NBER WORKING PAPER SERIES

# PUBLIC AND PRIVATE OPTIONS IN PRACTICE: THE MILITARY HEALTH SYSTEM

Michael D. Frakes
Jonathan Gruber
Timothy Justicz

Working Paper 28256
http://www.nber.org/papers/w28256

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
December 2020

The views expressed in this paper are our own and do not reflect the official policy or position of the Department of the Army, Department of Defense, U.S. Government, or the National Bureau of Economic Research. We are extremely grateful to Mike Dinneen and Daryl Crowe at the Military Health System and to Wendy Funk and Keith Hofmann at Kennell Inc. for making the MHS data available to us and for fielding endless questions. We acknowledge funding from NIA grant R01AG049898.

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NBER Working Paper No. 28256
December 2020
JEL No. H1,H51,I18

**ABSTRACT**

Recent debates over health care reform, including in the context of the Military Health System (MHS) and Veterans Health Administration, highlight the dispute between public and private provision of health care services. Using novel data on childbirth claims from the MHS and drawing on the combination of plausibly exogenous patient moves and heterogeneity across bases in the availability of base hospitals, we identify the impact of receiving obstetrical care on versus off military bases. We find evidence that off-base care is associated with slightly greater resource intensity, but also notably better outcomes, suggesting marginal efficiency gains from care privatization.

Michael D. Frakes
Duke University
School of Law
210 Science Drive
Box 90362
Durham, NC 27708
and NBER
Michael.frakes@law.duke.edu

Jonathan Gruber
Department of Economics, E52-434
Massachusetts Institute of Technology
77 Massachusetts Avenue
Cambridge, MA 02139
and NBER
gruberj@mit.edu

Timothy Justicz
United States Military Academy at West Point
606 Thayer Road
West Point, NY 10996
timothy.justicz@westpoint.edu

Health systems throughout the world typically consist of some mix of public and private health care delivery. In the U.S., most health care is delivered privately, albeit sometimes under contract with public payers, but health care for the U.S. military and veterans has historically been delivered largely through public systems. In many European nations, health care is typically delivered by public systems, while individuals can often "top up" their care using private arrangements with (often the same) providers. But one thing that appears common to all systems is a constant sense of dissatisfaction with the mix. For example, in the UK, the Prime Minister faces pressure to undo the increased tendering of private contracts that began in 2012 (Hussain 2020). On the other hand, in the United States, President Trump recently signed the Veterans Affairs' Mission Act, intended to allow some veterans to receive care from community providers outside of public VA Medical Centers – and this is opposed by many stakeholders, including the former head of the Veteran Affairs Department David Shulkin, who has argued that the VA has special expertise in treating certain issues (Shulkin 2018).

Therefore, understanding the implications of shifting care from public to private health systems, and vice versa, is a key issue worldwide. But this has been a difficult issue to study because the populations using these different systems are quite heterogeneous – and when individuals have a choice between systems, they may do so in a way which is correlated with unobserved determinants of health.

Perhaps for this reason, there is little work of which we are aware comparing delivery between public and private systems of care (particularly in the U.S).[2] There is a large literature that compares

[2] The one exception is a new working paper by Chan et al. (2020) which compares those who receive care inside or outside of the VA health care system. We discuss the comparison between our results and theirs in the conclusion.

public versus private *financing* of care, such as through the Medicare Advantage program versus traditional Medicare (e.g. Duggan, Gruber and Vabson, 2018; Curto *et al.*, 2019), or through private Medicaid HMOs versus government direct contracting with physicians (e.g. Geruso *et al.*, 2019). But the actual care delivered through these different financing mechanisms are often at similar sets of providers, so that these differences primarily reflect contracting and care management differences across the public and private sectors.

Closer in spirit are a number of papers that compare delivery of care at publicly owned versus privately owned hospitals; for example, Villa and Kane (2012) find that privatizing public hospitals in the United States results in increased occupancy, shorter stays, and the loss of unprofitable services. Various related studies in the international context use survey instruments to compare outcomes at public and private hospitals, finding that private facilities have both higher prices and higher quality.[3] But these international investigations are often subject to selection bias, with papers using propensity matching (Bjorvatn, 2018) and instrumental variables strategies (Pérotin *et al.*, 2013) finding substantial patient differences across the types of providers and little causal difference in quality.[4] Methodological challenges aside, inquiries into public-versus-private ownership of a particular hospital are unable to speak to the impact of an entirely public-versus-private *system* of care, which includes a comparison of the full provision of all of a patient's care—both inpatient and outpatient—and which includes a comparison of the care management differences across the public and private sectors.

[3] See for example Andaleeb (2000), Camilleri and O'Callaghan (1998), Taner and Antony (2006), and Yesilada and Direktor (2010).

[4] Systematic reviews by Tiemann *et al.* (2012) and Eggleston *et al.* (2008) conclude that existing studies do not demonstrate a convincing gap between private and public facilities.

Surprisingly, the best context for studying a mixed public-private system may be in the U.S.: the Military Health System (MHS). The MHS is a $50.6 billion/year program that provides care to active-duty military, their dependents, and military retirees, covering over 9 million eligible individuals. Crucially, MHS beneficiaries have access to government-owned and run facilities on military bases, as well as private providers that are contracted to the military through an insurance company. Care is split roughly equally between the two sources; 49 percent of outpatient encounters and more than 67 percent of hospitalizations for MHS beneficiaries take place with private providers (TriCare Management Activity, 2020).

The proper division of care on and off military bases is a source of controversy and policy action. In particular, the MHS announced plans in 2019 to repurpose roughly 17,000 medical providers (Philpott, 2019)—a development that is likely to push MHS beneficiaries to receive care from civilian facilities—and the Pentagon's proposed 2021 budget calls for transitioning roughly 200,000 non-active-duty beneficiaries to receiving care from civilian providers (Kime, 2020). Yet despite these policy actions, there is no convincing evidence as to whether moving care to civilian providers raises or lowers costs, or improves or deteriorates outcomes.

In this paper, we provide such evidence. This evidence is immediately relevant to the $50.6 billion MHS, one of our nation's largest health care programs. But it also has important implications for other systems in the U.S., such as the VA; more broadly, it speaks to the rigorous and ongoing debate between expanding or contracting the role of the private sector in delivering care in the U.S.[5]

[5] For instance, in a recent New York Times commentary, Aaron Carroll makes on argument on the contraction side of this debate, suggesting that the U.S. can learn "a thing or two" from Singapore's "largely privately financed public delivery system," the "opposite of what we have in the United States (Carroll, 2019).

A key feature of the military allows us to create a quasi-experimental analysis of the impact of systems of care on patient treatment and outcomes: exogenous moves. Moves across military bases are dictated by the needs of the military and are not determined by the choices of individuals which might be endogenous to their tastes for medical care. Combining beneficiary moves with another key feature of the military context—i.e., variation across bases in the availability of base hospitals—provides us with exogenous variation in access to a public system of care. A further advantage of studying the MHS is that there is a large sample of individuals who themselves receive care both on and off base for a major medical intervention: childbirth. This allows us to hold patient characteristics constant in comparing care delivered from different sources, as well as to take advantage of a detailed set of quality measures facilitated by the childbirth setting. During our sample period there are 776,074 births to 590,353 dependents of active-duty military, and 43.63% of children are delivered at MHS bases.

To carry out this study, we turn to an innovative data set that has been little used by economists, the Military Health System Data Repository data. These data provide complete medical claims for all military personnel and their dependents over the 2003-2013 period. Critically, they provide detail on care delivered on and off military bases.

Our analysis follows the approach of Finkelstein et al. (2016) in a discrete event framework. We consider every mother in our sample who gives birth at least twice. We then restrict our sample to all mothers who move to a new base between births, and we compare those mothers who see a change in the availability of military hospitals. That is, we compare mothers who move but both before *and* after the move do (or do not) have a military hospital nearby, to mothers who move and who see a change in their nearby access to military hospitals. In this way, we control for both underlying mother characteristics, as well as any effect of moves per se. Following Finkelstein et al. (2016), we can confirm that our estimates are causal by examining the previous births for all such mothers. We begin with a transparent presentation of mean birth outcomes among movers. We then move to an instrumental variables (IV) framework which allows us to carry out overidentification tests to confirm that the results are similar for mothers moving either closer or further from base hospitals when they give birth.

We find that mothers delivering off-base use more resources than those delivering on-base; total resource utilization appears to be about 1% higher for those using the private- rather than public-care system, primarily driven by higher Cesarean section rates off-base. At the same time, we find that the quality of care appears to be significantly higher for mothers delivering and receiving prenatal care off-base. We find that mothers and babies receiving off-base care have fewer complications and incidence of maternal or neonatal trauma. Our results suggest that, at current levels, shifting childbirth from on- to off-base is likely to be cost effective.

Our paper proceeds as follows. Section I provides background on the MHS. Section II discusses our data, while Section III describes our empirical strategy. Section IV shows results, and Section V concludes.

## Part I: Institutional Background

The Military Health System (MHS) is the primary insurer for all active-duty military, their dependents, and many military retirees through the TriCare program. Of the nearly 9 million patients covered by TriCare, only 20% are actively serving in the US military. TriCare is not involved in health care delivery in combat zones and operates separately from the Department of Veterans Affairs' Veterans Health Administration (Schoenfeld *et al.* 2017). For TriCare enrollees, care can be delivered in one of two ways: either directly at Military Treatment Facilities (MTFs) on military bases (direct care), or purchased from private providers (purchased care).

The 42 MTF hospitals in the U.S. provide both outpatient and inpatient care to TriCare enrollees.[6] MTF care represents the classic public delivery mechanism. All resources are owned by one of the branches of the U.S. military. Individual MTFs are managed by active-duty military officers who draw a salary that is not tied to the performance of their MTF. Their incentives to perform well come from a sense of duty as service-members and physicians, and from a desire to advance their careers and attain positions of greater responsibility. Medical departments or services, such as OB-GYN, are led by physicians or other providers as appointed by the MTF commander (HQDA, 2004).

For those treated at MTFs, the care is delivered by a mix of providers including active-duty military providers (49 percent), federal civilian employee providers (40 percent), and providers hired using contract mechanisms who work full time at the MTF (11 percent) (Defense Health Program, 2018). Providers are primarily salaried with payment not explicitly tied to either quantity or quality of care delivered.[7] In almost every aspect, care at MTFs approximates the type of publicly provided care delivered in the UK and other systems with public health care delivery.

[6] An additional 73 locations provide solely outpatient care.

[7] Military providers are on a military pay scale, while civilian providers are on the federal General Schedule (GS); both pay systems include base pay, and local cost of living adjustments. Contractors are flexibly hired to meet local needs. The contracting process solicits competitive bids to provide a service for an annual salary—once the contract is awarded the MTF commander does not have authority to alter its terms or to provide additional awards (DoD, 2019).

Alternatively, TriCare enrollees can receive “purchased care” outside the MTF. This care is delivered by a network run by a contracting insurer—United HealthCare, in the case of our sample period—where patients go to private providers within the insurer’s contracted network. This purchased care system very much parallels the public purchase of private care, such as through the Medicare Advantage program. However, contractors for TriCare are not paid a capitated rate per beneficiary per month. They are instead paid for their services and manage payment to providers on a per-claim basis. Therefore, by comparing direct to purchased care, we are comparing care provided directly by the government to care provided by private contractors paid by the government.

Providers under purchased care are paid Medicare rates, and all inpatient stays are subject to bundling into a single Diagnosis Related Group (DRG) based on age, sex, diagnoses, procedures, and discharge status using the Medicare Grouper. Individual discharges may also be further reimbursed for high cost and length-of-stay outliers. The TriCare Reimbursement Manual notes that, while this system is functionally identical to Medicare’s prospective payment system, weights and payments may vary because of the characteristics and needs of the beneficiaries (OASD, 2018).

In principle, enrollees who live within the “catchment area” of an MTF are supposed to go to the MTF for care. This area was defined as 40 miles originally, though the military has shifted to time-based boundaries. Our data show clearly that a mileage boundary rule was not rigorously enforced during our sample period. Those who live closer to an MTF are much more likely to go there, but with a more gradual fall off rather than a strong distance discontinuity.

Importantly, moves are not under the control of active-duty enrollees. Moves within the military are driven by Department of Defense personnel management strategies, motivated by staffing needs across units. As personnel leave or are promoted, units must be reorganized so that each formation has the appropriate composition. Official policy is that these decisions are made according to "current qualifications and ability to fill a valid requirement," and this takes priority over all other considerations, including individual preferences or time at current locations. Furthermore, assignments "will not be influenced by the employment, school enrollment, volunteer activities, or health of a Service member's family member" (DoD 2015). Several papers have demonstrated that the timing and frequency of relocations is not subject to soldier preferences, including Lyle (2006), Lleras-Muney (2010), Carter and Skimmyhorn (2017), and Carter and Wozniak (2018). Moves within a catchment area may be endogenous since they are unlikely to be driven by personnel management needs; we therefore exclude such moves from our analysis.

## Part II: Data

Our data come from the Military Health System Data Repository, a comprehensive set of health records collected at MTFs and from civilian providers reimbursed under TriCare. The data are comprised of several separate repositories, including administrative eligibility files and separate sets of claims data for direct and purchased care, both inpatient and outpatient. While TriCare does not pay claims for direct care, "encounter data is captured to indicate the types of care received, who provided the care, when the care was provided, etc" (OASD, 2012). These data are structured as if they were claims and include detailed information such as physician identifiers, diagnosis and procedure codes, length of hospitalization, and measures of treatment intensity. The sample period covers fiscal years 2003 through 2013.

In our comparison of the care provided at MTF hospitals versus civilian facilities, we focus on inpatient care for childbirth, for a number of reasons. First, we have a very large sample of births, as this is the most common type of hospital admission for the MHS population. Second, many women in the sample period deliver more than once, allowing us to control for unobservable heterogeneity by focusing on within-mother differences in outcomes across births. Third, the delivery context affords us the ability to explore both birth-specific measures of treatment intensity, like the prevalence of C-sections, and detailed health outcomes, such as preventable complications. Finally, admission for birth is nearly universal among pregnant women, minimizing the potential for selection into the sample on the dimension of whether to receive care at all.

We restrict our sample in two further ways to facilitate the comparability of on and off base care. First, we exclude active-duty service members (who account for 21 percent of births) because, as Frakes and Gruber (2019, 2020) document, they face different medical malpractice liability environments which would limit our ability to extrapolate our findings to other settings. Second, we remove retirees and their dependents (who account for only 3.5 percent of births) since under TriCare rules they have different cost sharing on- and off-base.

After restricting to mothers who give birth at least twice in our sample window, and who move across military installations between births (for reasons discussed below), we have a sample of 87,005 women who are admitted for labor and delivery 182,779 times. Out of these admissions, 55 percent are off-base, while 45 percent are at MTF hospitals.

We use several variables to measure treatment intensity. The most important is Relative Weighted Product (RWP), an encounter-specific metric created by the MHS to compare the intensities of inpatient resource use across the direct- and purchased-care systems. This measure is a function of both the DRG weight associated with the admission and the length of the inpatient stay. A RAND study found an 80 percent correlation between RWP and cost for surgical cases (Farley *et al.* 1999). The use of this RWP measure is necessary because, while the MHS records cost allocations to each inpatient stay both on and off the base, they only record charges for stays off the base.[8] In addition to RWP, we consider separately the rate of C-sections, the number of additional (non-C-section) procedures, the length of stay for mothers (bed days) and newborns (bassinet days), and the number of diagnostic procedures.[9]

In addition to treatment intensity, we consider several measures of care quality and patient outcomes. First, we consider measures indicating delivery complications. Complications are very common during childbirth, occurring in more than two-thirds of admissions in our sample. For example, the single most common is trauma or lacerations of the perineum, occurring in 40 percent of admissions.[10] In addition to the presence of any complication, we consider severe and preventable complications. Severe complications are a set of dangerous complications identified by the World Health Organization, including for example severe preeclampsia, a potentially life-threatening condition. Preventable complications include bleeding problems, such as post-partum hemorrhage and post-partum coagulopathy, and several conditions of labor such as unusually fast delivery, called

[8] We winsorize RWP at the 99th percentile to reduce the influence of outliers.

[9] Specifically, we follow the list of diagnostic procedures coded in Frakes and Gruber's (2019) analysis of diagnostic testing during MHS inpatient stays. As explained in Frakes and Gruber (2019), some form of continuous electronic fetal heart monitoring has become so common during labor and delivery now that the accessible CPT codes in the MDR database do not allow us to distinguish deliveries with and without this particular diagnostic tool. Accordingly, our diagnostic analysis can best be seen as capturing diagnostic tools other than continuous electronic fetal heart monitoring.

[10] We therefore exclude the least serious perineal lacerations from our measure. Nevertheless, nearly half of admissions experience some other form of complication.

precipitate delivery, or unusually long labor. Note that these categories are not mutually exclusive—bleeding problems are considered both severe and preventable.

Second, we measure neonatal mortality, or infant deaths during the first 28 days after birth.[11] Third, we look at unplanned readmissions of the mother within 30 days of discharge. Unplanned readmissions are inpatient admissions to short-term acute care hospitals within 30 days of discharge from an "index admission" (CMS 2016). [12]

## Part III: Empirical Strategy

The objective of this paper is to determine whether treatment intensity and quality differ between the "direct" (public) and "purchased-care" (private) systems—i.e., between MTF-based care / management and private-based care / management. We frame this empirical comparison by considering off-base private care the treatment, making those who give birth at MTFs the untreated group. The key inferential challenge for this exercise is that selection to purchased care is non-random. Simply comparing outcomes of direct and purchased-care encounters will be confounded by observable and non-observable differences between patients.

[11] Maternal mortality outcomes were, fortunately, too rare to offer precise estimates.

[12] We use a slightly modified version of the CMS "Planned Readmission Algorithm (Version 5.0)." We consider all admissions for birth to be index admissions. We exclude readmissions on the same day, where CMS would include these if the primary diagnosis was different. If there is more than one readmission within 30 days, only the first is considered a readmission. Therefore we have a dummy variable for each birth admission that indicates whether the *mother* has an unplanned readmission. A planned readmission is "defined as a non-acute readmission for a scheduled procedure," and a few procedures are always classified as planned, including organ transplants, chemotherapy, and rehabilitation. It is important to note that admissions for either acute conditions or for complications are never categorized as planned.

Finkelstein et al. (2016) develop an approach to address this concern in the context of Medicare spending. They face a similar challenge: they are interested in determining the extent to which geographic area differences in spending are due to true differences in area characteristics as opposed to the selection of patients who choose to live in those areas. Their approach is to create a sample of Medicare movers and to compare the change in movers spending based on the differences in average area spending in their ex-ante and ex-post locations. In their context, the concern is that such moves are endogenous – e.g. that unobservably sicker people will move to high spending areas, for example. To address this, Finkelstein et al. (2016) study the outcomes of movers before they move – showing that those who move to more and less expensive areas are quite similar before the move, but differ thereafter in ways correlated with area expense.

We can apply this same approach to the context of discrete medical events - with the further advantage that military moves are exogenous.

In particular, let $i$ denote the mother's initial location and $j$ denote her final location, so that for any outcome variable $Y_{ij}$ is the outcome for those who initially deliver at location $i$ and subsequently at location $j$. Location ($i$ or $j$) itself is specified so as to capture the availability of an MTF hospital at the base where the individual is stationed. Specifically, location ($i$ or $j$) takes on a value of 1 if individuals live more than 40 miles away from an MTF hospital, and 0 if they live within 40 miles of an MTF hospital.[13] So, for any outcome $Y$, we can measure the impact of losing access to an MTF hospital as $Y_{0,0} – Y_{0,1}$. Likewise, we can define the impact of gaining access to an MTF hospital as $Y_{1,1} – Y_{1,0}$.

[13] We utilize this 40-mile specification as the baseline to account for situations in which mothers live close to two bases. If the closest base does not have an MTF hospital but the second closest-base does, and the mother still lives within 40 miles of the MTF hospital on this second-closest base, we treat this scenario as one in which the mother has access to an MTF

There are two fundamental threats to identification in this context. The first is that movers and non-movers are not comparable. As we argued above, moves are assigned by the military and should not be endogenous to individual characteristics. But it is conceivable that pregnancy could impact the timing of moves. Moreover, it is possible that moving itself impacts birth outcomes. We can readily address both of these concerns by restricting our analysis only to mothers who move between births.

The second is the potential endogeneity of move location, despite the institutional factors that suggest exogenous moves. To assess this possibility, we pursue the discrete analogy to the approach of Finkelstein et al. (2016) and examine the *previous* birth of movers. That is, if those movers who are high risk are systematically moved to a base with an available base hospital, then this should show up in those same mothers having higher risk first births.

On a final note regarding potential endogeneity of moves, we restrict our inquiry to mothers with multiple births who move between births to a new base location. That is, the variation we capture in whether patients live within 40 miles of a base hospital derives from moves across bases that differ in their availability of a base hospital, rather than from internal moves within bases that cross this 40-mile threshold. Such within-base moves are more likely to be endogenous with respect to treatment decisions.

To transparently illustrate the power of this approach, we begin by showing simple comparisons of our key measures for the four sets of possible move combinations. We start with the sample of mothers whose first birth occurs when they live within 40 miles of an MTF hospital; within this sample,

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hospital. Alternatively, as discussed below, we specify location as taking on a value of 1 if the base closest to where the mother lives has an MTF. We find similar results across both approaches.

we then compare those whose second birth takes place after they move within 40 miles of a different MTF hospital ($Y_{0,0}$), to those whose second birth takes place after they move more than 40 miles away from any MTF hospital ($Y_{0,1}$). Likewise, we consider a sample of mothers whose first birth occurs when they live more than 40 miles from an MTF hospital; within this sample, we then compare those whose second birth takes place after they move more than 40 miles from a different MTF hospital ($Y_{1,1}$), to those whose second birth takes place after they move to within 40 miles of an MTF hospital ($Y_{1,0}$).

Of course, our approach has one other key difference from Finkelstein et al. (2016), which is that we are only measuring an intent to treat effect, since some of our movers will be close to military hospitals but still use non-military providers. To address this, we can implement an instrumental variables strategy. In particular, we can estimate second stage estimates of the form:

$$\Delta Y_{i,j} = \alpha + \beta * \{I(0,1) - I(1,0)\} + \delta * I(i=0) + \mu \mathbf{X} + \varepsilon \quad (1)$$

Where $\Delta Y_{i,j}$ is the change in outcomes for a mother whose birth locations are *i,j*

I(0,1) is an indicator variable for delivering off-base and then on-base

I(1,0) is an indicator variable for delivering on-base and then off-base

I(i=0) is an indicator for initial birth on the base

We control for certain observable birth characteristics (as of the second-birth) in **X**: dummies for calendar year, age group, sponsor’s pay-grade and sponsor’s race; in a specification check, as discussed below, **X** also includes dummies for various maternal risk-factors. To address the fact that choice of delivery location is endogenous, we instrument the endogenous regressors in the equation above. To identify the coefficient $\beta$, we use two instruments:

I(0,1) is an indicator variable for moving from within 40 miles of an MTF to a new location more than 40 miles from an MTF

I(1,0) is an indicator variable for moving more than 40 miles from an MTF to a new location within 40 miles of an MTF

These instruments use the exogenous variation in MTF access from move location as an instrument for the actual location of the birth. Moreover, the restriction of our model to incorporate symmetric responses to moves both away from and towards military facilities allows us to implement an overidentification test of our estimates.

The first stage for this IV model is shown in Table A1. Both instruments are highly significant with nearly equal and opposite signs. The F-statistic for the set of instruments is 557, well above the standard suggested by Lee et al. (2020).

One disadvantage of limiting our analysis to birth admissions is that pre-hospitalization care—prenatal care—affects birth outcomes. This is potentially problematic to the extent women may receive on-base prenatal care and deliver off-base, or vice versa. Indeed, there is a sizeable share of such “mixed care”. Of women who live within 40 miles of an MTF and who deliver on-base and for whom we can clearly identify pre-natal care, 22% get at least some of their pre-natal care off-base; conversely, of women who live more than 40 miles from an MTF and deliver off-base, 20% get at least some of their pre-natal care on-base.[14] We do not have a separate instrument for receipt of pre-natal versus delivery care, so we are treating these as a package test of public-versus-private delivery. Below, we attempt to assess the relative role of these two factors by looking at outcomes mostly determined

[14] This is partly because there are a number of military bases that don’t have an MTF but do have some medical services.

by pre-hospital care (low birthweight and premature births) and by looking at mothers who move during pregnancy.

## Part IV: Results

*Mean Outcomes*

As discussed above, we restrict the analysis to mothers with only two births who move between births to a new base location. Table 2 illustrates balance for our sample at the first birth before moving. This table has rows for each first-birth outcome, broken into sections for utilization and health outcomes. The first four columns focus on those whose first birth occurs when they live within 40 miles of an MTF hospital. In the first two columns, we compare first-birth means of the indicated measures for mothers whose second birth takes place after they move within 40 miles of a different MTF hospital ($Y_{0,0}$) with those for mothers whose second birth takes place after they move more than 40 miles away from any MTF hospital ($Y_{0,1}$); the third and fourth columns shows the difference in the relevant first-birth outcome between the two groups and its p-value. Likewise, in the second set of four columns, we consider the sample of mothers whose first birth occurs when they live more than 40 miles from an MTF hospital, and compare first-birth outcomes of those whose second birth takes place after they move more than 40 miles from a different MTF hospital ($Y_{1,1}$) , to those whose second birth takes place after they move within 40 miles of any MTF hospital ($Y_{1,0}$). Finally, the last column shows the p-value on a test of the difference between the two estimates in the third and seventh columns.

This table is generally consistent with balance between our treatment and comparison groups in the first birth before moving. Consider for example a key measure of outcomes, Cesarean section deliveries. The C-section rate for first births is almost equal for those who live near an MTF hospital for that first birth and then move, regardless of whether that moves takes them to a new location near an MTF hospital (23.6%) or to one not near an MTF hospital (23.2%); the difference of 0.4% has a p-value of only 0.275. Likewise, the C-section rate is nearly equal for those whose first birth occurs when they live in a location that is far from an MTF and then move, regardless of whether that move takes them to a new location far from an MTF hospital (25.1%) or to one that is near to an MTF hospital (25.4%); the difference of 0.3% has a p-value of 0.472. And these two estimates are very similar, with the p-value on the difference between the estimates of 0.772. It is notable that the estimates are higher for the first birth for those whose first birth is not near an MTF, but this cannot be interpreted causally since initial location is potentially endogenous.

The evidence of balance is consistent for all measures of utilization in the case of the first comparison, where we focus on those who live near an MTF for the first birth and then move. In the case of the second comparison, we do find significant first-birth differences for several measures (bed days, other procedures and diagnostics); however, in two of these measures, the differences in first-birth means are opposite in direction to the corresponding differences in second births, suggesting that any selection bias arising in who moves may bias *against* our ultimate findings.

The next panel focuses on outcomes. We find that there is modest imbalance for the any-complication measure (in the second comparison), although the impact is small and of the opposite sign to what we find for the second birth comparison. Otherwise, outcomes are balanced for the first birth.

Table 3 carries out a parallel analysis, but now focused on second births to provide our, arguably, causal estimates of delivering off-base. The results here are highly significant for most measures of utilization and outcomes, suggesting higher rates of utilization when deliveries are off-base. For example, for C-section delivery, we estimate that among those who live near an MTF hospital for that first birth and then move, if they move to another location near an MTF hospital, their C-section rate for the second birth is 27.7%, but if they move to a new location that is not near an MTF hospital, their C-section rate is a much higher 29.5%; the difference of 1.9% is highly significant. Likewise, for those whose first birth occurs when they live in a location that is far from an MTF hospital, we find that if they move to a new location that is also far from an MTF hospital, their C-section rate is 29.8%, whereas if they move to a new location that is near an MTF hospital, their C-section rate is a much lower 28.4%; the difference of 1.4% is also highly significant.

For utilization, where there was either no significant differences in first births or differences in the opposite direction, there is now significance in every single case for second births, other than for bassinet days in the second comparison. This provides clear evidence that when mothers give birth without access to an MTF hospital, their utilization is significantly higher.

For outcomes, we find highly significant outcomes for both comparisons for all measures of complications suggesting lower rates of complications when deliveries are off-base. The impacts are sizeable, with the rate of severe complication being less than two-thirds as large for those who move away from an MTF hospital rather than staying near an MTF hospital, and almost one-third higher for those who stay away from an MTF hospital rather than moving close to one. We do not find any significant impact on infant mortality, although this is partly due to imprecision; the estimates imply a large reduction in infant mortality for those moving away from an MTF hospital or staying away from an MTF hospital. And we see a large and significant reduction in unplanned readmissions for those who move away from an MTF hospital or those who stay away from an MTF hospital.

Overall, this clear and transparent presentation of the data yields two lessons. First, for those mothers who move, an observation of first-birth characteristics poses few concerns over selection bias compromising our investigation into the effects of off-base care. Second, there is strong evidence that living far from an MTF hospital leads to higher rates of utilization and better outcomes.

If moves to and from bases indeed provide an exogenous source of variation in MTF hospital access, then one would tend to expect estimates of similar size but opposite magnitude when drawing separately on moves away from MTF hospitals and on moves towards MTF hospitals. In Column 9 of Table 3, we offer a preliminary test of this prediction. With respect to various measures—e.g., C-sections—we cannot reject a symmetrical response (in absolute value terms) between a move that provides MTF hospital access and a move that removes it. However, in other cases—e.g., severe complications—we can reject same absolute effect sizes between these two types, generally finding slightly larger absolute effect sizes when drawing on moves that bring patients farther away from MTF hospitals. In the regression analysis and full IV analysis set forth below, we will formalize this overidentification test, allowing for the inclusion of both covariates and for different first-stage magnitudes across move types.

*Regression Analysis*

Table 4 presents the results of estimating equation (1) above. We first show OLS estimates, using the endogenous choice of delivering on versus off base. To the extent that this decision is driven solely by location, then the OLS estimates can be interpreted causally; but to the extent that individuals choose their delivery location based on underlying factors correlated with maternal or infant health, these estimates may be biased. We then show IV estimates, along with the over-identification statistic from the two instruments that arise from our two types of comparisons.

The OLS estimates indicate highly significant impacts of delivering off-base on utilization and outcomes, consistent with the findings from Tables 2 and 3. There are sizeable and significant increases in all utilization measures other than additional (non-C-section) procedures. There are also sizeable and significant reductions in complications, unplanned readmission, and infant mortality. The results are generally consistent with the conclusions from Tables 2 and 3: receiving care off-base leads to higher utilization but better outcomes.

The second column of Table 4 shows IV results. The utilization results are once again generally positive, albeit somewhat weaker than with OLS. We find that the total resource measure rises by 0.011, which is roughly 2% of the sample mean; that is, overall treatment intensity rises by 2%. There is a highly significant rise of 0.14 bed days, which is about 6% of the sample mean. Bassinet days rise as well, but the coefficient is much lower than under OLS and is not significant. As with OLS, there is a positive but insignificant impact on other procedures, while diagnostic tests rise by 0.059, which is an effect more than 50% of the sample mean.

Our results are consistent with much of the impacts we see being driven by higher rates of Cesarean delivery off-base. The rate of Cesarean section delivery is 2.9% higher off-base, which is more than 10% of the sample mean. The average admission with a C-section has a RWP 57% higher than that with no C-section. Therefore, our observed change in Cesarean delivery alone implies a 1.7% increase in RWP. The remaining increase in treatment intensity can be attributed to increased length of stay.

The outcome results are also generally sizeable and significant, indicating across the board reductions in bad outcomes. The probability of any birth complication is reduced by 0.092, which is roughly 20% of the sample mean. The reductions in severe complications of 2% and preventable complications of 9% are even relatively larger, amounting to almost 50% of the sample mean for each. Unplanned readmissions fall by 5 per 1000, which is about 40% of the sample mean. Infant mortality falls substantially as well, and by even more than indicated by OLS, but the coefficient is smaller than its standard error.

These sizeable outcome results strongly imply that the delivery of care off-base is cost effective. For example, the average amount allowed for C-section versus non-C-section deliveries off-base is $2,422.39 (in 2020 dollars). Multiplied by the increased rate of C-sections, this is $70.25 per admission. At the same time, the average readmission cost for our sample is $15,563. A 0.5% reduction in readmissions therefore saves $78.26 per delivery – larger than the costs of increased utilization. This ignores any additional health benefits from fewer complications.

The next column shows the p-value of the overidentification test for this IV estimation. In essence, the null hypothesis for this test is that we find similar effects when using moves away from MTF hospitals as an instrument and when using moves towards an MTF hospital as an instrument.

Encouragingly, in every case but one, the overidentification test passes; there is a marginal rejection for severe complications.

*Specification Checks*

We consider three specification checks of these results in Table 5. First, in column 1, we assess the impact of including potentially endogenous controls for diagnoses. These are all conditions that would generally necessitate a C-section, including the following: previous C-section, breech presentation, multiple birth, umbilical cord prolapse, placenta previa, and placental abruption. This allows us to capture any observable health differences across the comparison groups, but at the same time the coding of these conditions is done by the treating physician and may itself be endogenous to source of care. In any case, including these controls has virtually no impact on the results.

Second, in column 2, we parallel the analysis from Table 2 by looking at prior births. That is, we estimate equation (1), but change the outcome to a level, rather than a first difference, and we use the level of the outcome from the previous birth admission. Strikingly, we find *no* significant coefficients for previous births, and almost all of these tests pass their associated overidentification tests. These findings demonstrate sample balance at first births among movers, regardless of their ultimate moving destination. Consistent with the conclusions we drew from Table 2, these findings ease concerns over selection bias in the composition of moves associated with changes in MTF access.

Finally, we consider an alternative way of assessing “closeness”. A strong finding in the health economics literature is that individuals are much more likely to go to the hospital nearest to them (e.g. McClellan et al, 1994). We therefore recreate our instrument not based on whether there is an MTF hospital within 40 miles, but rather whether the nearest base has an MTF hospital. While correlated with our primary instrument, it is not collinear, with a correlation coefficient of 0.79. Yet, as the last two columns show, the results are quite similar.

*Mechanisms*

The results so far demonstrate quite strongly that delivering at an off-base hospital leads to higher utilization but better outcomes. In this section, we explore some mechanisms that might be driving this result.

As noted earlier, one open question is whether this result is driven by changes in prenatal care or by changes in hospital care. We attempt to separate these mechanisms in two ways in Table 6. First, we look at measures of infant outcomes that should be driven primarily by prenatal care: low birth weight and premature births. For both of these outcomes, the primary medical determinants are prenatal care, with hospital decisions having little impact. In the first two columns of Table 6, we show the results of estimating equation (1) for these alternative measures. Despite finding strong impacts on a variety of outcome measures in Tables 4 and 5, we find no effect on these measures, suggesting that the impacts documented in Tables 4 and 5 are not arising from changes in prenatal care. At the same time, even if some of the impact is arising through prenatal care, we may simply not have enough power to detect effects on these outcomes.

We therefore complement this approach with a second approach in Columns 3—6 of Table 6: examining separately outcomes for mothers who move before versus during pregnancy. Just as the location of moving is exogenous, the timing of moving should be exogenous as well. Therefore, if the impacts we estimate are determined by prenatal care differences, we should see weaker impacts for those who move during pregnancy. In fact, the results are quite comparable, and not statistically distinguishable for any of our key outcomes. This suggests once again that it is hospital care differences, not prenatal care differences, that are driving our results.

A second question is what makes on-base hospital care different. There are a wide variety of differences between MTF hospitals and non-MTF hospitals, ranging from the types of doctors that practice there to the management to the compensation structure. We cannot decompose all these alternatives; however, we do attempt to shed light on whether our findings arise due to one obvious difference between on-base and off-base doctors: the fact that much of the on-base physician workforce are active-duty military. Active-duty doctors may differ from civilian providers—whether civilian providers working on-base or off—for various reasons, including their career progression concerns, the chance that they may be deployed to combat zones, the frequency by which they may be reassigned locations and their general professional dispositions.

To explore this matter, we exploit the fact that care at MTF hospitals is provided by a mix of active-duty physicians and contracted private sector physicians. We then test for differential off-base effects (estimating our main model) depending on the share of on-base birth admissions in a given year and a given MTF that have an attending provider who is active-duty military; specifically, we split the on-base sample by above- and below-median active-duty OGBYN share. This share ranges from zero to one in our data, with a median of 0.55. Overall, the results from this exercise are inconsistent with any suggestion that the findings from Tables 4 and 5 are driven by the active-duty nature of the on-base physician workforce. As demonstrated by Table 7, we do not find systematically different results when focusing on bases with above- or below-median active-duty OBGYN shares.

## Part V: Conclusions

Health care in all developed nations is delivered by a mix of public and private systems. A central question for health care reform around the world is therefore the proper mix of public-versus-private delivery. But addressing this question is challenging since it requires comparing individuals across different health care systems who choose their location of care and therefore may differ in unobservable ways.

By studying the treatment of childbirth within the MHS, we can potentially address this shortcoming. The MHS is the largest broadly-mixed health care delivery system in the U.S., providing us with a large sample of births and excellent data with which to study treatments and outcomes. Drawing on births from the same mother before and after exogenous military moves, along with heterogeneity across bases in the availability of base hospitals, we are able to provide convincing estimates of the impact of private-versus-public delivery systems. We find that delivering off-base leads to higher treatment intensity – but better outcomes. The magnitudes of our findings imply that the better off-base care is cost effective.

This is a particularly timely finding given policy debates in the U.S. around the proper role of public-versus-private systems. In the near term, the MHS is planning to greatly reduce manpower at public facilities, while the Veterans Administration is considering allowing much broader use of private providers to deliver care. More broadly, discussions of moving from a mixed public-private system to a purely public system have become much more prominent in the U.S. Our findings provide some initial evidence that can help inform these debates.

A new working paper by Chan et al. (2020) undertakes similar analysis to ours within the VA. They consider a different population, patients receiving emergency care, and follow Doyle et al. (2015) in using exogenous variation in the propensity of ambulance companies to bring patients to VA versus private hospitals. Their findings are quite different than ours: they find that VA hospitals have significantly lower resource utilization and significantly better outcomes. Future work could usefully decompose the sources of difference in these estimates.

There are a variety of important next steps to further understand public-versus-private delivery of health care in the U.S. and around the world. Extending this work to other types of treatments is an obvious extension, although this likely requires alternative identification strategies given the infrequency of multiple comparable treatments for the same patient. Addressing this issue in an international context may be particularly important given the strong role played by public-versus-private health care systems in other nations.

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Table 1: Descriptive Statistics

| | Mean | SD | 25th Percentile | 75th Percentile |
|---|---|---|---|---|
| Bed Days | 2.315 | 1.890 | 2 | 3 |
| Bassinet Days | 2.467 | 4.535 | 1 | 2 |
| RWP | 0.499 | 0.154 | 0.392 | 0.695 |
| Procedures | 2.256 | 1.263 | 1 | 3 |
| Diagnostics | 0.085 | 0.748 | 0 | 0 |
| C-Section | 0.262 | 0.440 | 0 | 1 |
| Any Complication | 0.494 | 0.500 | 0 | 1 |
| Severe Complication | 0.041 | 0.199 | 0 | 0 |
| Preventable Complication | 0.223 | 0.416 | 0 | 0 |
| Infant Mortality (per 1,000) | 1.118 | 33.251 | 0 | 0 |
| Unplanned Readmission (per 1,000) | 12.372 | 110.540 | 0 | 0 |
| Low Birth Weight | 0.033 | 0.178 | 0 | 0 |
| Premature | 0.057 | 0.232 | 0 | 0 |
| Age | 26.933 | 4.844 | 23 | 30 |
| White | 0.777 | 0.416 | 1 | 1 |
| Black | 0.104 | 0.305 | 0 | 0 |
| Number of Admissions | 182,779 | | | |
| Number of Mothers | 87,005 | | | |

*Notes:* The sample consists of mothers who give birth at least twice, and who move across bases between births. *Bed Days* is the mother's length of stay. *Bassinet Days* is the child's length of stay, or the average length of stay for a multiple birth. *RWP* is the Relative Weighted Product, a measure designed by the Military Health System (MHS) to capture relative treatment intensity between on and off-base admissions. *Procedures* is the count of procedure codes recorded for the admission. *Diagnostics* is the number of purely diagnostic procedures, recorded elsewhere in the claims data. *C-Section* is a dummy equal to one for mothers who gave birth via Cesarean section. *Any Complication* is a dummy equal to one for admissions where at least one complication was recorded, excluding first- and second-degree perineal laceration. *Severe Complication* is a dummy equal to one when an admission includes a diagnosis for any of the following conditions: postpartum hemorrhage, severe pre-eclampsia, eclampsia, rupture of uterus, sepsis, or septicemia. *Preventable Complication* is a dummy equal to one when admission includes a diagnosis for any of the following conditions: fetal distress affecting management of mother, abnormality in fetal heart rate or rhythm, postpartum hemorrhage, long labor, uterine inertia, precipitate labor, or shoulder dystocia. *Infant Mortality* is measured within 28 days of birth. *Unplanned Readmission* is categorized according to the CMS algorithm. *Low Birth Weight* is an indicator for birth weight below 5 pounds, 8 ounces (2,500 grams). *Premature* is an indicator for delivery prior to full gestational age. *Age* is the age of the mother in years at the time of delivery. *White* and *Black* are indicators for the race of the active-duty sponsor since the mother's race is not observed.

Table 2: First Birth Means

| | Starting with MTF Access | | | | Starting Without MTF Access | | | | (3)+(7)=0 |
|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| | MTF/ MTF | MTF/ No MTF | Difference | p-value | No MTF/ No MTF | No MTF/ MTF | Difference | p-value | p-value |
| Panel 1: Utilization | | | | | | | | | |
| Bed Days | 2.535 | 2.530 | -0.005 | 0.792 | 2.475 | 2.519 | 0.045 | 0.014 | 0.078 |
| Bassinet Days | 2.596 | 2.613 | 0.017 | 0.700 | 2.620 | 2.622 | 0.002 | 0.963 | 0.711 |
| RWP | 0.496 | 0.496 | -0.001 | 0.630 | 0.497 | 0.498 | 0.001 | 0.752 | 0.894 |
| Procedures | 2.492 | 2.486 | -0.005 | 0.696 | 2.316 | 2.289 | -0.027 | 0.043 | 0.045 |
| Diagnostics | 0.062 | 0.059 | -0.003 | 0.607 | 0.068 | 0.088 | 0.020 | 0.004 | 0.022 |
| C-Section | 0.236 | 0.232 | -0.004 | 0.275 | 0.251 | 0.254 | 0.003 | 0.472 | 0.772 |
| Panel 2: Outcomes | | | | | | | | | |
| Any Complication | 0.594 | 0.585 | -0.009 | 0.056 | 0.543 | 0.530 | -0.012 | 0.025 | 0.000 |
| Severe Complication | 0.053 | 0.056 | 0.004 | 0.079 | 0.041 | 0.040 | -0.001 | 0.755 | 0.178 |
| Preventable Complication | 0.292 | 0.286 | -0.005 | 0.220 | 0.233 | 0.225 | -0.008 | 0.092 | 0.012 |
| Infant Mortality (per 1,000) | 1.420 | 1.462 | 0.042 | 0.908 | 1.286 | 1.223 | -0.063 | 0.872 | 0.972 |
| Unplanned Readmission (per 1,000) | 13.876 | 15.429 | 1.552 | 0.167 | 10.304 | 11.125 | 0.820 | 0.465 | 0.065 |
| N | 31,671 | 17,582 | | | 14,967 | 19,820 | | | |

*Notes:* Column 1 shows means for first-birth outcomes for mothers who lived within 40 miles of an MTF hospital, and who moved to within 40 miles of an MTF hospital at a different base at the time of their second birth. Column 2 shows first-birth means for mothers who also lived within 40 miles of an MTF hospital, but who moved to a different base and were no longer within 40 miles of an MTF hospital at the time of their second birth. Column 3 lists the difference between these groups. Column 4 gives the p-value from a t-test where the null hypothesis is that the means in column 1 and column 2 are the same. Columns 5 and 6 show first-birth outcome means for mothers who did not live within 40 miles of an MTF hospital. Mothers in column 5 moved to a different base, but remained more than 40 miles away from an MTF hospital, while those in column 6 moved to within 40 miles of an MTF hospital at a different base by the time of their second birth. Column 7 lists the difference between the means in columns 5 and 6, while column 8 reports the p-value for a t-test where the null hypothesis is that there is no difference. The p-values reported in column 9 are from a t-test where the null hypothesis is that the sum of columns 3 and 7 is zero.

Table 3: Second Birth Means

| | Starting with MTF Access | | | | Starting Without MTF Access | | | | (3)+(7)=0 |
|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| | MTF/ MTF | MTF/ No MTF | Difference | p-value | No MTF/ No MTF | No MTF/ MTF | Difference | p-value | p-value |
| Panel 1: Utilization | | | | | | | | | |
| Bed Days | 2.132 | 2.225 | 0.092 | 0.000 | 2.211 | 2.143 | -0.068 | 0.001 | 0.122 |
| Bassinet Days | 2.294 | 2.433 | 0.139 | 0.001 | 2.443 | 2.392 | -0.051 | 0.319 | 0.050 |
| RWP | 0.501 | 0.509 | 0.008 | 0.000 | 0.508 | 0.504 | -0.005 | 0.011 | 0.026 |
| Procedures | 2.122 | 2.183 | 0.062 | 0.000 | 2.186 | 2.097 | -0.089 | 0.000 | 0.187 |
| Diagnostics | 0.084 | 0.122 | 0.038 | 0.000 | 0.111 | 0.088 | -0.023 | 0.008 | 0.044 |
| C-Section | 0.277 | 0.295 | 0.019 | 0.000 | 0.298 | 0.284 | -0.014 | 0.004 | 0.205 |
| Panel 2: Outcomes | | | | | | | | | |
| Any Complication | 0.460 | 0.398 | -0.062 | 0.000 | 0.398 | 0.454 | 0.056 | 0.000 | 0.027 |
| Severe Complication | 0.041 | 0.026 | -0.015 | 0.000 | 0.031 | 0.039 | 0.008 | 0.000 | 0.000 |
| Preventable Complication | 0.214 | 0.151 | -0.063 | 0.000 | 0.150 | 0.205 | 0.055 | 0.000 | 0.001 |
| Infant Mortality (per 1,000) | 0.948 | 0.780 | -0.168 | 0.557 | 1.056 | 0.728 | -0.327 | 0.306 | 0.158 |
| Unplanned Readmission (per 1,000) | 13.179 | 10.730 | -2.449 | 0.018 | 8.246 | 14.010 | 5.764 | 0.000 | 0.025 |
| N | 31,671 | 17,582 | | | 14,967 | 19,820 | | | |

*Notes:* Column 1 shows means for second-birth outcomes for mothers who lived within 40 miles of an MTF hospital at the time of first birth, and who moved to within 40 miles of an MTF hospital at a different base. Column 2 shows second-birth outcome means for mothers who also lived within 40 miles of an MTF hospital at the time of first birth, but who moved to a different base and were no longer within 40 miles of an MTF hospital. Column 3 lists the difference between these groups. Column 4 gives the p-value from a t-test where the null hypothesis is that the means in column 1 and column 2 are the same. Columns 5 and 6 show second-birth outcome means for mothers who did not live within 40 miles of an MTF hospital at the time of first birth. Mothers in column 5 moved to a different base, but remained more than 40 miles away from an MTF hospital, while those in column 6 moved to within 40 miles of an MTF hospital at a different base. Column 7 lists the difference between the means in columns 5 and 6, while column 8 reports the p-value for a t-test where the null hypothesis is that there is no difference. The p-values reported in column 9 are from a t-test where the null hypothesis is that the sum of columns 3 and 7 is zero.

Table 4: Differenced Outcomes

| | OLS | IV | |
|---|---|---|---|
| | (1) | (2) | (3) |
| | $\beta$ | $\beta$ | p-value |
| Bed Days | 0.226*** | 0.141*** | 0.793 |
| | (0.034) | (0.044) | |
| Bassinet Days | 0.418*** | 0.110 | 0.790 |
| | (0.065) | (0.086) | |
| RWP | 0.014*** | 0.011*** | 0.571 |
| | (0.002) | (0.002) | |
| Procedures | 0.023 | 0.096 | 0.749 |
| | (0.077) | (0.110) | |
| Diagnostics | 0.102*** | 0.059*** | 0.976 |
| | (0.009) | (0.014) | |
| C-Section | 0.035*** | 0.029*** | 0.555 |
| | (0.004) | (0.005) | |
| Any Complication | -0.090*** | -0.092*** | 0.051 |
| | (0.016) | (0.020) | |
| Severe Complication | -0.019*** | -0.020*** | 0.043 |
| | (0.003) | (0.004) | |
| Preventable Complication | -0.082*** | -0.089*** | 0.587 |
| | (0.017) | (0.019) | |
| Infant Mortality (per 1,000) | -0.078 | -0.248 | 0.938 |
| | (0.281) | (0.586) | |
| Unplanned Readmissions (per 1,000) | -5.937*** | -5.032*** | 0.652 |
| | (1.346) | (1.874) | |
| N | 95,774 | 95,774 | |

*Notes:* All outcomes in this table are the first difference between the current and prior birth admission. All mothers in the sample moved across bases between births. Column 1 shows OLS estimates of the effect of a change in off-base admission between the current and prior birth. Possible values for the change in off-base are 1 (for a change from on to off-base), 0 (for no change), and -1 (for a change from off to on base). This specification includes an indicator for whether the prior birth took place off base. Column 2 shows 2SLS estimates where the change in off-base admission is instrumented with indicators for a move from MTF hospital to no MTF hospital, or from no MTF hospital to MTF hospital. MTF hospital is defined as the zip code of residence being within 40 miles of a hospital-level MTF with inpatient services. All moves are across bases. Column 3 reports the p-value from an overidentification test, where the null hypothesis is that the instruments are uncorrelated with the error term. The previous birth location indicator is also instrumented with an indicator for whether the mother lived within 40 miles of an MTF hospital. All regressions include controls for calendar year, age group, sponsor's pay grade, and sponsor's race. Standard errors are clustered at the base level.

Table 5: Specification Checks

| | Risk Factor Controls | | Lagged Outcomes | | Alternate Instrument | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| | $\beta$ | p-value | $\beta$ | p-value | $\beta$ | p-value |
| Bed Days | 0.147*** | 0.711 | -0.023 | 0.486 | 0.143*** | 0.342 |
| | (0.045) | | (0.022) | | (0.047) | |
| Bassinet Days | 0.115 | 0.833 | 0.081 | 0.670 | 0.145 | 0.657 |
| | (0.086) | | (0.055) | | (0.099) | |
| RWP | 0.011*** | 0.257 | 0.001 | 0.091 | 0.009*** | 0.046 |
| | (0.002) | | (0.002) | | (0.003) | |
| Procedures | 0.098 | 0.788 | 0.000 | 0.238 | 0.052 | 0.648 |
| | (0.110) | | (0.022) | | (0.111) | |
| Diagnostics | 0.061*** | 0.984 | -0.007 | 0.075 | 0.066*** | 0.219 |
| | (0.014) | | (0.007) | | (0.017) | |
| C-Section | 0.030*** | 0.234 | 0.002 | 0.074 | 0.028*** | 0.122 |
| | (0.005) | | (0.006) | | (0.006) | |
| Any Complication | -0.091*** | 0.079 | 0.002 | 0.013 | -0.093*** | 0.298 |
| | (0.019) | | (0.005) | | (0.021) | |
| Severe Complication | -0.020*** | 0.041 | 0.004 | 0.578 | -0.021*** | 0.173 |
| | (0.004) | | (0.002) | | (0.004) | |
| Preventable Complication | -0.089*** | 0.746 | 0.003 | 0.148 | -0.095*** | 0.556 |
| | (0.019) | | (0.004) | | (0.019) | |
| Infant Mortality | -0.224 | 0.957 | 0.049 | 0.642 | 0.272 | 0.337 |
| (per 1,000) | (0.588) | | (0.440) | | (0.556) | |
| Unplanned Readmissions | -5.029*** | 0.680 | 0.488 | 0.643 | -5.539*** | 0.899 |
| (per 1,000) | (1.870) | | (1.059) | | (2.090) | |
| N | 95,774 | | 95,774 | | 95,774 | |

*Notes:* The outcomes considered in columns 1-2 and 5-6 are the first difference between the current and prior birth admission. Columns 1 and 2 show results from a model that is similar to the main specification, with the addition of risk factors controls. These are indicators for conditions that increase utilization, primarily through necessitating C-sections: previous C-section, breech presentation, multiple birth, umbilical cord prolapse, placenta previa, and placental abruption. Outcomes in columns 3-4 are the level from the previous birth. This model does not include risk factor controls. Columns 5-6 report results from a model with an alternate set of instruments constructed using an indicator for whether the nearest base has an MTF hospital. All regressions include controls for calendar year, age group, sponsor's pay grade, and sponsor's race. Standard errors are clustered at the base level.

Table 6: Prenatal Care Tests

| | All | | Moved During Pregnancy | | Moved Before Pregnancy | |
|---|---|---|---|---|---|---|
| | (1)<br>$\beta$ | (2)<br>p-value | (3)<br>$\beta$ | (4)<br>p-value | (5)<br>$\beta$ | (6)<br>p-value |
| Low Birth Weight | 0.000<br>(0.003) | 0.941 | -0.004<br>(0.004) | 0.553 | 0.003<br>(0.004) | 0.506 |
| Premature | -0.001<br>(0.003) | 0.857 | -0.005<br>(0.006) | 0.756 | 0.003<br>(0.005) | 0.545 |
| Bed Days | | | 0.135***<br>(0.050) | 0.857 | 0.143***<br>(0.052) | 0.628 |
| RWP | | | 0.010***<br>(0.003) | 0.756 | 0.011***<br>(0.003) | 0.639 |
| Procedures | | | 0.089<br>(0.113) | 0.630 | 0.100<br>(0.110) | 0.959 |
| Diagnostics | | | 0.061***<br>(0.016) | 0.724 | 0.058***<br>(0.022) | 0.715 |
| Bassinet Days | | | -0.113<br>(0.100) | 0.740 | 0.268**<br>(0.121) | 0.729 |
| C-Section | | | 0.026***<br>(0.005) | 0.274 | 0.031***<br>(0.006) | 0.918 |
| Any Complication | | | -0.090***<br>(0.023) | 0.279 | -0.093***<br>(0.020) | 0.149 |
| Severe Complication | | | -0.023***<br>(0.005) | 0.411 | -0.018***<br>(0.005) | 0.075 |
| Preventable Complication | | | -0.094***<br>(0.021) | 0.750 | -0.085***<br>(0.020) | 0.617 |
| Infant Mortality (per 1,000) | | | -0.100<br>(0.798) | 0.987 | -0.355<br>(0.798) | 0.886 |
| Unplanned Readmissions (per 1,000) | | | -6.770**<br>(2.716) | 0.792 | -3.720*<br>(2.024) | 0.296 |
| N | 95,774 | | 40,332 | | 55,442 | |

*Notes:* All outcomes considered in this table are the first difference between the current and prior birth admission. Columns 1 and 2 estimate the effect of off-base admission on the probability of low birth weight or premature birth using our main specification. The remaining columns split the sample into women who moved during their pregnancy, and women who moved prior to their pregnancy. Moves are defined as changes in the nearest base measured using zip code. All regressions include controls for calendar year, age group, sponsor's pay grade, and sponsor's race. Standard errors are clustered at the base level.

Table 7: Proportion Active-Duty OBGYNs

| | Below Median | | Above Median | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| | $\beta$ | p-value | $\beta$ | p-value |
| Bed Days | 0.150** | 0.074 | 0.137** | 0.296 |
| | (0.064) | | (0.055) | |
| Bassinet Days | 0.078 | 0.953 | 0.205** | 0.884 |
| | (0.131) | | (0.098) | |
| RWP | 0.010*** | 0.174 | 0.013*** | 0.979 |
| | (0.003) | | (0.003) | |
| Procedures | 0.167 | 0.169 | 0.051 | 0.035 |
| | (0.128) | | (0.124) | |
| Diagnostics | 0.050*** | 0.037 | 0.070*** | 0.178 |
| | (0.019) | | (0.019) | |
| C-Section | 0.027*** | 0.192 | 0.035*** | 0.697 |
| | (0.006) | | (0.007) | |
| Any Complication | -0.072** | 0.087 | -0.107*** | 0.180 |
| | (0.031) | | (0.020) | |
| Severe Complication | -0.017*** | 0.165 | -0.021*** | 0.152 |
| | (0.006) | | (0.005) | |
| Preventable Complication | -0.077** | 0.590 | -0.097*** | 0.975 |
| | (0.031) | | (0.016) | |
| Infant Mortality | -0.273 | 0.597 | -0.217 | 0.338 |
| (per 1,000) | (0.870) | | (0.730) | |
| Unplanned Readmissions | -1.860 | 0.767 | -8.285*** | 0.324 |
| (per 1,000) | (3.331) | | (2.303) | |
| N | 41,348 | | 50,282 | |

*Notes:* All outcomes considered in this table are the first difference between the current and prior birth admission. The sample is split by the prevalence of active-duty military OBGYNs at the nearest MTF hospital. The prevalence of active-duty military OBGYNs is measured as the proportion of birth admissions where the attending physician is on active-duty. The median is 55%. All regressions include controls for calendar year, age group, sponsor's pay grade, and sponsor's race. Standard errors are clustered at the base level.

Table A1: First Stage

| | ΔOff-Base |
|---|---|
| | (1) |
| | $\beta$ |
| MTF Hospital to No MTF Hospital | 0.674*** |
| | (0.019) |
| No MTF Hospital to MTF Hospital | -0.638*** |
| | (0.013) |
| F-Statistic | 556.836 |
| p-value | 0.184 |
| Outcome Mean | 0.013 |
| $R^2$ | 0.437 |
| N | 17,003 |

*Notes:* Column 1 shows coefficients from an OLS regression where the outcome is the change in off-base status from the previous to the current birth. The p-value is for an F-test where the null hypothesis is that the two instruments are opposite and equal. The model includes controls for calendar year, age group, sponsor's pay grade, and sponsor's race. Standard errors are clustered at the base level.