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Abstract

Despite widespread adoption across the United States, there is little empirical evidence on whether Medicaid managed care (MMC) reduces costs without compromising health outcomes. This paper exploits an arbitrary component of MMC enrollment in New York to examine the causal effects of MMC on hospital responses and newborn health. During the study period, infants with birth weight below 1,200 grams were excluded from MMC and were instead served through the traditional fee-for-service (FFS) system. Using a regression discontinuity design framework, I find that infants enrolled in MMC stay fewer days in the hospital following birth and thus have less expensive visits. I show that this is driven by birth hospitals retaining more infants enrolled in FFS while transferring away those enrolled in MMC to another hospital. The effects are stronger when the birth hospital is spatially constrained and for infants with high predicted list prices. I find little effect on short-term health measured by mortality during hospitalization and the incidence of readmissions. I show that hospitals engage in these behaviors only when they have a high-quality hospital in close proximity, suggesting that hospitals do not sacrifice quality of care for cost reductions.

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1 Introduction

Over the past few decades, it has become increasingly common for US states to contract out the public health insurance, Medicaid, to private organizations known as managed care organizations. The fraction of total Medicaid beneficiaries who were enrolled in some form of managed care increased from 10% in the early 1990s to 74% by 2013 [Duggan and Hayford 2013; CMS 2015]. The rapid growth of Medicaid managed care (MMC) was largely driven by state mandates that required certain types of Medicaid beneficiaries to enroll in a managed care plan. The penetration rate is expected to rise even further in the coming years as a number of states are expanding the coverage of their MMC programs to broader populations, including those with complex medical needs [KFF, 2015]. In addition, Medicaid expansion following the Affordable Care Act will result in a still large increase in total Medicaid enrollment, and the vast majority of the newly enrolled will participate in MMC programs.

The increased adoption of MMC is based on the premise that it can shift incentives from relying on expensive services for treatment to focusing on preventive care, thus reducing costs while improving health. Under the traditional fee-for-service (FFS) system, Medicaid directly pays health care providers (such as hospitals and physicians) for each service that they provide.[1] Thus, this system gives providers an incentive to administer expensive and unnecessary care as long as it is deemed profitable. MMC introduces an intermediary into this payment process - the managed care health plan. Medicaid signs contracts with health plans for the delivery of services and reimbursement of health care providers, and pays health plans a flat monthly fee for each enrollee (i.e., capitation). In turn, health plans are responsible for meeting health care needs of their enrollees and reimbursing providers.[2] This reimbursement model incentivizes health care providers to reduce spending and to manage enrollees' health in order to avoid providing costly services.

Despite the theoretical appeal and widespread adoption, empirical evidence on whether MMC can reduce costs and improve health is surprisingly scarce and mixed. Several papers have exploited the state mandates to control for selection into managed care using a difference-in-difference type of approach (e.g., Duggan [2004]; Aizer et al. [2007]; Duggan and Hayford [2013]). However, there is little consensus on the effects of MMC or the mechanisms through which MMC can deliver efficient health care to Medicaid beneficiaries. As Duggan and Hayford [2013] note, "How states can achieve greater success in their MMC programs with respect to improved quality and lower Medicaid spending" still remains an important area for future research.

This paper examines how hospitals respond to MMC focusing on low birth weight infants in New York. I contribute to the MMC literature in three ways. First, I focus on one of the costliest populations who require intensive medical care, low birth weight infants. We know very little about how effective managed care is in serving this demographic, as participants of managed care have

[1]Many states use Diagnosis-Related Groups (DRGs) for hospital payments in their FFS programs [Quinn, 2008]. Each inpatient stay is classified into a DRG and Medicaid pays a fixed rate to hospitals based on the DRG assigned to the patient.

[2]Health plans choose a wide range of methods in reimbursing providers, from a fee-for-service method to capitation.

traditionally been healthier populations. As a number of states have began to expand MMC to those with critical conditions [Iglehart 2011; Libersky et al. 2013], however, it is timely and policy-relevant to understand whether MMC can successfully deliver medical care to them. Aggregate hospital costs of births are extremely high, ranked #4 in 2011 [HCUP, 2013]. Among those billed to Medicaid and to private insurance, costs of births were ranked on top. Very low birth weight infants (birth weight<1,500 grams) form a small minority of the total newborn population (1.3%), but these infants incurred about one third of total costs of birth. Whether managed care can provide cost-effective care to Medicaid beneficiaries with complex medical issues has important policy implications, not only do they have the greatest potential for cost savings but also because of their major health consequences depending on the quality of care. If managed care compromises health for some, it might be expected to occur among the least healthy and most clinically involved subpopulations.

Second, I take a new approach to identifying the causal effect of MMC on cost savings and health outcomes. In New York, Medicaid beneficiaries are mandated to enroll in an MMC plan, but a few subpopulations are excluded or exempt from MMC. In particular, during the study period, infants weighing less than 1,200 grams at birth were excluded from MMC and were instead served through the traditional FFS system [NYSDOH, 2000, 2001]. I take advantage of the natural experiment created by this discontinuous exclusion to examine the impact of receiving MMC instead of FFS in a regression discontinuity (RD) design framework. Moreover, exploiting the mandate rollout in New York, I employ a difference-in-difference (DD) approach and compare the DD estimates with the RD estimates to gain insights on hospital responses for different subpopulations. To further understand different "compliers" to each instrument, I estimate and compare mean complier characteristics [Angrist and Pischke, 2009].

Third, I provide evidence on how MMC affects hospitals' practice patterns. To my knowledge, previous studies have not been able to show direct evidence on how health care providers adjust their practice style as a response to MMC. The presence of the intermediary under MMC can affect both hospital payments (prices) and the amount of inpatient services (quantities). Negotiations between health plans and hospitals can result in lower prices and thus a reduction in costs. However, only when the lower prices are accompanied by an efficient reduction in quantities, MMC can achieve the goal of managing utilization and quality of care, thus improving health. Existing literature focuses on health plans' incentives because the information on provider payments is mostly unavailable and it is generally difficult to distinguish whether the effects are driven by the plan or the provider. A better understanding of plans' payments to hospitals for newborn medical care and the emergency of decision-making for critically ill newborns allow me to investigate how hospitals adjust their treatment choices in response to MMC.

It is clear that hospitals that maximize profits would like to hold onto more profitable patients while keeping away less profitable ones. When the infant is born, the hospital has to decide whether to retain the infant at its own facility or to transfer the infant to another hospital. Given that the marginal revenue (i.e., reimbursement payments for each infant) from providing care to infants enrolled in FFS is higher than the marginal revenue from infants enrolled in MMC,[3] hospitals would be more likely to transfer infants covered by MMC than those under FFS. This incentive would be stronger when hospitals' spatial constraints bind. That is, when there are only few beds available, the incentive to selectively keep more profitable infants would become greater. In addition, hospitals would be more likely to transfer infants enrolled in MMC when their expected costs of treatment are high. This is because infants with high costs of treatment are less profitable to hospitals, unless the reimbursement payments are completely adjusted for severity of conditions. I examine how the effects of MMC vary by hospital capacity and predicted list prices to test these predictions.

Based on my RD analysis, I show that hospitals engage in profit-maximizing behaviors consistent with the above predictions. I find that infants enrolled in MMC stay fewer days in the hospital, and thus have less expensive visits. I show that shorter length of stay of infants under MMC is in fact driven by transfers from a birth hospital to another hospital, especially when the birth hospital do not have enough Neonatal Intensive Care Unit (NICU) beds available. In addition, I find that infants with higher predicted list prices are more likely to be transferred. This is consistent with hospitals responding to financial incentives associated with MMC.

The consequences of transfer on health outcomes are ambiguous. Neonatal transfers are associated with increased mortality and higher risk of complications, while receiving hospitals in my sample are on average bigger, more-equipped, and of "higher-quality." I find little impact on short-term health measured by mortality during hospitalization and the incidence of readmissions during the first year of their lives. This suggests that infants with lower reimbursement payments are transferred away to a high-quality hospital, resulting in minimum harm in health outcomes. The lack of health impacts suggests that hospitals adjust their practice style for financial gains, but they are not willing to sacrifice health of their patients in doing so [Ho and Pakes, 2014].

Interestingly, I find that the above results are driven by infants born in New York City. There are few differences between MMC and FFS in other counties outside of New York City. Even when the hospital is spatially constrained, I find little evidence of differential probabilities of transfer between MMC and FFS in the rest of the state. I explore different structures of health care markets between New York City and other counties in New York to further understand the mechanism through which MMC affects hospitals. Especially, I consider proximity to high-quality hospitals as a potential mechanism. My hypothesis is that the dense health care market in New York City allows hospitals to have efficient communications with and easier access to potential receiving hospitals nearby, which are necessary for successful transfers. In other counties where hospitals are sparsely located, the cost of successfully transferring certain infants to another hospital in a timely manner may outweigh the benefit of it. To test this hypothesis, I compute distance from each birth hospital to its nearest hospital with a NICU facility and examine heterogeneity by proximity. I find that the effects are larger for birth hospitals that have hospitals with NICU nearby even *within* New York City. In addition, I show that the effects are stronger when these nearby hospitals with NICU are relatively less crowded.

[3]See Section 3.4 for details.

The remainder of the paper is organized as follows. Section 2 discusses relevant literature. Section 3 describes the brief history of MMC in New York and discusses the low birth weight exclusion, reimbursement methods under MMC, and transfer decisions for critically ill infants. Section 4 describes my data and presents descriptive statistics. Section 5 describes the main empirical strategy, while Section 6 presents the main RD estimates. To further understand the mechanism, Section 7 explores heterogeneity by spatial capacity, predicted list prices, proximity to the nearest hospital with NICU, and crowdedness at the destination hospital. Section 8 presents difference-in-difference estimates and complier characteristics for comparison between DD and RD estimates. Section 9 discusses the role of median household income in patient counties and overall cost implications. Section 10 concludes.

2 Related Literature

Given the importance of understanding the implications of Medicaid managed care, a number of studies have examined the impact of MMC on various dimensions, such as health care utilization, access to care, health outcomes, and health care expenditures since early 1990s. Surprisingly, however, there is no consensus on how MMC affects these outcomes or the mechanisms through which MMC can have certain impacts.

Several papers use local implementations of MMC mandates to address selection into managed care[4] using a difference-in-difference type of approach. Duggan [2004] is one of the earlier papers that exploited a local-level MMC mandate to correct for selection. He focuses on the impact on Medicaid expenditure, which is an important outcome as one of the main goals of MMC is to achieve savings in Medicaid spending. He finds that an MMC mandate in California led to an *increase* in government spending with no health improvement, suggesting that MMC rather decreased the program efficiency. 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 a nationally representative sample, Herring and Adams [2011] find no significant decrease in expenditures or improvement in access to care. Duggan and Hayford [2013] use data that cover all fifty US states and the District of Columbia to examine the effects of MMC on Medicaid expenditures. They show that shifting from FFS into MMC did not reduce Medicaid spending in a typical state. However, they find that MMC did reduce spending in states that had generous baseline Medicaid FFS provider reimbursement rates. Their results suggest that MMC could achieve savings mainly through the government's ability to negotiate lower prices with health plans, indicating MMC had little impact on actual provider practice.[5]

[4] Glied et al. [1997] show participations were positively selected (e.g., healthier) when enrollment into MMC was voluntary in New York City.

[5] Their findings are consistent with the literature on managed care in the private insurance market. For example, Cutler et al. [2000] examine the effects of managed care on price and quantity of health care for the privately insured, focusing on patients with heart disease. They show that unit prices (i.e., reimbursement payments) are lower under managed care than the traditional indemnity insurance, while they find relative modest differences in quantity (i.e.,

While Duggan and Hayford [2013] pay attention to the role of baseline Medicaid reimbursement rates, there are a few other papers that focus on different mechanisms of the success of MMC. Marton et al. [2014] show that how plans reimburse providers (e.g., fee-for-service versus capitation) and handle administrative responsibilities (which they call "plan design") greatly affect the successful reduction in utilization and spending. In addition, Van Parys [2015] examines Florida's 2005 Medicaid reform and shows that the types of competing health plans in regional health care markets have an impact on how plans reduce costs.

Another branch of the literature examines the effects of MMC on health care utilization and health outcomes. 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 found that MMC actually decreased the quality of prenatal care and increased the incidence of low birth weight, pre-term births, and neonatal mortality.[6,7] Their findings suggest that providers can respond to MMC by limiting care for certain populations, resulting in adverse effects on health. Kuziemko et al. [2013] provide evidence on risk-selection under MMC. They found 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.

Moreover, a number of papers document the effects of MMC on children's health care utilization. Baker and Afendulis [2005] find that MMC was associated with less emergency room use[8], more outpatient visits, and fewer hospitalizations for children, which might suggest an improvement in preventive care. However, they also show that MMC led to an increased reporting of poor access to care and lower satisfaction with recent visits, leaving the welfare implication of MMC inconclusive.[9] Gadomski et al. [1998] show that MMC is associated with an increase in ambulatory care and a reduction in both avoidable and general pediatric hospitalizations.[10]

This paper sheds new light on the MMC literature in three ways. First, unlike the previous studies that focus on a time variation across regions to identify the effects of MMC, I employ a new identification strategy using a cross-sectional variation in the MMC enrollment. An arbitrary component of MMC enrollment in New York creates a quasi-experiment where I can examine the causal effects of MMC in an RD framework. Second, I focus on how hospitals adjust their practice style in response to MMC. Few papers directly examine the response of health care providers,[11]

treatment patterns) and health outcomes.

[6]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 & birth outcomes - but show that their estimates are unlikely to be causal.

[7]On the contrary, some of the earlier findings suggest improvement in prenatal care [Krieger et al. 1992; Levinson and Ullman 1998; Howell et al. 2004].

[8]See also Garrett et al. [2003] & Dombkowski et al. [2004].

[9]Long and Coughlin [2001] find few differences in access to care, health care utilization, and satisfaction using the sample of children residing in rural Minnesota.

[10]See also Basu et al. [2004] & Bindman et al. [2005] for avoidable hospitalizations.

[11]Baker [1994] & Baker and Brown [1997] focus on MMC's spillover effects on health care providers. Currie and Fahr [2004] examine whether *private* managed care penetration affected hospitals' charity care. They find that for-profit hospitals in fact increased charity care as managed care penetration reduced the price paid by privately insured patients, making them relatively unattractive.

although it is clear that provider-level responses are highly correlated to the quality of care and patient health. Third, I explore a new mechanism through which MMC can achieve savings without compromising health. Especially, I provide suggestive evidence that easier access and better communication between hospitals are crucial in coordinating successful care for MMC patients.

This paper is also related to the literature on hospital responses to a change in prices.[12] Dafny [2005] shows that hospitals "upcode" patients to take advantage of large price increases for certain diagnoses.[13] Acemoglu and Finkelstein [2008] find a large increase in capital-labor ratios following a reform that decreased reimbursement for labor input.[14] 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 critically 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.

3 Background

In this section, I provide institutional details on MMC in New York and how it applies to newborns. Specifically, I discuss how the MMC mandate was implemented in New York and the exclusion of low birth weight infants. I provide details on state payment to health plans and plan payment to hospitals for Medicaid beneficiaries enrolled in managed care health plans. In addition, I describe background on transfer decisions of critically ill newborns.

3.1 Brief History of Medicaid Managed Care in New York

New York began to phase in mandatory managed care in Albany and four other upstate counties in October 1997. 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. According to Medicaid Managed Care Enrollment Reports, 95% of total eligibles were enrolled into MMC in December 2012.[15]

Figure 1 shows the trends in the share of infants covered by Medicaid in New York using inpatient discharge records. Medicaid coverage has increased over time, and around half of all births were

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

[13] See also Geruso and Layton [2015] & Sacarny [2015].

[14] See also Finkelstein [2007]. She examines hospital responses to an introduction of Medicare and finds that it was associated with an increase in market entry of new hospitals.

[15] https://www.health.ny.gov/health_care/managed_care/reports/enrollment/monthly/2012/docs/en12_12.pdf

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.

The share covered by HMO is not 100% even after the statewide implementation of the mandate due to four reasons. First, there were a few infants who were still covered by Medicaid FFS due to exclusions and exemptions from the MMC enrollment. Second, some infants whose parents failed to enroll their child into a managed care plan in a timely manner might show up as having the FFS coverage in the discharge records.[16] Third, even for infants who are subject to mandatory enrollment, the implementation might not be perfect or immediate due to some administrative issues. In addition, it is possible that other types of MCOs besides HMO were coded as the non-HMO category.[17] With the caveat that HMO may not be a perfect measure of MMC participation, I estimate the intent-to-treat effects of exceeding the birth weight threshold on outcomes in the following analysis.

3.2 Exclusion from MMC Below the Birth Weight Threshold at 1,200 Grams

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.[18] They are instead served through the fee-for-service system. This creates a discontinuous exclusion from MMC based on birth weight, which I exploit in a regression discontinuity design framework to estimate the causal effects of MMC in comparison to FFS.

As mentioned above, the birth weight threshold at 1,200 grams does not coincide with the rule-of-thumb threshold for very low birth weight at 1,500 grams. However, it coincides with one of the conditions that qualify children for Supplemental Security Income (SSI) payments. SSI provides monthly cash payments and Medicaid to the beneficiaries. When the child is in a medical facility, monthly cash payments are limited to $30, while Medicaid is responsible for payments of medical care. Since the amount of cash payments is fairly small and services provided to newborns enrolled in Medicaid are exempt from co-payment, SSI payments are unlikely to affect families' decision to utilize health care conditional on Medicaid participation.[19]

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

[17]For example, Prepaid Health Services Plans (PHSP), which has the same structure as HMO but primarily serve beneficiaries of government health insurance programs.

[18]Only 2% of total discharge records of low birth weight infants were admitted at 6 months or older in my sample. Therefore, distinguishing visits before and after 6 months essentially has no effect on statistical inference.

[19]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 can be an incentive for families to leave the facility early. However, this would go against finding a reduction in length of stay above the

However, if SSI participation due to the birth weight qualification induces people to participate in Medicaid who would otherwise be covered by another type of health insurance, it can affect both patient and provider behaviors [Currie and Gruber, 1996]. I examine whether the probability of receiving Medicaid discontinuously increases below the threshold. I find that exceeding the birth weight cutoff in fact decreases the probability of Medicaid participation but the estimate is not statistically significant (RD estimate: -0.024; robust standard error: 0.026). This could be due to the small number of infants who actually take up SSI based on birth weight while in the hospital, or because majority of those who qualify for SSI already have Medicaid through the mother. Regardless, little impact on Medicaid participation suggests that SSI had limited impact on medical care of newborns around the 1,200 grams threshold. Nevertheless, I do not restrict my estimation to Medicaid participants since there could be a differential selection into Medicaid below and above the threshold.[20] In addition, I repeat the estimations for two other states (New Jersey and Maryland) where the SSI rule applies but the managed care exclusion does not, and I find no effects on discharge outcomes for this sample. This again suggests that SSI had little impact on hospital care for these very low birth weight infants.

Those who are excluded from MMC enrollment are generally medically complicated and expensive to treat. For instance, in New York, only 1% of infants weighed less than 1,200 grams at birth, but they accounted for 22.3% of total costs between 1995 and 2013 (Figure 2). Other populations who were excluded from MMC enrollment include nursing home residents and people residing in state psychiatric facilities during the study period [Sparer, 2008]. These groups were excluded initially due to several concerns raised by both health plans and beneficiaries. Health plans had little experience with severely ill populations and lacked the coordinated delivery system for these populations. Beneficiaries were also concerned about inadequate provider networks under MMC.

However, the state has been gradually phasing in mandatory enrollment into MMC for these populations, 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.[21] I repeat my estimations using the discharge records after April 2012 and I find no effects on provider practice during this period, suggesting that my results are not driven by something other than the exclusion from MMC.

3.3 State Payment to Health Plans

The state negotiates with each health plan to determine monthly capitation payments.[22] 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

threshold.

[20] The MMC mandate might have affected Medicaid enrollments above the threshold by affecting parental preferences for Medicaid participation [Currie and Fahr, 2005]. 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.

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

[22] Holahan and Schirmer [1999] summarize MMC payment methods and capitation rates from a national survey.

vary by age, sex, and region. These rates are applicable for 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 has 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].[23]

The New York State Medicaid program paid a monthly capitation rate of $138 on average for newborns younger than 6 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 the following section.

3.4 Plan Payment to Hospitals

Under the FFS system in New York, most inpatient services are reimbursed based on a Diagnosis-Related Group (DRG) assigned to a given patient.[24] The FFS base rates for each hospital are publicly available on the New York State Department of Health (NYSDOH) website, along with weights for each DRG. The state Medicaid program uses these FFS rates for inpatient payments for patients enrolled in FFS.

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 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 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. NYSDOH also provides inpatient payment rates for MMC on their website.[25] These MMC rates are intended to be used by health plans as base rates in negotiation with hospitals. These MMC rates are generally lower than the FFS rates that the state uses to directly pay hospitals. In 2009, for instance, the base discharge rate for FFS was $6,471.31

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

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

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

on average, while the base contract discharge rate for MMC was $5,284 on average.

This suggests that hospitals are paid different amounts for providing care to infants enrolled in FFS and those enrolled in MMC. Consider a patient with a DRG "Neonate BWT <1500G W Major Procedure" treated at NewYork-Presbyterian Hospital, one of the largest hospitals in New York. In 2009, the DRG weight for this particular DRG was 18.0256. The base discharge payment for this hospital was $9,017.24 under FFS while the suggested base contract discharge payment was $6,331.27 under MMC. The DRG-adjusted discharge payment for this hospital then becomes $162,541.16 if the patient was enrolled in FFS and $114,124.94 if enrolled in MMC. Although this is only illustrative since the exact MMC rates are not available, if health plans pay the rates that are similar to the rates suggested by the state, hospitals' marginal revenue from providing care to infants enrolled in FFS would be much higher than marginal revenue from infants enrolled in MMC.

Given higher reimbursement payments for infants enrolled in FFS than for infants enrolled in MMC, a hospital maximizing profits would clearly like to attract more infants under FFS than those under MMC. To elaborate, consider a hospital maximizing profits from infants enrolled in Medicaid, subject to a spatial constraint. When the baby is born, the hospital decides whether to retain the baby at its own facility or to transfer the baby to another hospital. It follows that the hospital would choose the number of infants enrolled in each program such that the respective reimbursement payments equal to the marginal costs plus the shadow price of the spatial constraint. Thus, assuming the marginal costs of treatment are the same between two systems for a given condition, the hospital would be more likely to hold onto infants enrolled in FFS while transferring infants enrolled in MMC, since the reimbursement payments are higher under FFS.

Note, however, that this effect would largely depend on whether the hospital's spatial constraint binds or not. If the hospital has enough number of beds, it would still be profitable to admit infants covered by MMC to its own facility as long as the reimbursement payments exceed the marginal costs of providing the necessary care to them. In contrast, when there are only few beds available, the hospital has stronger incentives to keep the infants with higher marginal revenue (i.e., infants under FFS) while transferring the less profitable infants (i.e., infants enrolled in MMC).

In addition, the hospital's decision depends on the marginal costs of treating the infants. For infants with high expected costs, the MMC reimbursement payments might not be high enough (relative to the FFS payments) unless the reimbursement payments are perfectly adjusted for severity. In this case, the hospital would have stronger incentives to transfer infants enrolled in MMC than infants enrolled in FFS.

I test these predictions in the following analysis. First, infants covered by MMC are more likely to be transferred than infants covered by FFS. Second, the effect is stronger when the birth hospital is spatially constrained. Third, the effect is also stronger when the expected costs of treating the infants are high.

3.5 Transfer of Critically Ill Newborns

In-utero transport following prenatal diagnosis of high-risk deliveries is recommended as it is associated with lower mortality and fewer complications compared to postnatal transport.[26] However, as not all high-risk pregnancies can be predicted nor transferred, postnatal transport is not completely avoidable. Inter-hospital transfer is therefore an option for infants who require specialized or intensive care in case they are born in inadequately-equipped facilities.

In my sample of infants, 70% of transfers occur within the first three days after birth (Figure 3). Immediate and detailed communication between the referring hospital and the receiving hospital is thus crucial. Since a lot of costly and important decisions are made right after birth, it is hard to imagine health plans having a large influence on these decisions. In addition, due to the emergency of neonatal transports, prior authorization is not required [NYSDOH, 2016], suggesting that transfer decisions are essentially made by hospitals.

Moreover, the literature documents that longer duration of transport is associated with increased neonatal mortality [Mori et al., 2007] and poor physiologic status of newborns [Arora et al., 2014]. This suggests that shorter distance between hospitals is important for successful transfers without compromising health of transferred infants. The mode of transport is generally ground ambulance for short-distance up to 25 miles. For medium distance up to 150 miles, helicopter transport is considered. Airplane transport is for long-distance farther than 150 miles [Ohning, 2015].

Figure 4 describes mean characteristics of birth hospitals and receiving hospitals in my sample. Receiving hospitals on average have more number of 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 are generally transferred to "higher-quality" hospitals that are bigger and better-equipped. Taken together, implications on health outcomes are unclear as inter-facility transfers are associated with increased risk of complications. I examine various health outcomes to assess whether care provided at higher-quality hospitals after transport can offset the potential harm on health caused by inter-hospital transport.

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 from 1995-2013.[27] This data set contains the universe of inpatient discharge records, thus almost all births. There are 4.8 million hospital records of newborns over this period in New York. A large sample is necessary for estimating effects among the relatively small population of low birth weight infants. 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,

[26]For instance, see Arad et al. [1999], Mohamed and Aly [2010], Nasr and Langer [2011] & Nasr and Langer [2012].
[27]Data access to HCUP was provided by the National Bureau of Economic Research (NBER).

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. I can track the infants mostly up to one year, as most of infants in my sample do not show up again beyond one year after birth and none of them appear two years after birth.

In addition, I use American Hospital Association (AHA) Annual Survey of Hospitals from 1995-2013.[28] This dataset contains detailed information on hospitals such as hospital name, location, staffing, and facilities. I use these various hospital characteristics to better understand the mechanisms through which MMC affects hospital practice. I also use enrollment reports from NYSDOH from 1997-2011, which provide a monthly list of health plans operating in each county and the number of enrollees for each plan.

Table 1 provides summary statistics of my main analysis sample, infants in New York from 2003-2011. I focus on periods between 2003 and 2011 to exploit the feature that allows me to track patients over time and to exclude the periods when the exclusion was no longer valid. Looking at 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. Note that 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 rendered 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.[29] In the full sample, infants stay on average 4 days in the hospital. Death is a rare event, around 0.32%. 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 grams threshold. Below the threshold, 95% of Medicaid beneficiaries are enrolled in non-HMO category, which indicates that the exclusion is strictly implemented. Hospital visits are extremely expensive for these very low birth weight infants. Total charges are over \$200,000 below and \$140,000 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 higher 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 majority of them utilize NICU (74-75%).

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

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

5 Empirical Strategy

To examine the effects of MMC in comparison to FFS, I exploit the 1,200 grams threshold in a regression discontinuity design framework. That is, I compare those who weigh just below the 1,200 grams threshold and thus are served through Medicaid FFS to those who weigh just above the threshold and thus participate 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 outcome variables 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 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 effect 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.[30] 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 the regression discontinuity design is that control over birth weight is imprecise. Figure 5 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 no 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 a 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. Taken together, I find no evidence of manipulation around the 1,200 grams threshold.[31,32]

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

[31] I further test whether birth weight is manipulated for infants with high expected costs. Specifically, I compute predicted list prices from regressing total charges on diagnosis and procedure fixed effects. I then divide the sample by quartiles of the predicted list prices. I find no evidence of heaping even for infants in the top quartile of expected costs (Appendix figure B.1).

[32] Additionally, I repeat the estimations excluding heaps and also only restricting to heaps. I find that the results are robust to these restrictions, suggesting that these observed heaps are likely random and thus do not interfere with identification.

The imperfect control over birth weight implies that the assignment around the threshold is as good as random [Lee and Lemieux, 2010]. To further test the validity of the RD design, I examine whether the discharge records are similar in observable characteristics around the threshold. Since it is difficult to accurately predict birth weight prior to delivery, it is unlikely that characteristics of patients and birth hospitals are discontinuously different across the threshold. As expected, Appendix Figures B.2 and B.3 show that patient and hospital characteristics are smooth across the threshold. Table 2 summarizes the RD estimates for these baseline characteristics. None of the estimates are statistically significant, indicating that the exclusion in fact created a random variation in the enrollment into MMC.

6 Main Results

In this section, I present main results separately for New York City in Section 6.1 and counties outside of New York City in Section 6.2.

6.1 New York City

6.1.1 At Birth Hospitals

Since treatment at birth can change the course of subsequent hospital care, I distinguish visits at birth from subsequent visits. I first present how infants born in New York City are treated differently at birth depending on their birth weight. Panel A of Table 3 shows the RD estimates at birth hospitals and Figure 6 presents the corresponding figures.[33]

Panel (a) of Figure 6 shows a clear increase in the probability of having Medicaid HMO as the primary expected payer. This corresponds to an increase of 23 percentage points, which constructs a fuzzy regression discontinuity design framework. The Medicaid HMO participation rate below the threshold is close to zero, which indicates that the exclusion from MMC enrollment based on birth weight is strictly implemented. To test whether the discontinuity is driven by some other treatment at the same threshold such as SSI participation, I examine New Jersey over the same time period. I find that the Medicaid HMO participation does not discontinuously change at the threshold (RD estimate: 0.012; robust standard error: 0.014).

Column 2 of Table 3 shows that length of stay drops by 12% above the threshold.[34] The large reduction in length of stay results in lower charges and lower costs by similar magnitudes. The shorter length of stay at birth hospitals could either be due to earlier routine discharges or other non-routine dispositions such as transfers to another hospital shortly after birth. I find that the probability of transfer in fact increases by 2.4 percentage points above the threshold, which corresponds to a 34% increase relative to the mean transfer rate (7%) in the estimation window.[35]

[33] Appendix Figure B.4 shows that these main RD estimates are not sensitive to the choice of bandwidth and polynomials.

[34] 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.

[35] To examine the role of transfers, I focus on infants who are routinely discharged from birth hospitals. I find

This effect could be generated either by hospitals excessively transferring out infants above the threshold, hospitals holding onto infants below the threshold more than usual, or a combination of both. Panel (e) of Figure 6 suggests that the positive effect on the probability of transfer may be driven by the lower likelihood of transfer right below the threshold. For infants below the threshold, hospitals would weigh the benefit of higher reimbursement payments against the risk of treating the infants at relatively inadequate facilities. Since the risk may be too great for infants further below the threshold, hospitals would keep the healthiest among the infants enrolled in FFS, those right below the threshold. This may indicate hospital-side moral hazard in response to higher reimbursement payments, in the absence of health benefits [Almond and Doyle, 2011]. I further discuss this issue in Section 7.2.

Hospitals can also respond to the discrepancy in payments by "upcoding." Hospitals can receive much higher reimbursement payments by upcoding a neonate as having major problems than having no major problems conditional on birth weight.[36] Given the higher base rates for infants covered by FFS, hospitals have a bigger incentive to upcode those below the 1,200 grams threshold than those above. I test for upcoding by examining whether the likelihood of being coded as "Prematurity with major problems" as opposed to "Prematurity without major problems" discontinuously increases below the threshold.[37] However, I find no evidence of upcoding in my sample.

Subsequently, I examine whether the less generous reimbursement model above the threshold leads to worse health outcomes at birth hospitals. If FFS infants receive more resources than MMC infants even among those who remain at the birth hospital, there may be negative health consequences for infants enrolled in MMC. I examine mortality during hospitalization at birth hospitals. The point estimate is positive but insignificant (RD estimate: 0.019; robust standard error: 0.016), suggesting that there is little evidence on differential amount of care provided at birth hospitals or its impact on mortality on average.

6.1.2 Aggregating Subsequent Visits

Exploiting the encrypted person identifiers, I further examine subsequent care provided to these infants. Panel B of Table 3 shows the effects on individual-level outcomes that aggregate outcomes at birth hospitals with outcomes at transferred hospitals (if transferred). Since infants who are transferred to another hospital receive additional care from the transferred hospital, there may be little difference in total amount of care in aggregate. I find that the magnitudes of shorter length of stay, lower charges, and costs are in fact smaller when including the care provided at transferred

no effects on length of stay or cost measures for this group of infants (RD estimate for log(length of stay): -0.017; standard error: 0.026). Although 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, this is suggestive that transfer is likely be the main driver of the reduction in length of stay at birth hospitals.

[36] For instance, the DRG weight for a DRG "Neonate, Birthwt 1000-1249G w/ Resp Dist Synd/Oth Maj Resp Or Maj Anom" was 5.5247, while the weight for a DRG "Neonate, Birthwt 1000-1249G W OR W/O Other Significant Condition" was 3.9165 in 2009.

[37] This analysis is limited as the exact DRG system that New York used is not available in the HCUP data for New York SID. I use Medicare-severity DRGs (MS-DRGs) instead.

hospitals. Length of stay is shorter above the threshold by 9% and the estimate is marginally significant at the 10% level.[38]

Subsequently, I estimate how the shorter length of stay above the threshold affects the probability of readmission and individual-level mortality during hospitalization (columns 5 and 6 of Table 3 panel B). Note, however, that the prediction on health outcomes is ambiguous due to the higher probability of transfer above the threshold. On the one hand, the receiving hospitals are generally of higher-quality than the birth hospitals, which could result in improvement in health outcomes for infants under MMC. On the other hand, inter-hospital transport is known to be associated with increased mortality and risk of complications, suggesting a potential deterioration in health for infants enrolled in MMC.[39] In fact, I find no statistically significant effects on these health outcomes. Little impact on health may indicate that the reduction in length of stay is efficient, as it achieves cost savings without compromising health.

Additionally, I examine various outcomes associated with the quality of care and patient health, including readmissions due to preventable conditions,[40] level IV NICU stays, utilization of occupational therapy, physical therapy, respiratory therapy, and speech therapy services. I do not detect any statistically significant effect on these measures, suggesting that MMC had limited impact on health and actual services that patients received except *where* they received them.

Finally, panel C of Table 3 shows the RD estimates on individual-level outcomes controlling for hospital fixed effects. Including hospital fixed effects barely affects the estimates but increases precision. This suggests that the effects in fact come from within-hospital differences in treatment depending on the infant's insurance status. Since the cost-to-charge ratio is hospital-specific, controlling for hospital fixed effects would reduce noise in the total costs variable. In fact, the 9% reduction in total costs becomes marginally significant. In panel D, I control for physician fixed effects. The estimates become smaller in magnitude and lose statistical significance, suggesting that physician fixed effects rather introduce noise to the estimations. These results imply that the effects come from hospital-level responses to the difference in reimbursement payments.

6.2 Rest of the State

In this section, I repeat the estimations for counties outside of New York City. In the RD estimation window around the threshold, I observe discharge records from 42 counties outside of New York City. Although the geographic area these counties cover is much bigger than New York City, there are fewer number of discharge records in the rest of the state. Table 4 summarizes the effects on outcomes at birth hospitals (panel A) and Figure 7 shows the corresponding figures. Panel B of Table 4 presents the RD estimates on aggregated outcomes including outcomes at transferred hospitals.

[38]The corresponding figures are shown in Appendix Figure B.5.

[39]Unfortunately, I am unable to identify the directly impact of transfer. Since transfer is not randomly assigned, the resulting outcomes are confounded by selection into transfer.

[40]I follow the definition of avoidable hospitalizations used in Parker and Schoendorf [2000] & Dafny and Gruber [2005].

The probability of having Medicaid HMO as the primary expected payer increases discontinuously at the threshold by 15 percentage points, which is slightly lower than the New York City estimate. Panel (a) of Figure 7 shows that the Medicaid HMO participation is close to zero below the threshold, while it jumps discontinuously to around 20% above the threshold. Unlike New York City, however, I find no effects on all other 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 (or the number of hospitals) is much larger in New York City compared to the rest of the state, which would affect the level of competition in local health care markets and thus the strength of incentives to reduce costs and improve quality.[41] The density of local health care markets can also have an impact on hospital practice style by allowing hospitals to share responsibilities of treating local patients. In Section 7.3, I pay a particular attention to the role of proximity between hospitals in understanding this geographic heterogeneity.

7 Heterogeneity in New York City

To further understand how hospitals respond to MMC in New York City, I conduct four heterogeneity analyses. In Section 7.1, I examine the role of spatial capacity in hospitals' transfer decisions. In Section 7.2, I examine predicted list prices of newborns to evaluate whether hospitals are especially responsive to infants who are costly to treat. Section 7.3 considers proximity to a high-quality hospital as a possible factor driving the geographical difference between New York City and other counties. Finally, Section 7.4 examines heterogeneity by crowdedness at potential destination hospitals.

7.1 Role of Capacity

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.[42] Although entering the NICU market has a large fixed cost, marginal costs of providing neonatal incentive care is relatively low. Therefore, the hospital has an incentive to utilize empty beds.[43] That is, as long as the reimbursement payments are higher than the relatively moderate

[41] Unfortunately, the number of plans is not available at the borough level within New York City. Thus, simple comparisons by the number of plans (or hospitals) are fraught with endogeneity of the plan (or hospital) entry and exit, and I do not have a valid instrument for the number of plans (or hospitals) to further investigate this mechanism.

[42] In my New York City sample, 98% of the discharge records in the RD estimation window were from hospitals that provides neonatal incentive care.

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

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 should be pronounced when the hospital has few NICU beds available.

To test this hypothesis, I exploit a 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.[44] 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 the 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 not likely a binding restriction.

I compare months where the NICU occupancy is below median with months where the NICU occupancy is above median at a given hospital in a given year. Within hospital-year comparisons ensure that the comparison is made at a 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 5. When the NICU occupancy is above median, the reductions 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 NICU occupancy is below median (i.e., hospitals have enough number of beds), I find little effect of MMC on all outcomes, consistent with the spatial constraint playing an important role.

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. Since the NICU occupancy measured at the month level cannot directly be compared to the number of NICU beds, it is unclear whether high NICU occupancy necessarily indicates 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 occupancy rate. I compare below- and above-median months using this measure, and find similar results (Appendix Table C.1). This supports the above finding that the hospital's incentives become stronger when it is spatially constrained.

7.2 Predicted List Prices

In this section, I examine which group of infants is most affected by hospitals' financial incentives. If hospitals are profit-maximizing, they are more likely to respond to infants whose marginal costs are high. Unless the reimbursement payments are perfectly adjusted for severity, infants with high

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

predicted costs of treatment are especially costly to hospitals. To test this hypothesis, I create a measure of predicted costs of treatment. Specifically, I compute predicted list prices by regressing total charges on diagnosis fixed effects and procedure fixed effects. This measure thus estimates the expected total charges solely based on severity of the patient's conditions.[45]

I find that the results are driven by those with higher predicted list prices (Table 6). This is consistent with hospitals responding more strongly for those whose expected costs of treatment are high. If the lower reimbursement payments for infants enrolled in MMC do not cover the expected costs of these infants, hospitals should be more likely to transfer these infants to another hospital. For infants with low 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.

For infants with high predicted list prices, I find that mortality during hospitalization at birth hospitals increases above the threshold and the estimate is marginally significant at the 10% level. This may be due to hospitals shifting resources to infants under FFS with higher reimbursement payments. If it results in hurting health for some infants above the threshold, it may be expected to occur among the most high-risk subpopulations. This suggests that the effects are unlikely to be driven alone by hospitals' moral hazard exploiting higher reimbursement payments for infants below the threshold. The effects are at least partly generated by hospitals' differential treatment to infants above the threshold. However, I find no statistically significant difference in individual-level mortality across the threshold (RD estimate: 0.032; robust standard error: 0.023), suggesting that a small discrepancy in mortality at birth disappeared within a year and hospitals' practice style influenced by MMC had limited impact on mortality.

7.3 Proximity to a High-Quality Hospital

In this section, I focus on the geographical difference between New York City and the rest of the state. I consider proximity to a high-quality hospital as a potential source of heterogeneity. Since easier access and efficient communication between the birth hospital and the receiving hospital may be crucial for successful transfers, some hospitals may be able to selectively transfer infants when necessary, while it may not be a feasible option for others. For some hospitals, the costs of timely transfers may outweigh the financial benefits of transferring certain infants.[46]

I consider hospitals with NICU as potential receiving hospitals with "high-quality." Restricting to hospitals with NICU is a natural choice given that birth hospitals respond more when they have few NICU beds available. To measure proximity, I first geocode the center point of each hospital zip code. Then I compute the distance from a birth hospital to all other hospitals with NICU. I use the distance from a birth hospital to the nearest hospital that provides a NICU facility as a proximity

[45] I find that predicted list prices in fact vary a lot within DRGs, with mean \$84,632 and standard deviation \$72,134.

[46] Ho and Pakes [2014] show that highly capitated plans are willing to send patients to relatively far hospitals to achieve price reductions, but they find no evidence that plans compromise quality of care or patient health as a result.

measure.[47] The distance between hospitals is much shorter in New York City compared to other counties outside of New York City (Appendix Figure B.7). The median distance of the proximity measure 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 NICU close by with hospitals that have a hospital with NICU far away relative to the median distance *within* New York City. Table 7 reports the RD estimates for each group. The results show that even within New York City, hospital responses are driven by hospitals that have a hospital with NICU close by. This suggests that proximity to a potential destination hospital plays an important role in birth hospitals' decision making process. Given the longer 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 differ across the threshold.

I find a rather large and positive effect on mortality for hospitals that have a hospital with NICU close by. I examine another measure of proximity to examine the robustness of the estimates. Specifically, since the main mode of transport is ground ambulance, I compute driving time using Google Map APIs between hospitals to conduct a heterogeneity analysis by driving time (Appendix Table C.2). I find that the reduction in length of stay and the increase in the probability of transfer are driven by hospitals with a shorter driving time to the nearest hospital with NICU. The mortality effect disappears (RD estimate: 0.023; robust standard error: 0.020), suggesting the positive mortality effect is likely spurious.

7.4 Crowdedness at a Destination Hospital

Since financial incentives to transfer is especially large when hospitals are spatially constrained, I examine the role of crowdedness at potential destination hospitals. I first consider the nearest hospital with a NICU facility as a destination hospital following the previous section. In my sample, around 32% of total transfers occur to the nearest hospital with NICU. The idea is that the birth hospital's decision to transfer infants would depend on whether the potential receiving hospital has enough number of beds available or not.

As in Section 7.1, I use the NICU occupancy to measure how crowded the nearest hospital with NICU is. Table 8 shows that the effects are stronger in months where the nearest hospital with NICU is relatively less crowded. This is consistent with spatial capacity playing a role in transfer decisions.

Additionally, I consider a "typical destination" hospital as a potential receiving hospital. For each hospital, I define the typical destination hospital as the receiving hospital of the majority of (any) neonatal transfers from a given hospital. Around 51% of total transfers end up at these typical destination hospitals. I examine the crowdedness at the typical destination hospital using the NICU occupancy measure. 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 C.3). These results suggest that receiving hospitals have an incentive to take the transferred infants when they

[47] When the nearest hospital with NICU is in the same zip code as the birth hospital, the distance is coded as zero.

have idle beds, since it is profitable to them as long as the marginal costs of providing NICU to the infants are lower than the reimbursement payments.

Another potential reason why these hospitals would take the transferred kids may be associated with the bargaining process with health plans. In negotiation between health plans and hospitals over hospital payments for Medicaid patients, hospital quality plays a crucial role in determining the bargaining power of hospitals. This is because hospitals in the Medicaid market compete on quality not on price since the price that Medicaid patients pay is administered. Therefore, hospitals with higher quality likely have more bargaining power and thus command higher prices [Gaynor et al., 2015]. As mentioned above, receiving hospitals are generally bigger and better-equipped. Although I do not observe the hospital payments that plans make in my data, if receiving hospitals receive more generous payments from health plans than birth hospitals that transfer out the infants, receiving hospitals will have higher returns to providing care to these infants. This is consistent with the reallocation patterns I find in the data.

8 Estimating Difference-in-Difference Estimates

In this section, I employ a difference-in-difference approach using the rollout of the MMC mandate across counties in New York. The mandate was phased in starting from 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 during the birth year of all newborns born between 1995-2011. In a difference-in-difference framework, I estimate the effects of MMC on newborns who are induced to enroll in MMC due to the mandate implemented in their county. 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), 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 robustness check. Standard errors are clustered at the county level.

Panel A of Table 9 shows estimates for the outcomes from the baseline difference-in-difference estimations 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. This is mainly due to two reasons: heterogeneous compliance across counties and a general upward trend in MMC participation. Point estimates for length of stay, total charges, and total costs are smaller in magnitude compared to my RD estimates, but they also show that these outcomes decline following the MMC mandate.

I further investigate the difference between two estimates in Section 8.1. There is no change in the probability of transfer and mortality during hospitalization following the mandate in the whole sample of newborns. To test the parallel trends assumption of the difference-in-difference approach, 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 difference-in-difference specification.

To compare the difference-in-difference estimates with my RD estimates for very low birth weight infants, I repeat the estimation by birth weight groups. Since I use 150 grams as my main bandwidth, I divide the sample into birth weight groups in 150-gram increments. The difference-in-difference estimates for those whose birth weight is between 1,200 grams and 1,350 grams are thus the relevant comparison group for my RD estimates. In Figure 8, I plot the difference-in-difference estimates for each birth weight group along with 95% confidence intervals. My main RD estimates along with 95% confidence intervals from New York City in 2003-2011 are shown 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 less than 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 10 percentage points for all birth weight groups above the threshold. The effect of MMC on length of stay is noisy for low birth weight infants, although the point estimate for the 1,200-1,350 gram group is within the confidence intervals of the RD estimate. The difference-in-difference estimates indicate that there is little change in length of stay following the mandate for infants with normal-range birth weight.

The difference-in-difference estimates for log(total charges) are surprisingly similar to my RD estimate and this reduction in total charges is of similar magnitude throughout the whole range of birth weight. This suggests that there is a general decline in total charges for inpatient services following the mandate. The estimates for log(total costs) are imprecise for low birth weight infants. However, the estimates for healthy-range infants are negative and statistically significant. These results indicate that hospitals engage in some cost-reduction measures in response to the MMC mandate for infants across the whole range of birth weight.

Consistent with the RD estimate, the difference-in-difference estimate for the probability of transfer is positive and of a similar magnitude for the 1,200-1,350 gram group. As transfers are rare for healthier infants, I find little change in the probability of transfer for infants who weigh more than 2,500 grams. This suggests that cost reductions for healthier infants are achieved through another mechanism other than transfers. There is little effect on mortality throughout all birth weight groups.

8.1 Complier Characteristics

To further gain insights on the difference between RD estimates and DD estimates, I examine hospital 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 their birth weight exceeding the 1,200 grams threshold. Compliers under the DD specification are those who are induced to enroll in MMC due to the state mandate. It is impossible to identify compliers since counterfactual outcomes are not observable, but it is possible to describe the distribution of their characteristics. I compute mean characteristics of the compliers following Angrist and Pischke [2009] and Almond and Doyle [2011]. Refer to Appendix Section A for details.

Table 10 presents the mean complier characteristics for both RD and DD samples. 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, compliers and the overall sample within the RD estimation window are fairly similar in terms of the number of beds, staffs, 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. 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. The number of lives covered in capitated services arrangement is lower for compliers than for the overall sample within the estimation window. 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 type of 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.

Similar to the compliers to the RD framework, column 3 shows that hospitals that comply with the state mandate have fewer lives covered in capitated services arrangement and more infants covered by Medicaid. However, compliers to the DD framework are different in many dimensions from complier to the RD framework. They are less likely to have a NICU facility or be a teaching hospital. They also tend to have fewer beds, staffs, and patients compared to the RD compliers. This suggests that compliers to DD may employ different types of tools in achieving cost savings. Differences in complier characteristics suggest that treatment effects are likely different for these two instruments, which reconciles with smaller DD estimates relative to the RD estimates.

Moreover, the mean hospital characteristics of compliers in my RD estimations are a lot different from the full sample mean shown in column 4. The RD Compliers on average have more beds, staffs, and equipments. This is expected because low birth weight infants are treated in hospitals that are likely different from general hospitals for healthier newborns.

9 Discussion

9.1 Median Household Income

Since pregnant women and children are exempt from Medicaid co-payments, there is no direct financial incentives for families to respond to the birth weight exclusion conditional on Medicaid participation. However, the composition of families that hospitals face can affect hospitals' practice style. For instance, hospitals who serve a large population of Medicaid beneficiaries would be affected by the managed care mandate differently from hospitals who mainly serve patients covered by private insurance. Table 11 shows the heterogeneity in responses by county-level median household income. I construct the county-level median household income measure using the average quartile of the median household income across the patient zip codes for each county.

The estimates show that the effects are driven by counties with the lowest median household income. Column 1 shows that the first stage is the strongest in the lowest quartile counties. This is mostly due to a high share of Medicaid recipients in the poorest counties, which is as expected since Medicaid participation is highly correlated with household income. Even taking account the difference in first stage, the intent-to-treat estimates on provider practice measures indicate that the effects are large and detected only in these poorest counties - suggesting that hospitals respond to the composition of their patient base.

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. Moreover, it may be simply due to the extent of exposure to MMC. As I discussed in Section 8.1, compliers tend to stay in hospitals with a higher fraction of infants enrolled in Medicaid. This suggests that hospitals who treat many infants covered by Medicaid might be more aware of the policy and thus likely to employ tools to adjust their practice style accordingly.

Transfers usually require parental consent and since transferring infants can cause an enormous amount of stress and anxiety to parents [Hawthorne and Killen, 2006], parents might intervene in hospitals' transfer decisions.[48] Moreover, parents might respond differently depending on their socioeconomic status. However, since income levels for Medicaid eligibility apply at the state level, there is little variation across counties in terms of parental socioeconomic status among those who are enrolled in Medicaid. The largest effects from the bottom quartile are thus likely driven by hospital responses to a large share of Medicaid beneficiaries rather than by differential response of parents depending on the their socioeconomic status.

9.2 Cost Implications

In the New York City sample, I find that total costs computed at the individual level drop by 9% according to my preferred specification with hospital fixed effects (panel C of Table 3). This

[48] Arguably, parents of infants are unlikely to object to physicians' suggested treatment plans due to large informational advantages physicians have over newborn treatment [Shigeoka and Fushimi, 2014].

amounts to an average reduction of \$8,764 (=0.093×\$94,237) for infants right below the threshold in 2011 values. 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, this suggests that hospitals indeed provide less amount of 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]. Little impact on health measures, however, suggests that the reduction in costs due to MMC may be efficient as it was achieved without hurting health.

However, the current study has a few limitations to conduct 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 observe neither death or other health care utilization outside of the hospital (e.g., outpatient visits) nor longer-term outcomes in years following birth. In addition, there may be other forms of "costs" besides health consequences such as parental disutility from separation/transfer, which I do not observe.

Moreover, there may also be general equilibrium effects.[49] I examine whether the change in hospital practice for infants enrolled in MMC had a spillover effect on non-Medicaid patients. Keeping in mind that there can be selection into Medicaid due to the MMC mandate [Currie and Fahr, 2005], I find that the effects are still driven by Medicaid patients and find no effects on non-Medicaid population (e.g., those insured by a private insurance company). Although I am unable to estimate complete general equilibrium effects due to data limitations, my findings suggest MMC had an impact on hospitals by inducing them to engage in cost-reduction measures with minimum harm on short-term health.

10 Conclusion

Recognizing the limitations of the fee-for-service system, the US health care market has increasingly adopted new payment systems that promote more efficient delivery of health care (e.g., by rewarding an improvement in quality of care without unnecessarily increasing costs) [Hackbarth et al. 2008; Arrow et al. 2009]. Notably, the Affordable Care Act introduced accountable care organizations for Medicare populations that share similar incentives and goals as managed care organizations under Medicaid. This paper provides important implications for responses of health care providers to these incentives.

I find that hospitals reduce costs by transferring infants under MMC to another hospital while holding onto infants enrolled in FFS. Hospital responses are especially large when they are spatially

[49] For example, Baker [1994] shows that HMO penetration had an impact on normal FFS physicians. Baker and Brown [1997] also show that managed care can affect the entire health care market through a spillover effect on broad health care providers.

constrained. In addition, the effects are stronger for infants with high predicted list prices. I find little short-term effect on health measured by mortality during hospitalization or readmissions during the first year. I show that these results are driven by New York City, while I find little difference between MMC and FFS in counties outside of New York City.

I examine the role of proximity from a birth hospital to the nearest hospital with NICU as a constraint for hospitals to engage in transfers. I find that even within New York City, the effects are driven by hospitals that have a hospital with NICU nearby, indicating that proximity between hospitals affects hospitals' practice style. Moreover, I show that the effects are stronger when these nearby "high-quality" hospitals are relatively less crowded.

My findings suggest that hospitals respond to financial incentives stemming from different reimbursement models by adjusting their practice style. However, I find no evidence that hospitals compromise quality of care or patient health by engaging in this profit-seeking behavior. However, there could be longer-term consequences which cannot be examined in the current study. For future research, it would be useful to examine longer-term health outcomes to fully understand the consequences of MMC.

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11 Figures

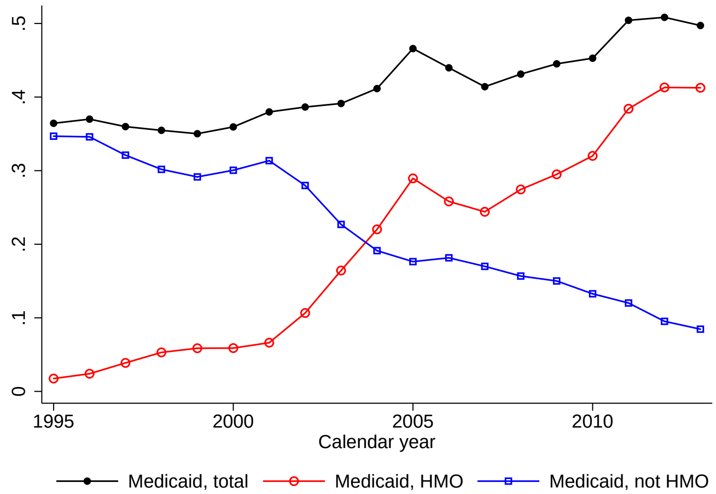


Figure 1: Share of infants covered by Medicaid, New York, 1995-2013

Notes: HMO stands for Health Maintenance Organization, a type of managed care organizations (MCOs).
Source: State Inpatient Databases of Healthcare Cost and Utilization Project

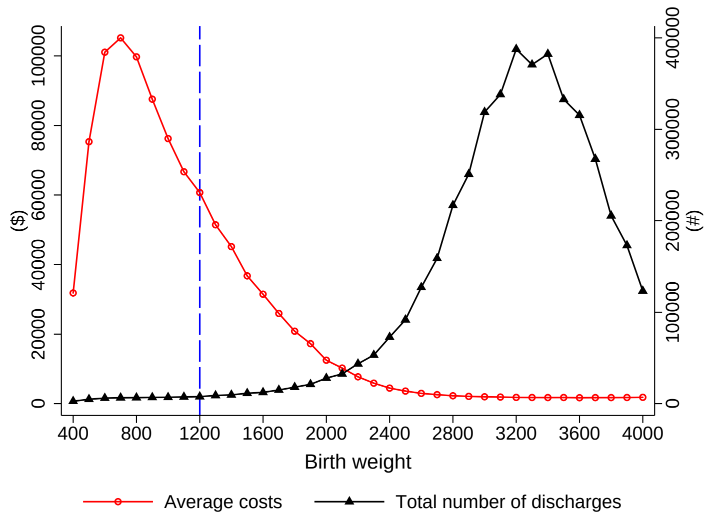


Figure 2: Average hospital costs and total discharges by birth weight, New York, 1995-2013

Notes: Average costs are computed for each 100 gram bin using total charges multiplied by cost-to-charge ratio. Total number of discharges are computed for each 100 gram bin using the number of discharges with valid birth weight information.

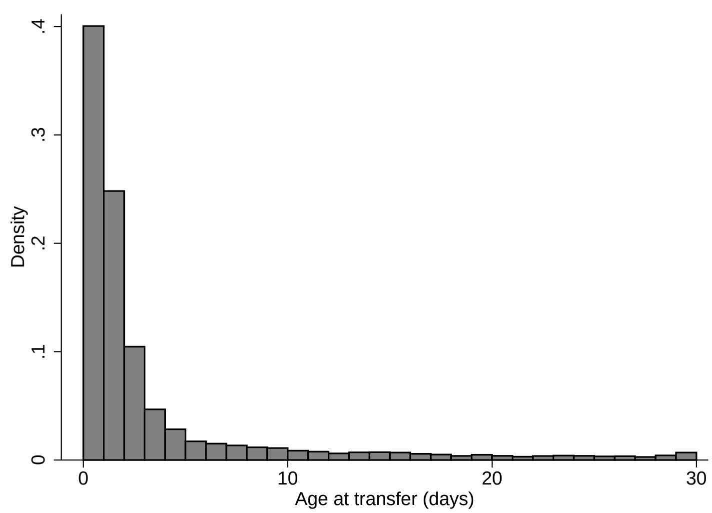


Figure 3: Age at transfer in the first month

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.

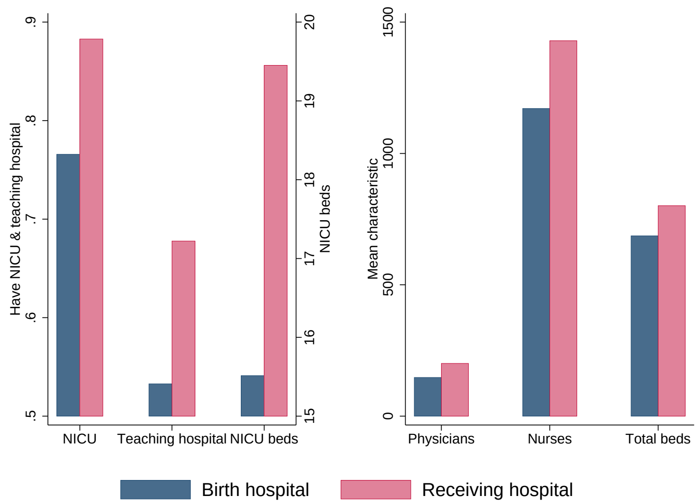
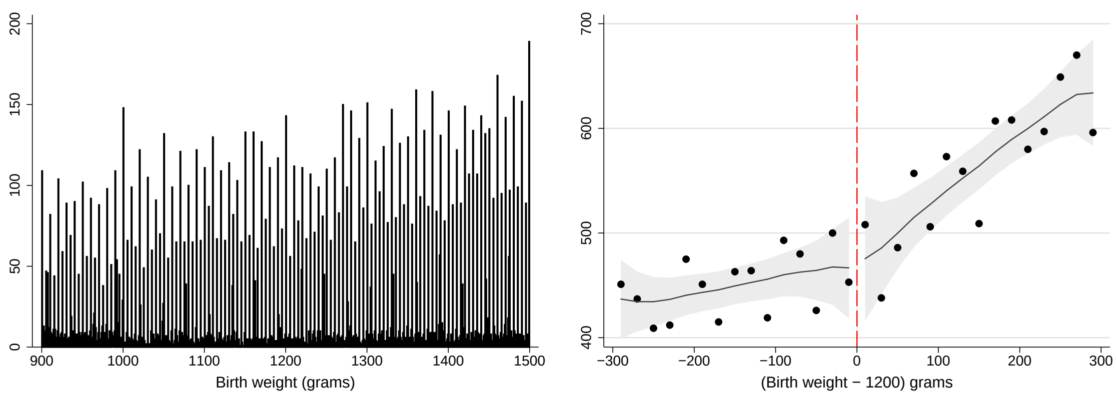


Figure 4: Characteristics of birth hospitals and receiving hospitals

Notes: Blue bars summarize mean characteristics of birth hospitals. Red bars describe mean characteristics of hospitals that receive transfers.

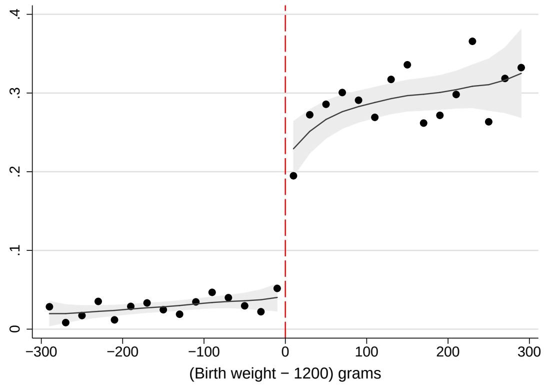


(a) Frequency for each gram

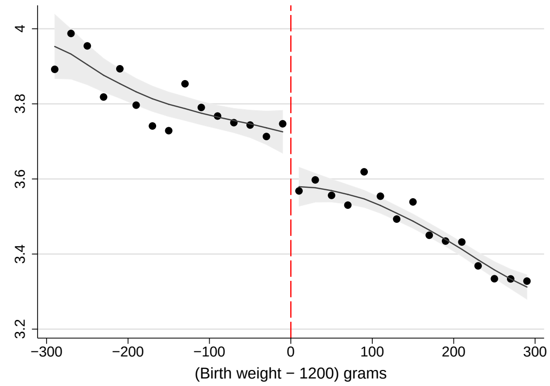
(b) Mean frequency for each 20-gram bin

Figure 5: Frequency of the running variable

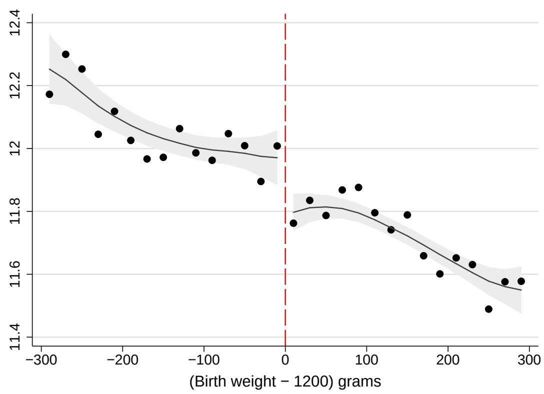
Notes: Panel (a) plots the frequency of birth weight at each gram. Panel (b) plots mean frequency for each 20-gram bin (dots) along with a local linear regression fitted lines (solid lines) and 95% confidence intervals below and above the threshold. I use the triangular kernel and a bandwidth of 150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



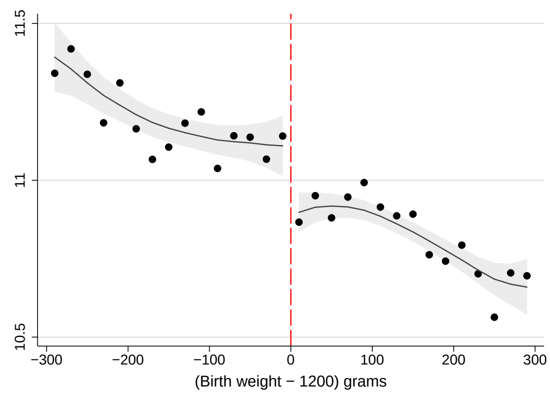
(a) Medicaid HMO



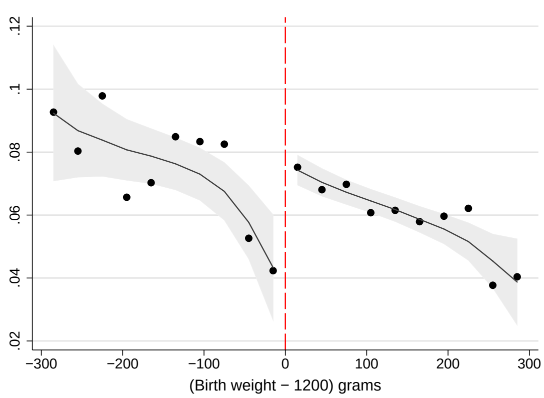
(b) Log(length of stay)



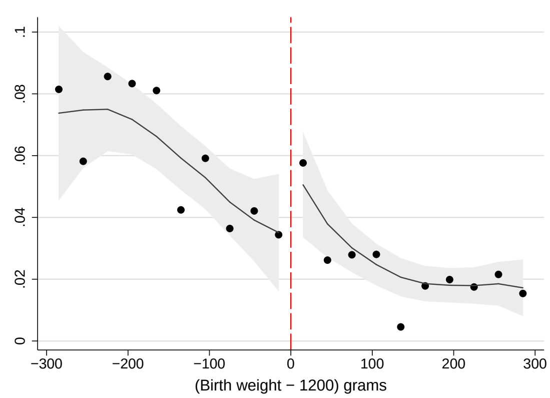
(c) Log(total charges)



(d) Log(total costs)



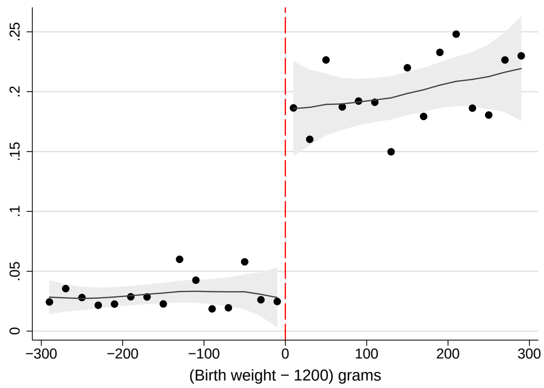
(e) Transfer



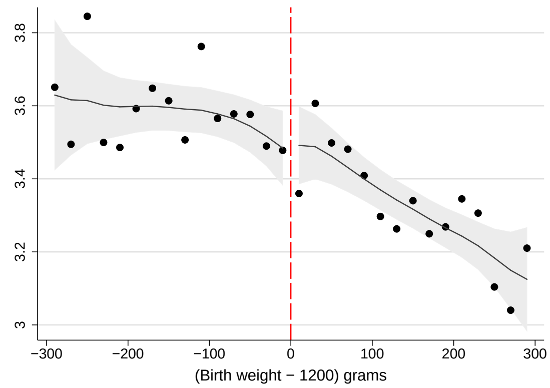
(f) Mortality during hospitalization

Figure 6: Effects of birth weight≥1,200 grams on discharge outcomes, New York City

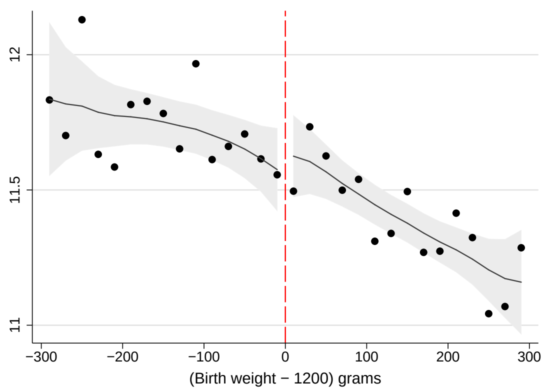
Notes: Panels (a)-(d) plot mean values of each outcome variable for each 20-gram bin (dots) along with a local linear regression fitted lines (solid lines) and 95% confidence intervals below and above the threshold. Each 20-gram bin contains roughly 250 discharge records. For panels (e) and (f) I use a bigger 30-gram bin for better visibility since transfer and death are both rare and thus noisy. Each 30-gram bin contains around 420 discharge records. I test whether using wider bins oversmooths 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.



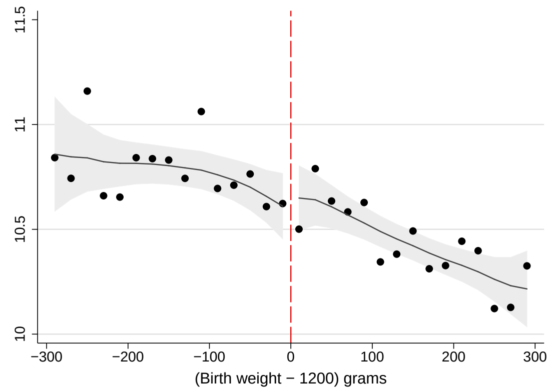
(a) Medicaid HMO



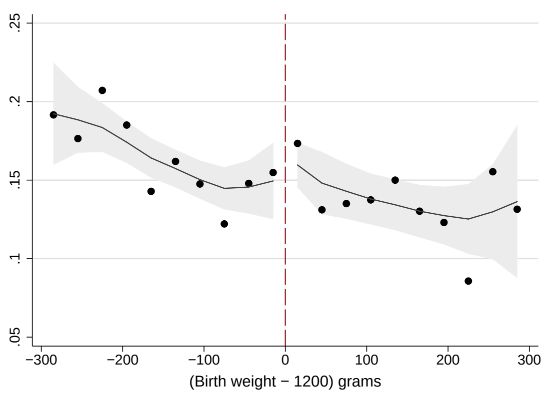
(b) Log(length of stay)



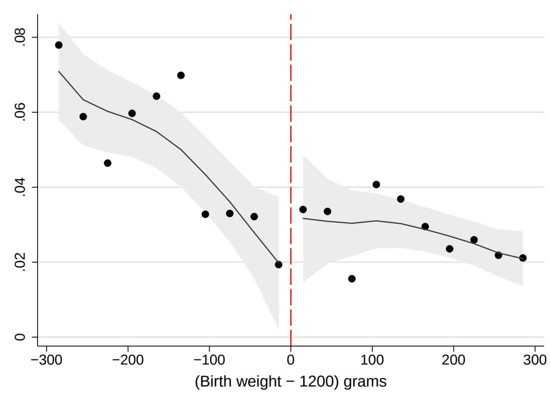
(c) Log(total charges)



(d) Log(total costs)



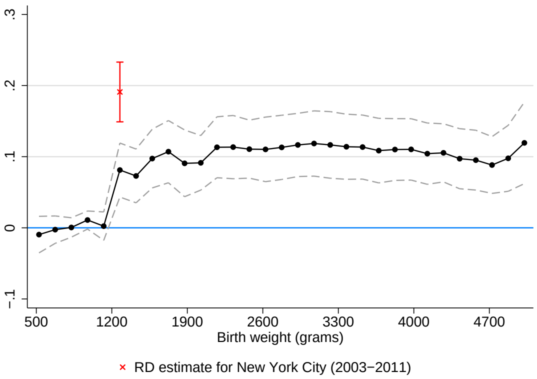
(e) Transfer



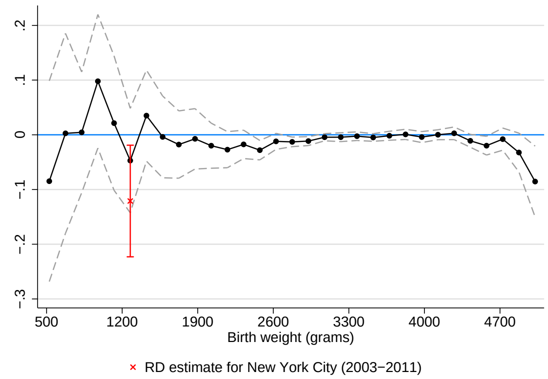
(f) Mortality during hospitalization

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

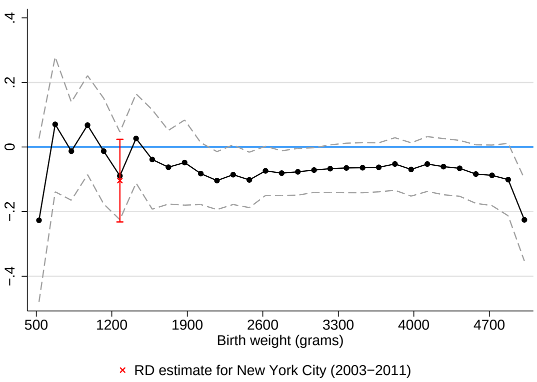
Notes: Panels (a)-(d) plot mean values of each outcome variable for each 20-gram bin (dots) along with a local linear regression fitted lines (solid lines) and 95% confidence intervals below and above the threshold. Each 20-gram bin contains roughly 250 discharge records. For panels (e) and (f) I use a bigger 30-gram bin for better visibility since transfer and death are both rare and thus noisy. Each 30-gram bin contains around 420 discharge records. I test whether using wider bins oversmooths 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.



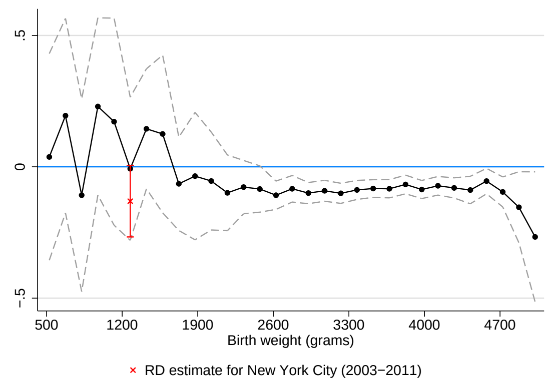
(a) Medicaid HMO



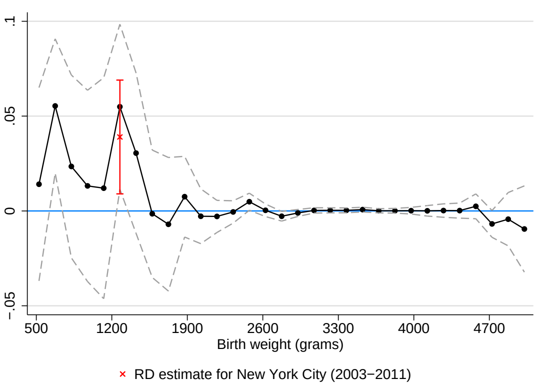
(b) Log(length of stay)



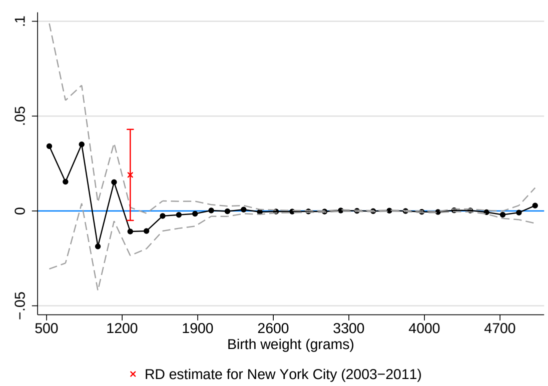
(c) Log(total charges)



(d) Log(total costs)



(e) Transfer



(f) Mortality during hospitalization

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

Notes: I estimate a difference-in-difference model for each birth weight group in 150-gram increments. 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 along with its 95% confidence intervals.

12 Tables

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

	(1)	(2)	(3)
		Near the 1,200 grams 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

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)	(9)
	Female	White	Black	Hispanic	Asian	Median income	Admission hour	Scheduled	Weekend
Panel A. Patient characteristics									
Birth weight≥1,200 g	0.011	-0.023	0.015	0.015	-0.004	0.032	-17.483	0.034	-0.019
	(0.024)	(0.021)	(0.021)	(0.016)	(0.010)	(0.059)	(38.008)	(0.028)	(0.021)
Observations	7480	7177	7177	7177	7177	4617	5141	3357	7480
Adjusted R^2	-0.002	0.201	0.107	0.048	0.039	0.338	0.002	0.221	0.002
Mean below cutoff	0.497	0.355	0.316	0.145	0.054	2.353	12:54	0.713	0.261
Mean above cutoff	0.493	0.374	0.309	0.135	0.047	2.420	12:49	0.731	0.260
Bandwidth (grams)	150	150	150	150	150	150	150	150	150
	NICU	Teaching hospital	NICU beds	Physicians	Nurses	Total admissions	Total beds	Births	Percent capitated
Panel B. Hospital characteristics									
Birth weight≥1,200 g	-0.002	0.009	-0.193	-7.346	-14.516	-560.159	-11.567	-97.628	0.288
	(0.009)	(0.017)	(0.478)	(11.330)	(35.162)	(814.747)	(18.180)	(98.570)	(0.276)
Observations	6278	7477	6278	7477	7477	7477	7477	7477	5707
Adjusted R^2	0.397	0.395	0.420	0.345	0.445	0.427	0.379	0.421	0.451
Mean below cutoff	0.955	0.715	20.7	180.1	1287.3	35357.2	753.1	4044.2	2.722
Mean above cutoff	0.945	0.698	20.4	187.4	1279.3	34946.2	732.3	3994.7	2.964
Bandwidth (grams)	150	150	150	150	150	150	150	150	150

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. 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
Adjusted R^2	0.127	0.041	0.179	0.152	0.022	0.005
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	Individual level mortality
Panel B. Aggregating outcomes at transferred hospitals						
Birth weight≥1,200 g	0.229***	-0.090*	-0.073	-0.103	-0.000	0.015
	(0.018)	(0.049)	(0.062)	(0.067)	(0.021)	(0.016)
Observations	5490	4065	4048	3082	4065	2735
Adjusted R^2	0.127	0.041	0.185	0.158	0.015	0.004
Mean below cutoff	0.034	52.0	$246,489	$94,236	0.140	0.040
Mean above cutoff	0.278	42.5	$210,762	$78,461	0.110	0.039
Bandwidth (grams)	200	150	150	150	200	100
	Medicaid HMO	Log(LOS)	Log(total charges)	Log(total costs)	Readmission	Individual level mortality
Panel C. Aggregating outcomes at transferred hospitals, with hospital fixed effects						
Birth weight≥1,200 g	0.229***	-0.080*	-0.058	-0.093*	0.003	0.017
	(0.018)	(0.044)	(0.046)	(0.054)	(0.021)	(0.016)
Observations	5490	4065	4048	3082	4065	2735
Adjusted R^2	0.161	0.270	0.520	0.439	0.037	0.009
Mean below cutoff	0.034	52.0	$246,489	$94,236	0.140	0.040
Mean above cutoff	0.278	42.5	$210,762	$78,461	0.110	0.039
Bandwidth (grams)	200	150	150	150	200	100
	Medicaid HMO	Log(LOS)	Log(total charges)	Log(total costs)	Readmission	Individual level mortality
Panel D. Aggregating outcomes at transferred hospitals, with physician fixed effects						
Birth weight≥1,200 g	0.239***	-0.058	-0.058	-0.081	-0.009	0.014
	(0.019)	(0.047)	(0.053)	(0.062)	(0.023)	(0.017)
Observations	5489	4064	4047	3081	4064	2734
Adjusted R^2	0.158	0.211	0.443	0.368	0.024	0.075
Mean below cutoff	0.034	52.0	$246,489	$94,236	0.140	0.040
Mean above cutoff	0.278	42.5	$210,762	$78,461	0.110	0.039
Bandwidth (grams)	200	150	150	150	200	100

Notes: Panel A shows the RD estimates for each outcome from records at birth hospitals. Panel B shows the RD estimates for the aggregated outcome that combine each outcome at birth hospitals with the outcome at transferred hospitals 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. Panel C includes hospital fixed effects and panel D includes physician 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. 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
Adjusted R^2	0.089	0.319	0.420	0.385	0.201	-0.010
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	Individual level mortality
Panel B. Aggregating outcomes at transferred hospitals						
Birth weight≥1,200 g	0.152***	0.042	0.057	0.070	-0.002	0.018
	(0.018)	(0.062)	(0.070)	(0.071)	(0.021)	(0.015)
Observations	4571	3414	3407	3180	3415	2263
Adjusted R^2	0.089	0.249	0.379	0.328	0.019	-0.010
Mean below cutoff	0.033	50.3	$208,840	$76,748	0.113	0.034
Mean above cutoff	0.196	41.5	$170,969	$61,676	0.093	0.030
Bandwidth (grams)	200	150	150	150	200	100

Notes: Panel A shows the RD estimates for each outcome from records at birth hospitals. Panel B shows the RD estimates for the aggregated outcome that combine each outcome at birth hospitals with the outcome at transferred hospitals 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. The means of logged outcomes are reported in levels.
* Significant at 10%, ** significant at 5%, *** significant at 1%.

Table 5: 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
Adjusted R^2	0.132	0.021	0.184	0.149	0.001	0.003
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
Adjusted R^2	0.129	0.029	0.198	0.158	0.007	0.008
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

Notes: Panel A shows the RD estimates for months where the NICU occupancy is below median for a given hospital in a given year. Panel B shows the RD estimates for relatively more crowded months where the NICU occupancy is above 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 6: 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
Adjusted R^2	0.105	0.059	0.194	0.168	0.010	0.005
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
Adjusted R^2	0.146	0.038	0.175	0.159	0.026	0.006
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

Notes: Panel A shows the RD estimates for infants whose predicted list charges are below, while panel B shows the RD estimates for infants whose predicted list charges are above 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 7: Heterogeneity by distance to the nearest hospital with NICU, 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 distance						
Birth weight≥1,200 g	0.233***	-0.178**	-0.219**	-0.177	0.037*	0.060***
	(0.026)	(0.080)	(0.105)	(0.111)	(0.020)	(0.022)
Observations	2447	1814	1803	1335	2447	1210
Adjusted R^2	0.128	0.048	0.109	0.164	0.012	0.008
Mean below cutoff	0.031	54.1	$320,579	$112,818	0.057	0.037
Mean above cutoff	0.270	44.2	$267,058	$92,524	0.064	0.042
Bandwidth (grams)	200	150	150	150	200	100
Panel B. Above the median distance						
Birth weight≥1,200 g	0.227***	-0.089	-0.025	-0.115	0.014	-0.015
	(0.025)	(0.068)	(0.078)	(0.087)	(0.018)	(0.021)
Observations	3039	2248	2243	1761	3039	1524
Adjusted R^2	0.125	0.040	0.206	0.120	0.032	0.003
Mean below cutoff	0.035	49.9	$186,532	$80,272	0.080	0.039
Mean above cutoff	0.284	40.3	$159,059	$65,323	0.066	0.032
Bandwidth (grams)	200	150	150	150	200	100

Notes: Panel A shows the RD estimates for hospitals whose distance to the nearest hospital with NICU is below median, while panel B shows the RD estimates whose distance is above 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 crowdedness at the nearest hospital with 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
Adjusted R^2	0.122	0.051	0.201	0.131	0.010	0.014
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
Adjusted R^2	0.150	0.066	0.196	0.139	0.044	0.011
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

Notes: Panel A shows the RD estimates for months where the NICU occupancy at the nearest hospital with NICU is below median, while panel B shows the RD estimates for months where the NICU occupancy at the nearest hospital with NICU is above 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: 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
Adjusted R^2	0.152	0.010	0.287	0.118	0.007	0.000
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
Adjusted R^2	0.164	0.011	0.294	0.120	0.007	0.000
Mean	0.170	3.8	$7,132	$3,446	0.011	0.004

Notes: Panel A presents a difference-in-difference estimate for each outcome without including 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 10: Mean hospital characteristics

	(1)	(2)	(3)	(4)
	RD estimation window [1050 g,1350 g]		DD	Full sample
Characteristic	Complier mean	Overall mean	Complier mean	Overall mean
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
Observations		8848		4173544

Notes: First column presents mean characteristics of compliers within the estimation window following Angrist and Pischke [2009] and Almond and Doyle [2011]. Second column shows the overall mean characteristics within the estimation window. Third column describes the complier mean for the difference-in-difference specification. Last column shows the full sample mean.

Table 11: Heterogeneity by county-level median household income

	(1)	(2)	(3)	(4)	(5)	(6)
	Medicaid HMO	Log(LOS)	Log(total charges)	Log(total costs)	Transfer	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
Adjusted R^2	0.137	0.480	0.483	0.606	0.276	0.014
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
Adjusted R^2	0.141	0.246	0.302	0.317	0.204	0.003
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
Adjusted R^2	0.080	0.265	0.473	0.470	0.268	-0.020
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
Adjusted R^2	0.067	0.061	0.193	0.139	0.061	-0.003
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

Notes: Each panel shows the RD estimates in counties for each quartile of median household income. 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%.

Appendix A. Computing Complier Characteristics

I follow the estimation proposed by Almond and Doyle [2011]:

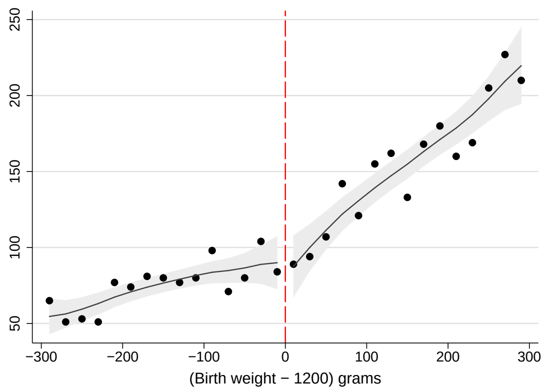
$$E(X|compliers) = \frac{p_C + p_A}{p_C}\left[E(X|D=1, Z=1) - \frac{p_A}{p_C + p_A}E(X|D=1, Z=0)\right] \tag{3}$$

where X indicates hospital characteristics, D denotes the treatment, which is the Medicaid HMO participation in my context. Z denotes the instrument. p_A is the proportion of always takers and p_N is the proportion of never takers. Using these estimates, I compute the proportion of compliers, $p_C = 1 - p_A - p_N$. I use sample means for those 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 $E(X|D=1, Z=0)$. The below tables describe each parameters 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 shown in Table 10.

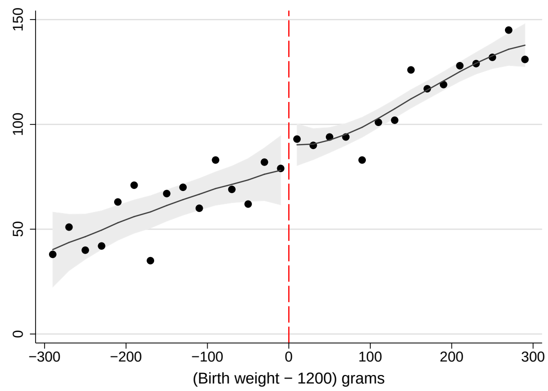
	RD	DD
Z	Birth weight≥1,200 g	Years following the state mandate
$p_A = P(MMC=1, Z=0)$	0.04	0.05
$p_N = P(MMC=0, Z=1)$	0.74	0.73
$p_C = 1 - p_A - p_N$	0.22	0.22

	RD		DD	
Characteristic	$E(X\|D=1, Z=1)$	$E(X\|D=1, Z=0)$	$E(X\|D=1, Z=1)$	$E(X\|D=1, Z=0)$
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
Observations	8848	8848	4173544	4173544

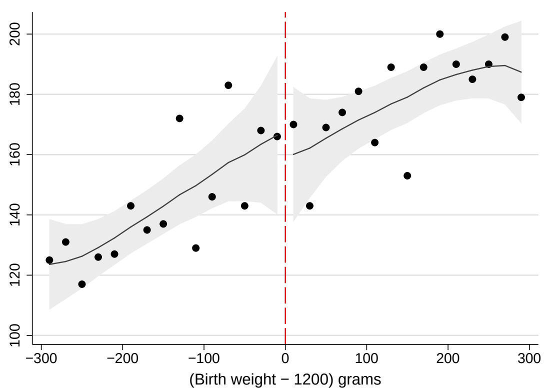
Appendix B. Figures



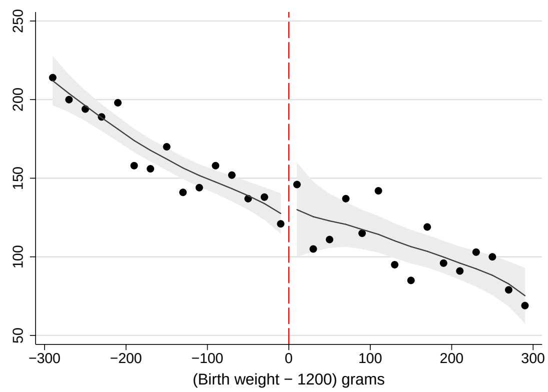
(a) Bottom quartile



(b) Q2



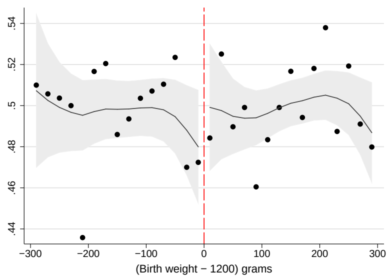
(c) Q3



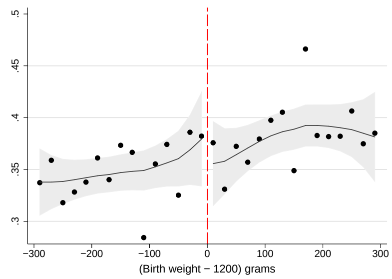
(d) Top quartile

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

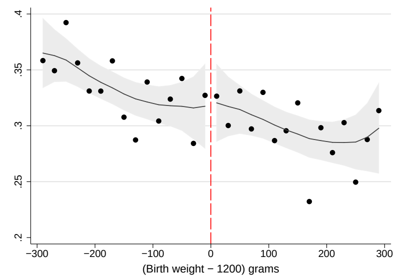
Notes: Predicted list prices are computed from regressions of total charges on diagnosis and procedure fixed effects. I divide the sample by quartiles using these predicted cost measures. Each panel plots mean frequency for each 20-gram bin (dots) along with a local linear regression fitted lines (solid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



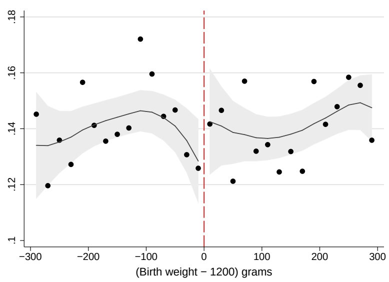
(a) Female



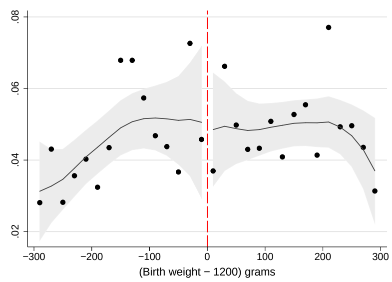
(b) White



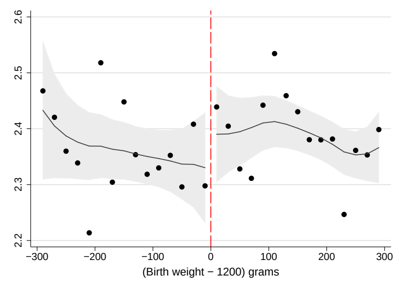
(c) Black



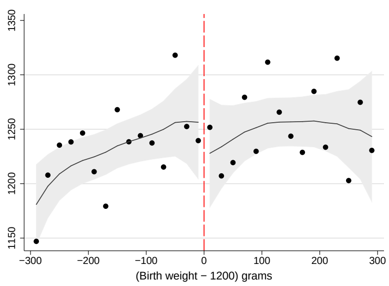
(d) Hispanic



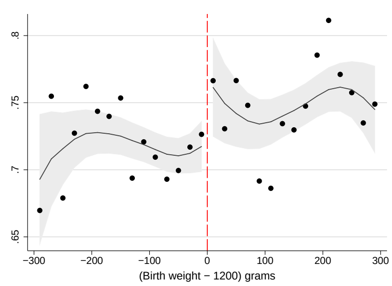
(e) Asian



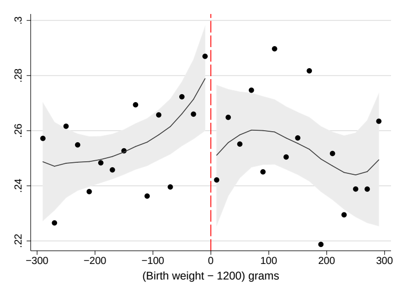
(f) Median household income



(g) Admission hour



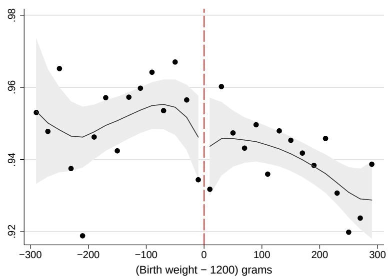
(h) Admission scheduled



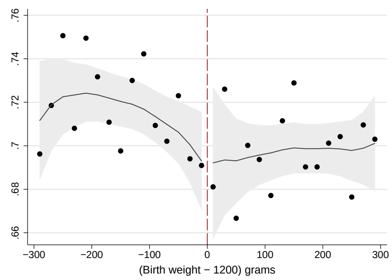
(i) Admission in a weekend

Figure B.2: Patient characteristics

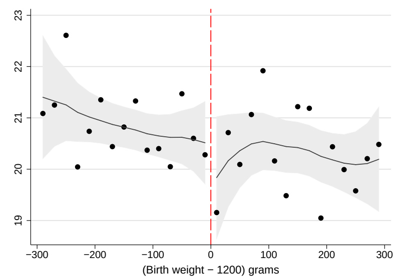
Notes: Each panel plots mean values of each outcome variable for each 20-gram bin (dots) along with a local linear regression fitted lines (solid lines) and 95% confidence intervals below and above the threshold. I use the triangular kernel and a bandwidth of 150 grams for local linear regressions. Median household income indicates a quartile of the estimated median household income of residents in the patient's zip code. The quartile ranges from 1 to 4, indicating the poorest to wealthiest zip codes. Admission hour is coded in military time (e.g., 1:30 p.m. is represented as 1330).



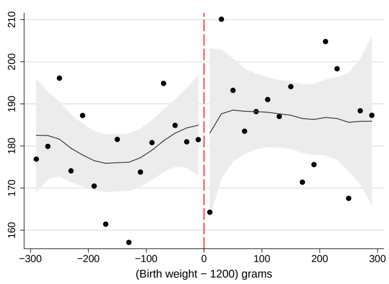
(a) NICU



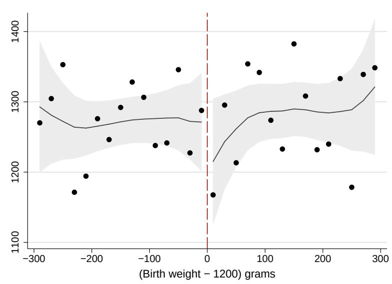
(b) Teaching hospital



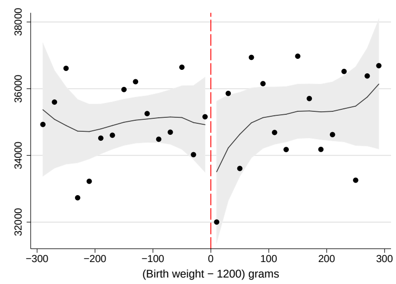
(c) NICU beds



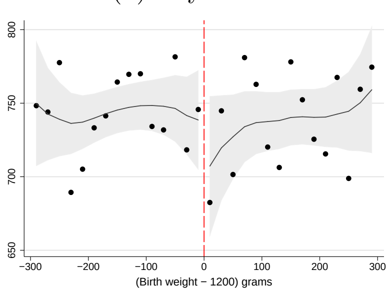
(d) Physicians



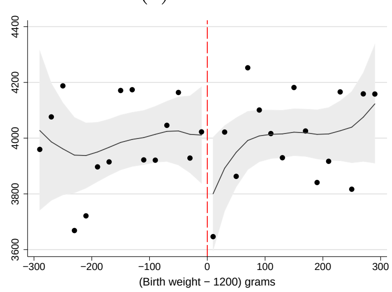
(e) Nurses



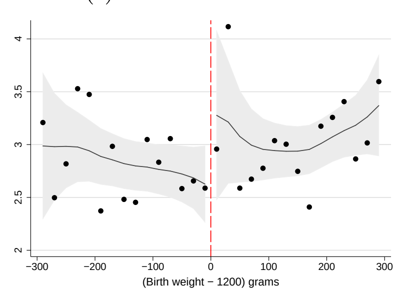
(f) Total admissions



(g) Total beds



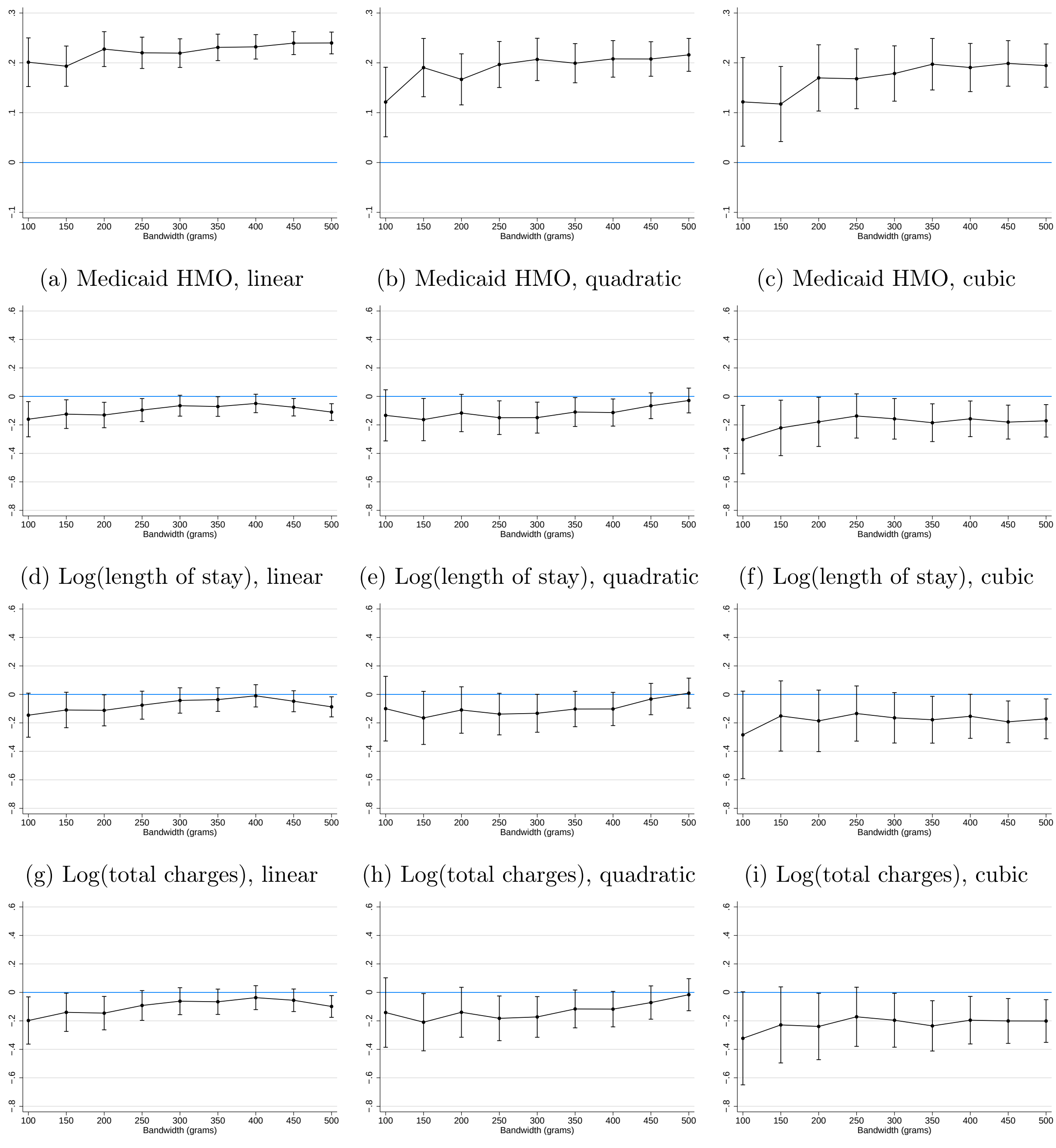
(h) Births



(i) Percent net revenue, capitated

Figure B.3: Hospital characteristics

Notes: Each panel plots 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. I use the triangular kernel and a bandwidth of 150 grams for local linear regressions.



(a) Medicaid HMO, linear (b) Medicaid HMO, quadratic (c) Medicaid HMO, cubic

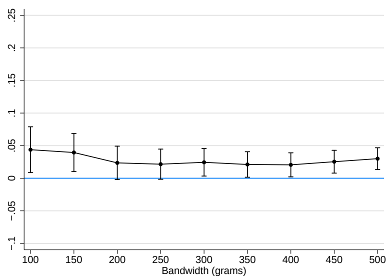
(d) Log(length of stay), linear (e) Log(length of stay), quadratic (f) Log(length of stay), cubic

(g) Log(total charges), linear (h) Log(total charges), quadratic (i) Log(total charges), cubic

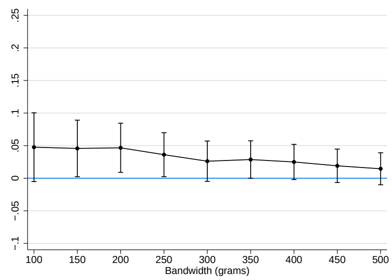
(j) Log(total costs), linear (k) Log(total costs), quadratic (l) Log(total costs), cubic

Figure B.4: Sensitivity to bandwidth and polynomial, New York City

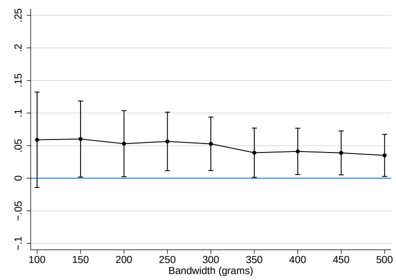
Notes: I repeat the estimation for each outcome for different choice of bandwidth and polynomial. I use a range of bandwidths from 100 grams to 500 grams varying the degree of polynomials from degree 1 (linear), degree 2 (quadratic), to degree 3 (cubic).



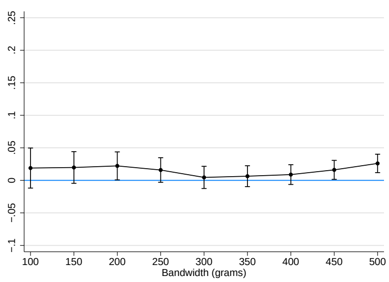
(m) Transfer, linear



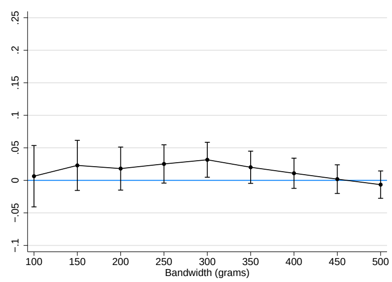
(n) Transfer, quadratic



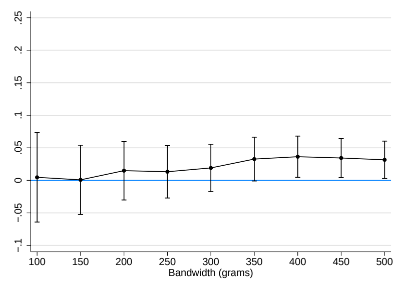
(o) Transfer, cubic



(p) Mortality, linear



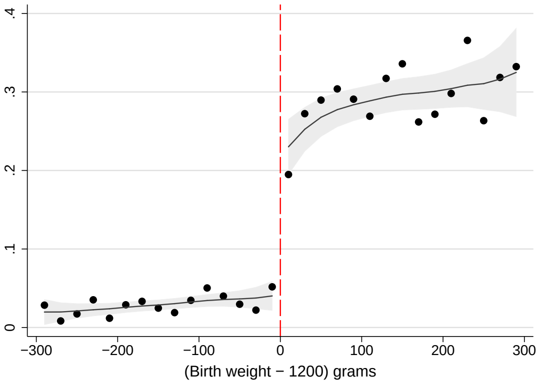
(q) Mortality, quadratic



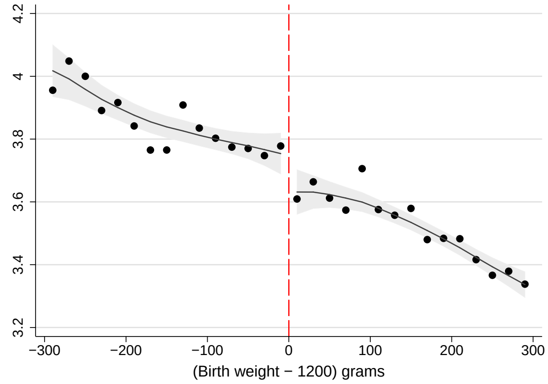
(r) Mortality, cubic

Figure B.4: Sensitivity to bandwidth and polynomial, New York City (continued)

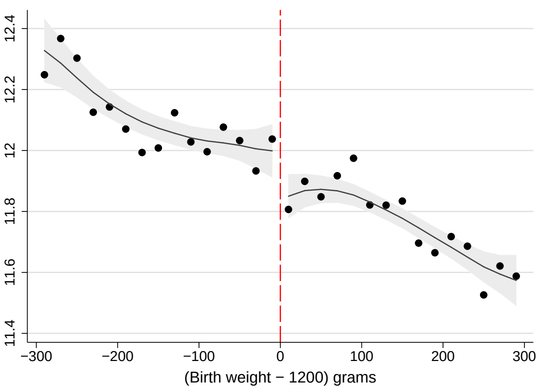
Notes: I repeat the estimation for each outcome for different choice of bandwidth and polynomial. I use a range of bandwidths from 100 grams to 500 grams varying the degree of polynomials from degree 1 (linear), degree 2 (quadratic), to degree 3 (cubic).



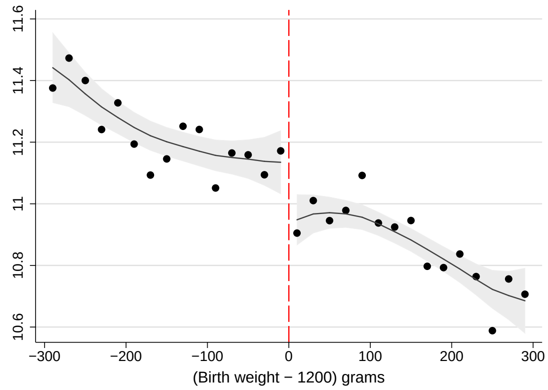
(a) Medicaid HMO



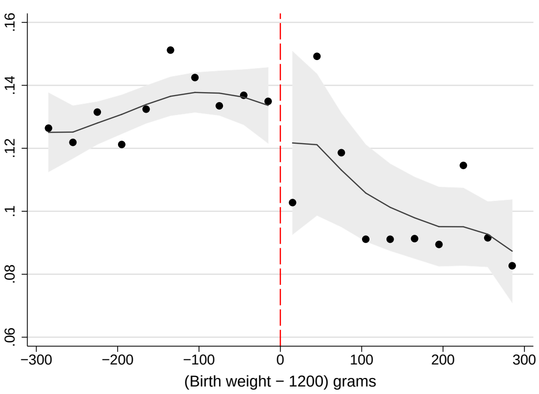
(b) Log(length of stay)



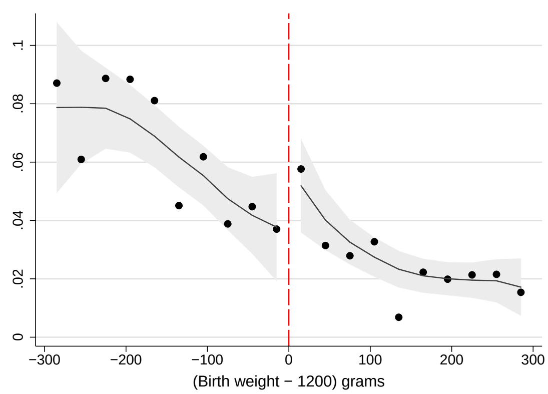
(c) Log(total charges)



(d) Log(total costs)



(e) Readmission



(f) 1 year mortality during hospitalization

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

Notes: Each outcome aggregates the value at birth hospitals with the value at transferred hospitals at the individual level. 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 readmission and death are both rare and thus noisy. Each 30-gram bin contains around 420 discharge records. I test whether using wider bins oversmooths 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.

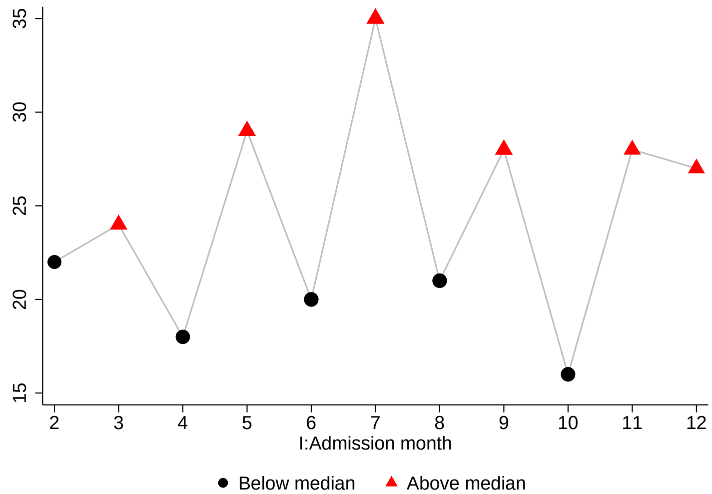


Figure B.6: An example hospital, 2005

Notes: This figures illustrates the monthly NICU occupancy for an example hospital in 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.

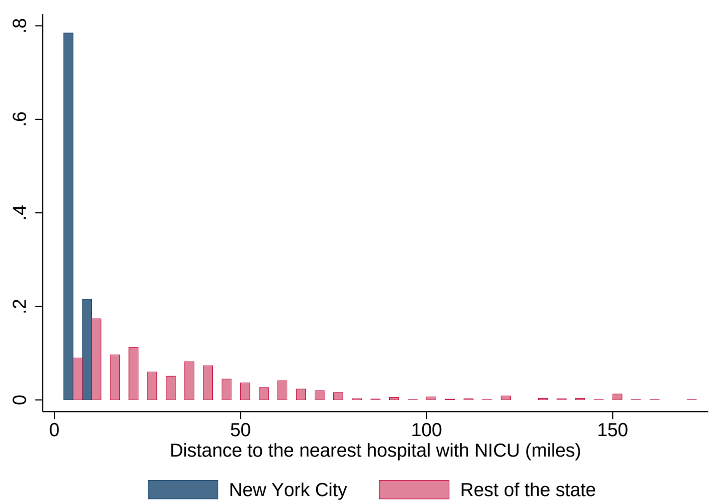


Figure B.7: Proximity to the nearest hospital with a NICU facility

Notes: Blue bars show the density of New York City hospitals by the distance to the nearest hospital with NICU. Red bars show the density for hospitals outside of New York City.

Appendix C. Tables

Table C.1: Heterogeneity by NICU crowdedness, relative to the number of beds, 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 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
Adjusted R^2	0.128	0.023	0.217	0.182	0.007	0.002
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
Adjusted R^2	0.116	0.040	0.236	0.210	0.016	0.006
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

Notes: I divide each month's NICU occupancy 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 where this NICU occupancy rate is below median for a given hospital in a given year. Panel B shows the RD estimates for months where the NICU occupancy rate is above 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 C.2: Heterogeneity by driving time to the nearest hospital with 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
Adjusted R^2	0.142	0.169	0.209	0.276	0.098	0.005
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
Adjusted R^2	0.123	0.016	0.195	0.141	0.008	0.007
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

Notes: Panel A shows the RD estimates for hospitals whose distance to the nearest hospital with NICU is below median, while panel B shows the RD estimates whose distance is above 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 C.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
Adjusted R^2	0.119	0.030	0.155	0.138	0.008	0.023
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
Adjusted R^2	0.152	0.050	0.177	0.187	0.022	-0.001
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

Notes: I define a typical destination hospital for each hospital as the hospital where the given hospital is most likely to transfer their infants to. Panel A shows the RD estimates for months where the NICU occupancy at the typical destination hospital with NICU is below median, while panel B shows the RD estimates for months where the NICU occupancy at the typical destination hospital is above 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%.