptual Framework

My results show that hospitals tend to choose a lower level of care for MMC infants than for FFS infants. Given that hospitals are paid prospectively based on diagnosis, I develop a simple framework of provider responses to FFS and MMC under a prospective payment system.[45] I discuss under which conditions the chosen level of quantity is likely lower for an infant enrolled in MMC than for an infant enrolled in FFS. Suppose that the hospital receives prospective payment for providing inpatient services to a given infant based on the infant's DRG. I define the hospital's profit to be revenue minus total costs.

$$\pi(q) = R - C(q) = a \cdot \omega - C(q) \tag{3}$$

where a denotes the hospital base payment and ω denotes the service intensity weight for DRG classification. Total costs depend on q, the quantity of inpatient services provided. Note that revenue is constant under the prospective payment system.

Intuitively, since the hospital revenue R does not depend on q, the hospital's choice of q would not change once R changes (from FFS to MMC). Here, I assume that the *physician* is the key decision-maker who chooses the level of services provided to the infant. Additionally, I assume that the physician's utility depends both on the hospital's profit and the benefits to the infant:

$$U(\pi(q), B(q))$$

where $B(q)$ denotes the infant's total benefits from hospitalization. Let $b(q)$ denote marginal benefit. The first order condition from the physician's utility maximization problem is as follows.

$$\frac{\partial U}{\partial \pi}\frac{d\pi}{dq} + \frac{\partial U}{\partial B}\frac{dB}{dq} = 0 \tag{4}$$

Using equation (3), equation (4) can be written as

$$\frac{\partial U/\partial B}{\partial U/\partial \pi} b(q) = c(q) \tag{5}$$

where $c(q) > 0$ denotes marginal cost. Equation (5) suggests that the physician chooses the level of quantity that sets the weighted marginal benefit to the infant equal to the marginal cost to the hospital. The weight $MRS_{B,\pi} = \frac{\partial U/\partial B}{\partial U/\partial \pi}$ measures the rate at which the physician is willing to trade off marginal profit to the hospital for marginal benefit to the patient. In other words, $MRS_{B,\pi}$ measures how much the physician values the benefits to the patient relative to the hospital profit. I consider two cases depending on whether $MRS_{B,\pi}$ is a function of π.

<u>Case 1</u> $MRS_{B,\pi}$ *depends on* π*, i.e., there are "income effects" in the physician's preferences.*

In this case, the prospective payment amount a affects the choice of q. For instance, consider $U(\pi(q), B(q)) = \pi(q)B(q)$. Then the equation (5) becomes $\frac{a\cdot\omega - C(q)}{B(q)} b(q) = c(q)$. If a is lower for an MMC infant than for a FFS infant, the slope of the physician's indifference curve will be flatter and the chosen level of q will be lower for an MMC infant.

However, the physician's choice of q is unlikely to depend on the level of hospital revenue since the

[45] I follow the basic setup from Ellis and McGuire (1986).

amount of care provided to a single infant would have a very small effect on the total revenue of the hospital. I consider a case where the physician's choice of q is independent of hospital revenue below.

Case 2 $MRS_{B,\pi}$ *does not depend on* π*, i.e., there are no "income effects" in the physician's preferences.*

Since the slope of the physician's indifference curve does not depend on π, the amount of prospective payment does not affect the choice of q. For instance, consider $U(\pi(q), B(q)) = \pi(q) + B(q)^2$. Then the equation (5) becomes $2B(q)b(q) = c(q)$. Under this scenario, this simple model predicts that infants enrolled in both FFS and MMC will receive the *same* amount of care even with a different level of prospective payment.

Case 2 cannot explain my empirical result showing that hospitals provide less care to infants enrolled in MMC than to infants enrolled in FFS. This suggests the need for a theoretical model that would rationalize how the chosen level of inpatient services could be different between MMC and FFS when both systems use the prospective payment system.[46]

[46] Competitive pressure from health plans may lead to a reduction in q for infants enrolled in MMC under two assumptions. First, bargaining between health plans and hospitals induces hospitals to choose physicians who provide less care. Second, those physicians differentially provide less care to infants enrolled in MMC than to infants enrolled in FFS. However, both of these two assumptions require testing and validation.

Appendix B. Computing Complier Characteristics

I follow the estimation proposed by Almond and Doyle (2011) to compute complier characteristics:

$$E(X|compliers) = \frac{p_C + p_A}{p_C}\left[E(X|D=1, Z=1) - \frac{p_A}{p_C + p_A}E(X|D=1, Z=0)\right]$$

where X indicates hospital/patient characteristics, D denotes the treatment, which is MMC participation in my context. Z denotes the instrument, which is exceeding the 1,200-gram threshold under the RD framework and the county-specific MMC mandate under the DD framework. p_A is the proportion of always takers, and p_N is the proportion of never takers. Assuming monotonicity (i.e., no defiers), I compute the proportion of compliers using the estimates, $p_C = 1 - p_A - p_N$.[47]

Given the independence of Z, I use the sample proportion of those enrolled in MMC even though their birth weight is below the threshold to estimate p_A in the RD framework. Similarly, for the DD framework, I use the sample proportion of those enrolled in MMC even though the MMC mandate is not implemented in their county. To estimate p_N for the RD framework, I use the sample proportion of those who are not enrolled in MMC even though their birth weight is above the threshold. For the DD framework, I use the sample proportion of those who are not enrolled in MMC even though the MMC mandate is implemented in their county.

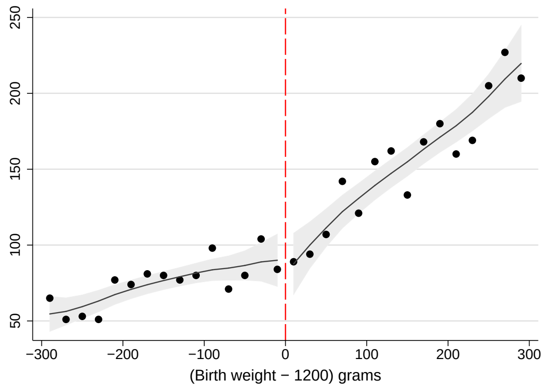
I use sample means for those who are affected by the instrument and participate in Medicaid HMO to estimate $E(X|D=1, Z=1)$ and sample means for those who are not affected by the instrument but participate in Medicaid HMO to estimate $E(X|D=1, Z=0)$. Tables below present each parameter for two instruments and show the estimates of $E(X|D=1, Z=1)$ and $E(X|D=1, Z=0)$ used in computing complier means in Table 11.

	RD	DD
Z	Birth weight≥1,200 g	Years following the MMC mandate
p_A	0.04	0.05
p_N	0.74	0.73
$p_C = 1 - p_A - p_N$	0.22	0.22

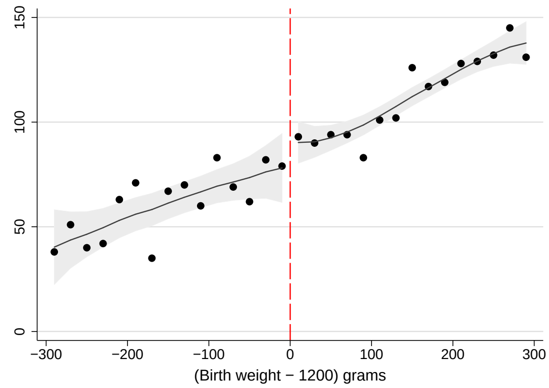
[47] The size of compliers can also be estimated from a simple regression of D on a binary Z.

	RD		DD	
	$E(X\|D=1,Z=1)$	$E(X\|D=1,Z=0)$	$E(X\|D=1,Z=1)$	$E(X\|D=1,Z=0)$
Panel A. Hospital characteristics				
Total beds	745.0	675.7	641.1	670.5
NICU beds	20.2	18.2	14.1	12.8
Number of physicians	177.1	108.7	148.8	150.2
Number of nurses	1256.5	1078.0	1039.1	790.5
Total admissions	34684.6	31752.9	30693.1	25785.4
Total births	3819.4	3505.5	3626.9	3213.5
NICU	0.92	0.88	0.80	0.76
Teaching hospital	0.68	0.59	0.56	0.57
Indigent care	0.71	0.65	0.69	0.31
Lives covered, capitated (*1995 values*)	6488.8	3423.4	5613.2	4831.9
Share covered by Medicaid, infants	0.57	0.54	0.59	0.57
Share covered by Medicaid, all patients	0.36	0.34	0.36	0.39
Share covered by HMO, infants	0.18	0.19	0.17	0.20
Share covered by HMO, all patients	0.21	0.21	0.20	0.17
Panel B. Patient characteristics				
Birth weight (grams)	1278.7	1120.6	3265.8	3277.2
Fraction low birth weight (<2,500 grams)	1.00	1.00	0.07	0.08
Female	0.49	0.43	0.48	0.49
White	0.21	0.22	0.27	0.28
Black	0.37	0.33	0.22	0.31
Hispanic	0.22	0.22	0.27	0.22
Asian	0.06	0.04	0.10	0.04
Median income for patient zip code, quartile 1	0.53	0.38	0.47	0.17
Median income for patient zip code, quartile 2	0.20	0.32	0.22	0.33
Median income for patient zip code, quartile 3	0.16	0.13	0.18	0.47
Median income for patient zip code, quartile 4	0.11	0.18	0.13	0.04
Admission scheduled	0.61	0.59	0.83	0.69
Admission on the weekend	0.25	0.33	0.23	0.25
Observations	8848	8848	4173544	4173544

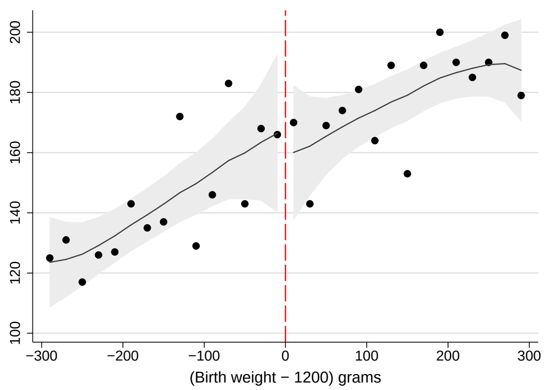
Appendix C. Figures



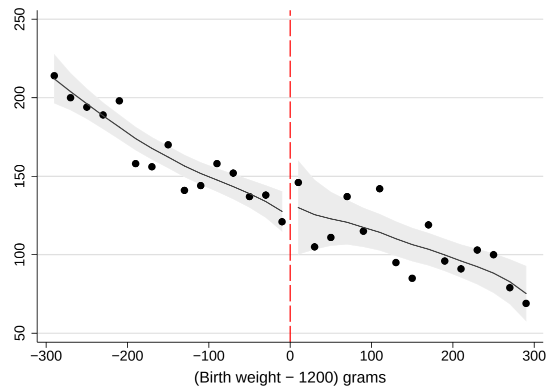
(a) Bottom quartile



(b) Q2



(c) Q3



(d) Top quartile

Figure C.1: Mean frequency of the running variable by each 20-gram bin, by predicted list prices

Sources: HCUP State Inpatient Databases
Notes: Predicted list prices are computed from regressions 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 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.

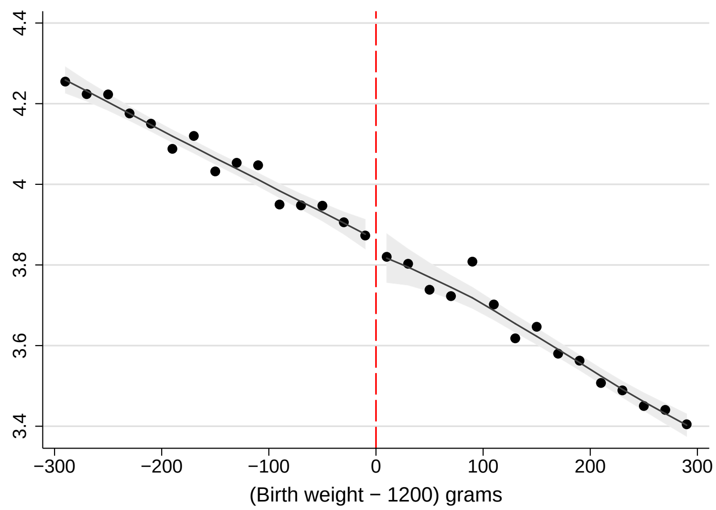
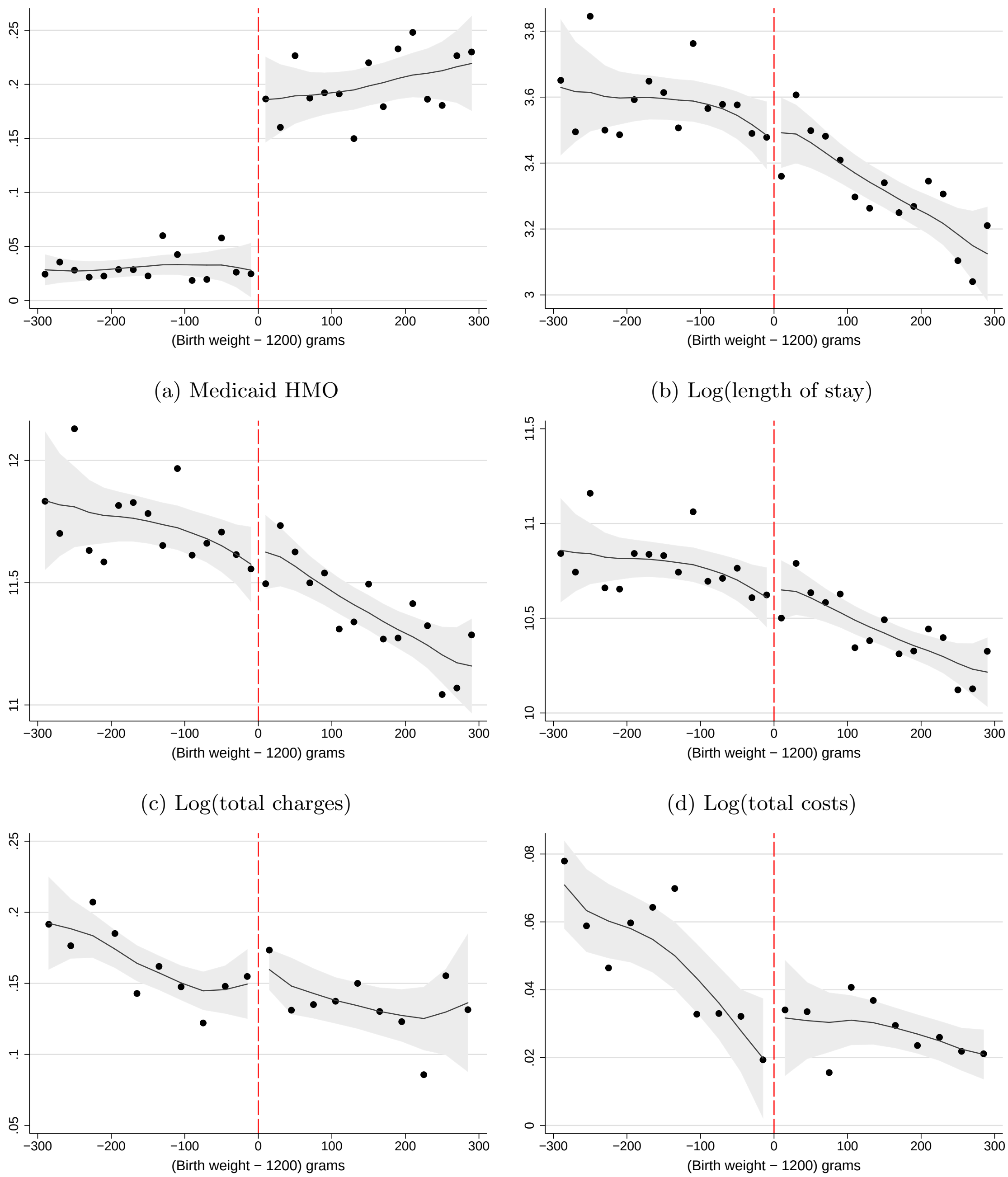


Figure C.2: Log(length of stay) for infants routinely discharged

Sources: HCUP State Inpatient Databases

Notes: The figure plots mean values of log(length of stay) for each 20-gram bin (dots) along with a local linear regression fitted lines (solid lines) and 95% confidence intervals below and above the threshold. The sample is restricted to those who are routinely discharged from birth hospitals. Each 20-gram bin contains roughly 250 discharge records. I use the triangular kernel and a bandwidth of 150 grams for local linear regressions.



(a) Medicaid HMO

(b) Log(length of stay)

(c) Log(total charges)

(d) Log(total costs)

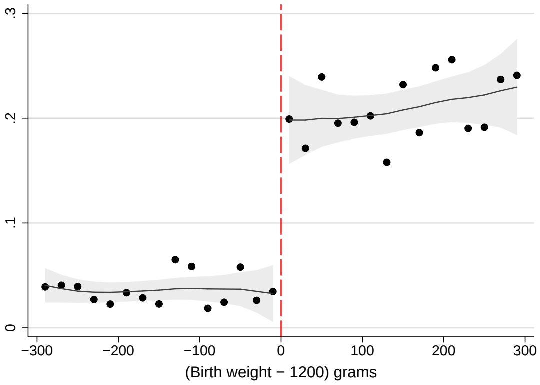
(e) Transfer

(f) Mortality during hospitalization

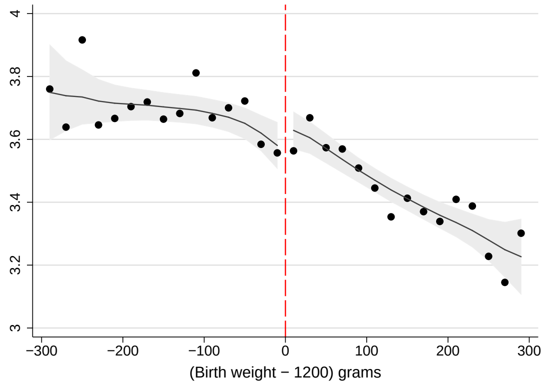
Figure C.3: Effects of birth weight≥1,200 grams on discharge outcomes at birth, rest of the state

Sources: HCUP State Inpatient Databases

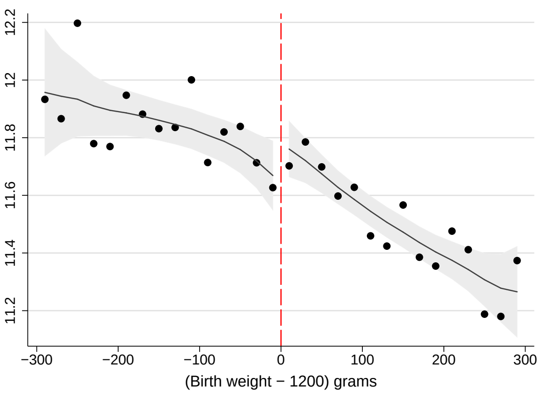
Notes: Panels (a)-(d) plot mean values of each outcome variable for each 20-gram bin (dots) along with a local linear regression fitted lines (solid lines) and 95% confidence intervals below and above the threshold. Each 20-gram bin contains roughly 250 discharge records. For panels (e) and (f) I use a bigger 30-gram bin for better visibility since transfer and death are both rare events and thus noisy. Each 30-gram bin contains around 420 discharge records. I test whether using wider bins over-smooths the data following Lee and Lemieux (2010) but find no evidence of it. I use the triangular kernel and a bandwidth of 150 grams for local linear regressions.



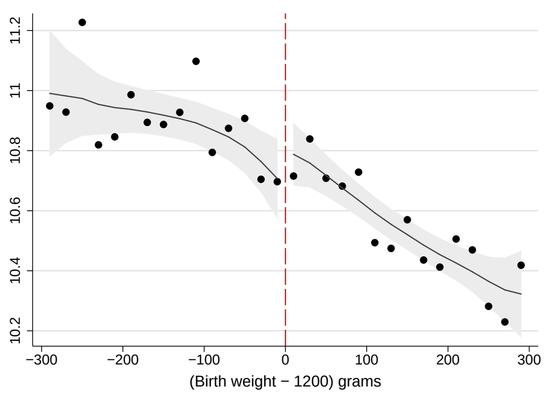
(a) Medicaid HMO



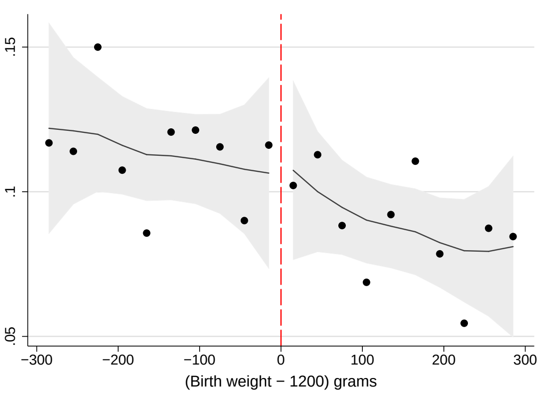
(b) Log(length of stay)



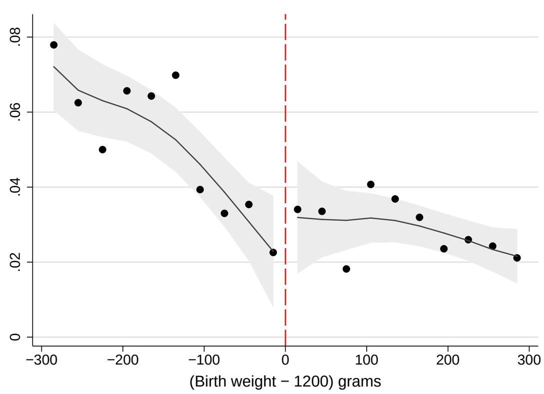
(c) Log(total charges)



(d) Log(total costs)



(e) Readmission



(f) 1-year mortality during hospitalization

Figure C.4: Effects of birth weight≥1,200 grams on aggregated discharge outcomes, rest of the state

Sources: HCUP State Inpatient Databases

Notes: Panels (a)-(d) plot mean values of each outcome variable for each 20-gram bin (dots) along with a local linear regression fitted lines (solid lines) and 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). Each 20-gram bin contains roughly 250 discharge records. For panels (e) and (f) I use a bigger 30-gram bin for better visibility since transfer and death are both rare events and thus noisy. Each 30-gram bin contains around 420 discharge records. I test whether using wider bins over-smooths the data following Lee and Lemieux (2010) but find no evidence of it. I use the triangular kernel and a bandwidth of 150 grams for local linear regressions.

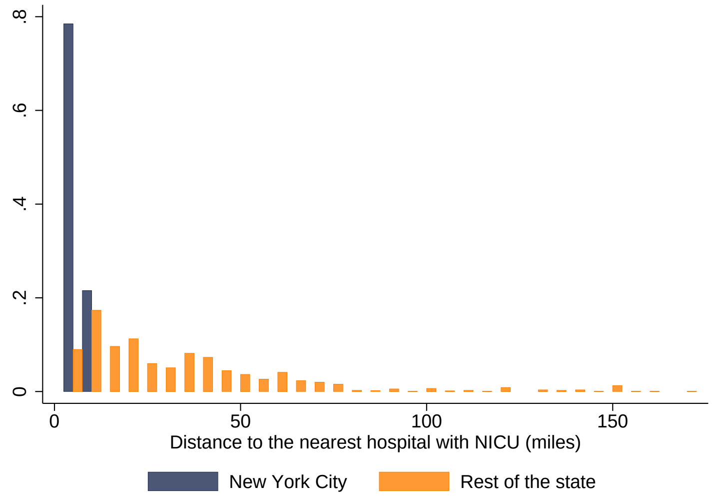


Figure C.5: Proximity to the nearest hospital with a NICU facility

Sources: HCUP State Inpatient Databases and AHA Annual Survey of Hospitals
Notes: Navy bars show the density of New York City hospitals by the distance to the nearest hospital with a NICU. Orange bars show the density of hospitals outside of New York City.

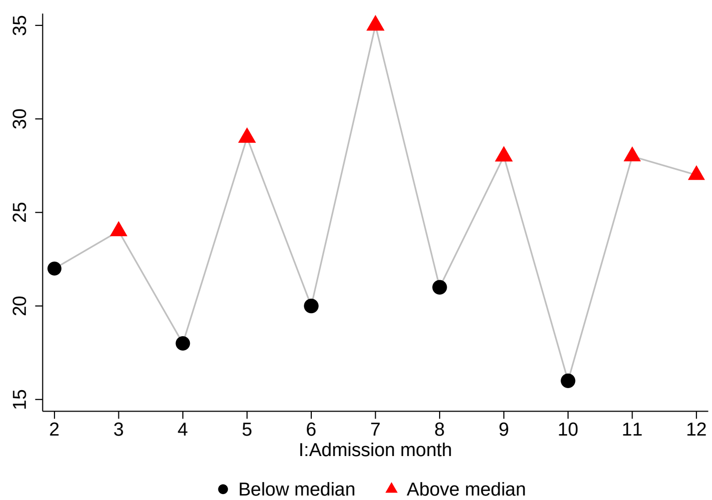
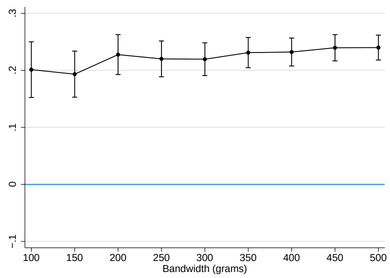
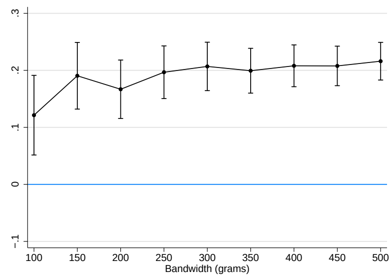


Figure C.6: An example hospital, 2005

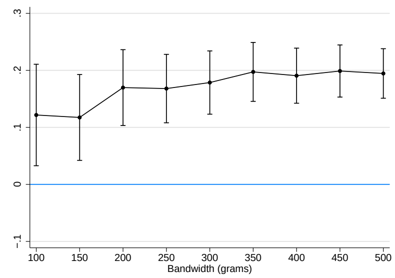
Sources: HCUP State Inpatient Databases and AHA Annual Survey of Hospitals
Notes: This figures illustrates the monthly NICU occupancy for an example hospital in the year 2005. For instance, around 22 infants were admitted to NICU in January 2005 and stayed for at least 10 days. I use this value as an indication of the NICU occupancy for infants born in February. The figure shows that there is a large variation in the NICU occupancy across months.



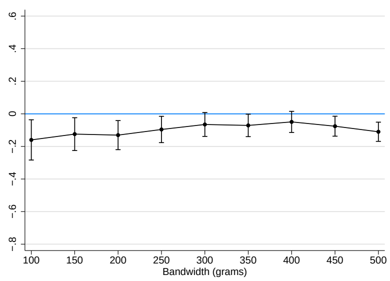
(a) Medicaid HMO, linear



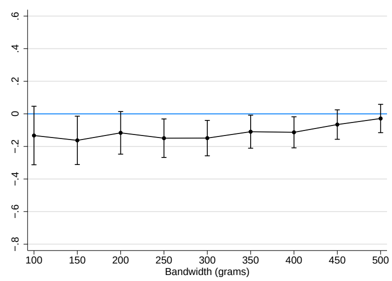
(b) Medicaid HMO, quadratic



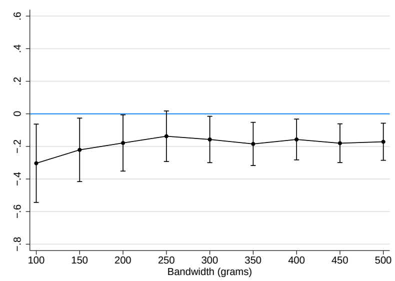
(c) Medicaid HMO, cubic



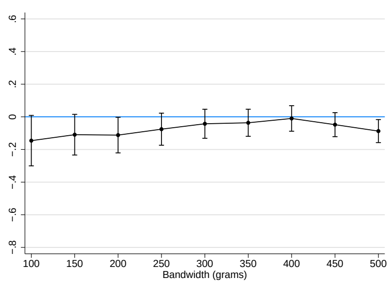
(d) Log(length of stay), linear



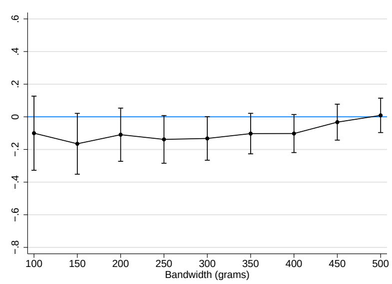
(e) Log(length of stay), quadratic



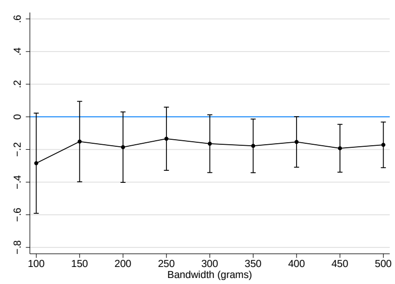
(f) Log(length of stay), cubic



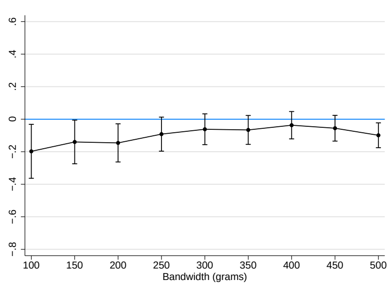
(g) Log(total charges), linear



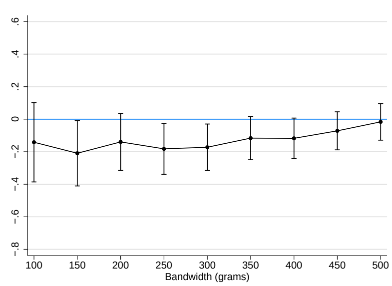
(h) Log(total charges), quadratic



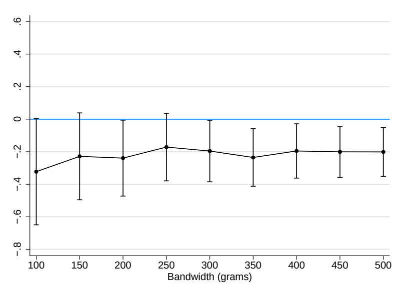
(i) Log(total charges), cubic



(j) Log(total costs), linear



(k) Log(total costs), quadratic

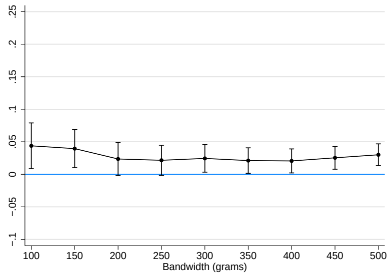


(l) Log(total costs), cubic

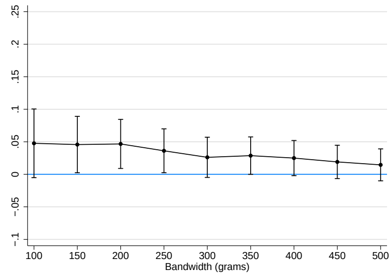
Figure C.7: Sensitivity to bandwidth and polynomial, New York City

Sources: HCUP State Inpatient Databases

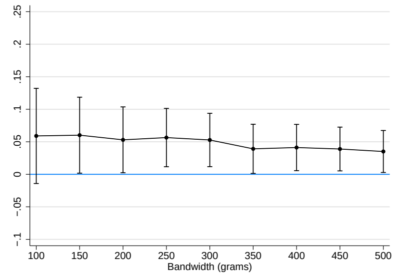
Notes: I repeat the estimation for each outcome for a different choice of bandwidth and polynomial. I use a range of bandwidths from 100 grams to 500 grams varying the degree of polynomials from degree 1 (linear), degree 2 (quadratic), to degree 3 (cubic).



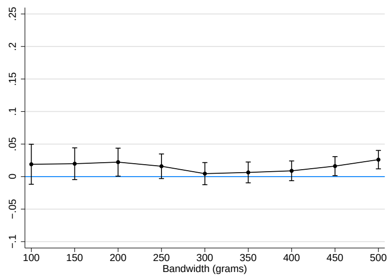
(m) Transfer, linear



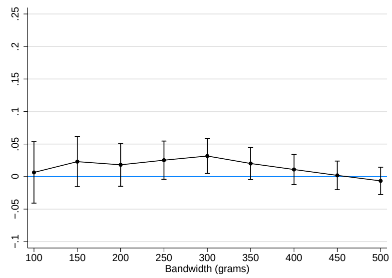
(n) Transfer, quadratic



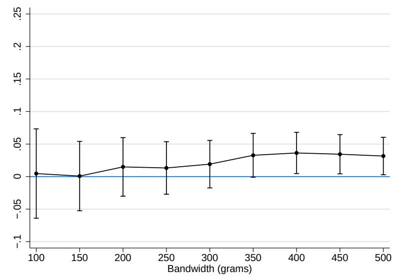
(o) Transfer, cubic



(p) Mortality, linear



(q) Mortality, quadratic



(r) Mortality, cubic

Figure C.7: Sensitivity to bandwidth and polynomial, New York City (continued)

Sources: HCUP State Inpatient Databases
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).

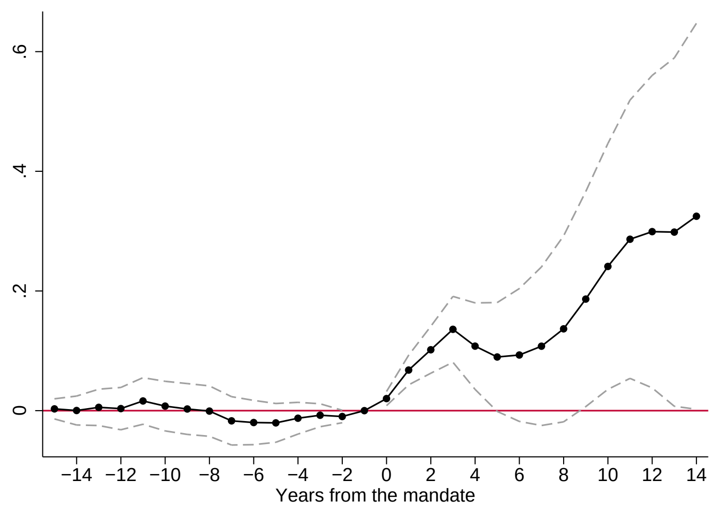


Figure C.8: Medicaid HMO participation by years from the MMC mandate

Sources: HCUP State Inpatient Databases
Notes: The above figure plots estimates from a regression of an indicator for Medicaid HMO 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 95% confidence intervals computed based on standard errors clustered at the county level.

Appendix D. Tables

Table D.1: Effects of birth weight≥1,200 grams on other health/quality outcomes, New York City

	(1) Avoidable readmission	(2) Level IV NICU stay	(3) Any NICU stay	(4) Chest X-ray	(5) Ultrasound	(6) Implant	(7) Physical therapy	(8) Respiratory therapy	(9) Speech therapy
Above	0.002	-0.002	0.008	-0.028	-0.022	-0.006	0.041**	-0.007	0.006
	(0.013)	(0.019)	(0.017)	(0.025)	(0.021)	(0.011)	(0.019)	(0.020)	(0.019)
Observations	4065	4315	4315	3221	3221	3221	4315	3221	3221
Mean below cutoff	0.052	0.873	0.905	0.801	0.895	0.025	0.127	0.947	0.091
Mean above cutoff	0.043	0.869	0.905	0.754	0.885	0.024	0.118	0.893	0.080
Bandwidth (grams)	150	200	200	150	150	150	200	150	150

Sources: HCUP State Inpatient Databases and AHA Annual Survey of Hospitals
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.
* Significant at 10%, ** significant at 5%, *** significant at 1%.

Table D.2: Heterogeneity by NICU crowdedness, relative to the number of beds, New York City

	(1) Medicaid HMO	(2) Log(LOS)	(3) Log(total charges)	(4) Log(total costs)	(5) Transfer	(6) Mortality
Panel A. Below the median NICU occupancy relative to the number of beds						
Birth weight≥1,200 g	0.205***	-0.043	-0.048	0.024	0.018	0.020
	(0.035)	(0.078)	(0.101)	(0.098)	(0.026)	(0.030)
Observations	1266	947	942	732	1266	645
Mean below cutoff	0.017	53.0	$284,947	$107,507	0.058	0.036
Mean above cutoff	0.242	43.8	$253,561	$92,292	0.046	0.030
Bandwidth (grams)	200	150	150	150	200	100
Panel B. Above the median NICU occupancy relative to the number of beds						
Birth weight≥1,200 g	0.244***	-0.222***	-0.249***	-0.221**	0.033*	0.028
	(0.030)	(0.076)	(0.092)	(0.098)	(0.019)	(0.029)
Observations	1744	1302	1298	982	1744	859
Mean below cutoff	0.016	53.1	$287,583	$106,648	0.040	0.040
Mean above cutoff	0.261	42.3	$230,545	$86,728	0.051	0.039
Bandwidth (grams)	200	150	150	150	200	100

Sources: HCUP State Inpatient Databases and AHA Annual Survey of Hospitals
Notes: I divide the monthly NICU occupancy measure by the number of NICU beds. Since the mean length of stay for infants who stay in NICU for at least 10 days is around one month, this measure roughly captures the daily occupancy rate in a given month. Panel A shows the RD estimates for months when this relative NICU occupancy rate is below the median for a given hospital in a given year. Panel B shows the RD estimates for months when the relative NICU occupancy rate is above the median for a given hospital-year. 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.
* Significant at 10%, ** significant at 5%, *** significant at 1%.

Table D.3: Heterogeneity by crowdedness at the typical destination, New York City

	(1)	(2)	(3)	(4)	(5)	(6)
	Medicaid HMO	Log(LOS)	Log(total charges)	Log(total costs)	Transfer	Mortality
Panel A. Below the median NICU occupancy at the typical destination						
Birth weight≥1,200 g	0.228***	-0.194**	-0.236**	-0.219**	0.038	0.022
	(0.028)	(0.077)	(0.099)	(0.106)	(0.023)	(0.027)
Observations	1826	1349	1343	1015	1826	904
Mean below cutoff	0.019	52.4	$276,442	$106,429	0.067	0.027
Mean above cutoff	0.262	42.1	$228,440	$84,086	0.064	0.033
Bandwidth (grams)	200	150	150	150	200	100
Panel B. Above the median NICU occupancy at the typical destination						
Birth weight≥1,200 g	0.261***	-0.133	-0.134	-0.279**	0.008	0.018
	(0.038)	(0.102)	(0.119)	(0.133)	(0.023)	(0.037)
Observations	1256	939	936	692	1256	647
Mean below cutoff	0.031	52.3	$264,805	$104,435	0.064	0.051
Mean above cutoff	0.320	43.6	$234,905	$90,673	0.062	0.039
Bandwidth (grams)	200	150	150	150	200	100

Sources: HCUP State Inpatient Databases and AHA Annual Survey of Hospitals
Notes: I define a typical destination hospital as the receiving hospital of the majority of any neonatal transfers from a given hospital. Panel A shows the RD estimates for months when the NICU occupancy at the typical destination hospital with a NICU is below the median, while panel B shows the RD estimates for months when the NICU occupancy at the typical destination hospital is above the median in a given hospital-year. 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.
* Significant at 10%, ** significant at 5%, *** significant at 1%.

Table D.4: Difference-in-difference estimates, sample composition

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	LBW	Medicare	Medicaid	Private	Self-pay	No charge	Other
Panel A. Without county-specific time trends							
MMC mandate	-0.002*	0.004	-0.042***	0.027***	0.018**	0.001	-0.007
	(0.001)	(0.005)	(0.012)	(0.010)	(0.008)	(0.001)	(0.007)
Observations	4173544	4173544	4173544	4173544	4173544	4173544	4173544
Mean	0.081	0.002	0.409	0.506	0.065	0.000	0.018
Panel B. With county-specific time trends							
MMC mandate	0.000	0.005	-0.023***	0.005	0.009	0.001	0.003
	(0.001)	(0.006)	(0.007)	(0.005)	(0.005)	(0.001)	(0.003)
Observations	4173544	4173544	4173544	4173544	4173544	4173544	4173544
Mean	0.081	0.002	0.409	0.506	0.065	0.000	0.018

Sources: HCUP State Inpatient Databases
Notes: Panel A presents a difference-in-difference estimate for each outcome without including the county-specific trends. Panel B shows the estimates including the county-specific trends. LBW stands for low birth weight infants.
* Significant at 10%, ** significant at 5%, *** significant at 1%.

Table D.5: 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	0.004	-0.009*	-0.008*	-0.002***	-0.000	-0.012	-0.006
	(0.005)	(0.005)	(0.004)	(0.001)	(0.006)	(0.008)	(0.008)
Observations	1721856	1721856	1721856	1721856	1721856	1721856	1721856
Mean	0.129	0.077	0.061	0.003	0.012	0.074	0.007
Panel B. With county-specific time trends							
MMC mandate	0.005	-0.011*	-0.007**	-0.002	-0.000	-0.012***	-0.006*
	(0.007)	(0.006)	(0.003)	(0.001)	(0.003)	(0.004)	(0.003)
Observations	1721856	1721856	1721856	1721856	1721856	1721856	1721856
Mean	0.129	0.077	0.061	0.003	0.012	0.074	0.007

Sources: HCUP State Inpatient Databases and AHA Annual Survey of Hospitals

Notes: Panel A presents a difference-in-difference estimate 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.

* Significant at 10%, ** significant at 5%, *** significant at 1%.

Table D.6: Heterogeneity by county-level median household income

	(1) Medicaid HMO	(2) Log(LOS)	(3) Log(total charges)	(4) Log(total costs)	(5) Transfer	(6) Mortality
Panel A. Quartile 1						
Birth weight≥1,200 g	0.301***	-0.349***	-0.250**	-0.339***	0.078***	0.043
	(0.039)	(0.091)	(0.123)	(0.121)	(0.028)	(0.028)
Observations	1290	976	973	734	1290	688
Mean below cutoff	0.040	52.3	$252,267	$103,430	0.083	0.028
Mean above cutoff	0.324	42.6	$219,470	$81,610	0.099	0.032
Bandwidth (grams)	200	150	150	150	200	100
Panel B. Quartile 2						
Birth weight≥1,200 g	0.247***	-0.029	-0.010	-0.026	0.004	0.013
	(0.023)	(0.075)	(0.089)	(0.096)	(0.020)	(0.021)
Observations	3492	2599	2595	2107	3492	1721
Mean below cutoff	0.032	49.6	$194,713	$77,260	0.120	0.042
Mean above cutoff	0.296	40.1	$157,699	$62,790	0.114	0.036
Bandwidth (grams)	200	150	150	150	200	100
Panel C. Quartile 3						
Birth weight≥1,200 g	0.158***	0.014	-0.079	0.023	0.011	-0.006
	(0.030)	(0.091)	(0.099)	(0.108)	(0.023)	(0.025)
Observations	1497	1107	1101	939	1497	741
Mean below cutoff	0.019	53.9	$268,293	$98,228	0.064	0.026
Mean above cutoff	0.190	44.9	$214,479	$77,044	0.055	0.033
Bandwidth (grams)	200	150	150	150	200	100
Panel D. Quartile 4						
Birth weight≥1,200 g	0.118***	0.001	0.050	0.049	0.019	0.027*
	(0.019)	(0.071)	(0.081)	(0.083)	(0.020)	(0.016)
Observations	3782	2797	2787	2507	3782	1848
Mean below cutoff	0.037	49.5	$232,172	$79,622	0.115	0.033
Mean above cutoff	0.178	40.5	$196,712	$66,658	0.105	0.031
Bandwidth (grams)	200	150	150	150	200	100

Sources: HCUP State Inpatient Databases

Notes: Each panel shows the RD estimates for counties classified into each quartile of a county-level median income measure. I take an average of median household income levels across zip codes in each county to construct the county-level income measure. Here, I use county as a service area for a hospital since hospitals typically serve an area larger than a zip code. 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.

* Significant at 10%, ** significant at 5%, *** significant at 1%.