Can Health Care Information Technology Save Babies?

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Amalia R. Miller[*] and Catherine E. Tucker[‡]

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Abstract

Electronic Medical Records (EMRs) facilitate fast and accurate access to patient records, which could improve diagnosis and patient monitoring. Using a 12-year county-level panel, we find that a 10 percent increase in births that occur in hospitals with EMRs reduces neonatal mortality by 16 deaths per 100,000 live births. This is driven by a reduction of deaths from conditions requiring careful monitoring. We also find a strong decrease in mortality when we instrument for EMRs adoption using variation in state medical privacy laws. Rough cost-effectiveness calculations suggest that EMRs are associated with a cost of $531,000 per baby's life saved.

[*]University of Virginia, Charlottesville, VA and RAND Corporation, Arlington, VA.

[†]MIT Sloan School of Management, Cambridge, MA.

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1 Introduction

The 2009 Health Information Technology for Economic and Clinical Health (HITECH) Act, part of the American Recovery and Reinvestment Act (ARRA), devoted \$19.2 billion to increase the use of Electronic Medical Records (EMRs) by healthcare providers. Underlying this substantial public subsidy is a belief that creating an electronic rather than a paper interface between patient information and healthcare providers can improve healthcare quality and also save money. However, as of yet, there has been little conclusive empirical research to support such assumptions. In this paper, we ask whether EMRs can improve neonatal mortality rates.

Each year 18,000 babies die in the United States within their first 28 days of life. This high rate of neonatal mortality means that the United States is ranked 43rd in the world, equal with Montenegro, Slovakia and the United Arab Emirates, and behind 24 of the 27 members of the European Union (UNICEF, 2009). One difference between the European and Asian countries that rank highest in infant survival and the United States is those countries' intensive usage of healthcare IT (Bristol, 2005). It is possible that in the United States, the lack of digitization of patient records means that maternal-fetal medicine specialists have difficulty monitoring and accessing prior patient data in the manner required by modern medical science (Nielson et al., 2000). For example, if a doctor has access to EMRs they can calculate and chart an accurate fetal cardiovascular profile instantaneously for a pregnancy complicated by a dangerous condition such as hydrops (Hofstaetter et al., 2006). Accuracy of documentation may also be improved when a county moves towards electronic records: Bernstein et al. (2005) finds that replacing paper obstetric records with electronic ones reduces the incidence of missing charts from 16% to 2%.

We use data from birth and death records for all US counties to measure neonatal mortality rates at the county level. We combine these with national data on adoption of EMRs by US hospitals in each of these counties to construct a 12-year panel. We then run panel regressions which include multiple controls for hospital and county characteristics and county and year fixed effects. We estimate a negative association between the county-level birth-weighted proportion of hospitals that have adopted EMRs and the neonatal death rate. This drop is larger when we look at the effect of combining EMRs with obstetric-specific technologies and digital storage and decision support technologies. We also show that this result is robust when we consider counties that have only one hospital, in which case we are effectively using a hospital fixed effects specification with a binary adoption measure.

Our results imply that a 10 percent increase in basic EMRs adoption would reduce neonatal mortality rates by 16 deaths per 100,000 live births. In our county-year sample, this is about 3 percent of the mean (of 521) and 0.3 percent of the standard deviation (of 4700) of neonatal mortality. Beyond this, a 10 percent increase in hospitals that adopt both EMRs and obstetric-specific computing technology reduces neonatal mortality by 40 deaths per 100,000 live births. Rough cost-effectiveness calculations suggest that EMRs are associated with a cost of $531,000 per baby saved. To ensure that the negative effect that we measure really is associated with improved the improved monitoring capacity of EMRs, we also break down our analysis for deaths associated with factors that are more or less likely to be affected by the improved monitoring and more systematic care possible with healthcare IT. We find a substantial decline in neonatal deaths associated with prematurity and maternal complications of pregnancy, but not for deaths linked to accidents, sudden infant death syndrome (SIDS) or congenital defects.

Despite the rich set of controls and fixed effects in our main models, it may still be problematic to interpret this relationship causally if there are unobserved and confounding changes in county or hospital characteristics over time that are correlated with IT adoption. For example, if a hospital decides to specialize in more high-risk cases, it may invest in more technology and also experience worse health outcomes. In that case, inadequate controls for patient risk factors and pre-treatment health would cause us to under-estimate the beneficial effects of healthcare IT.[1]

To overcome this potential identification challenge, we estimate an instrumental variables specification that exploits variation across states and over time in state health privacy laws. These regulations restrict the ability of hospitals to exchange and use electronic patient information and consequently reduce the attractiveness of healthcare IT (see Miller and Tucker, 2009a). When we use instrumental variables to identify causal relationships, we find that the effects of healthcare IT on neonatal outcomes may be even larger than the correlations in our panel regressions would suggest.

Building on research such as Currie and Gruber (1996), we then explore whether EMRs reduce or increase disparities in birth outcomes. When we allow the effects of healthcare IT in our instrumental variables estimates to vary by education, marital status, race, and ethnicity we find larger gains for African-Americans and Hispanics and for births to less educated and unmarried women.

Our findings contribute to previous research in economics that has investigated how medical interventions can improve neonatal outcomes. Examples include Miller (2006) on midwives, Bitler and Currie (2005) on nutritional programs for pregnant women and Currie and MacLeod (2008) on tort reform. In the realm of technology, the focus has been on evaluating technologies specific to neonatology, such as neonatal intensive care units (Baker and Phibbs, 2002).

Our findings also contribute to a health policy literature that examines the effect of EMRs. These studies have found it difficult to document precise effects, partly because they relied on data that was limited either by a short time or limited geographical coverage. Studies that document the adoption decision of individual hospitals or hospital systems provide suggestive

[1] Alternatively, if patients become wealthier, hospitals may adopt IT due to better finances, and at the same time experience improved healthcare outcomes because they treat patients with better nutrition. This could lead researchers to over-estimate the effects of healthcare IT on health outcomes.

evidence that IT may improve clinical outcomes (Kuperman and Gibson, 2003; Garg et al., 2005; Chaudhry et al., 2006), but there are also examples of unsuccessful implementations (Ash et al., 2007). These mixed experiences left open the question of what impact large-scale adoption might have, and their small sample sizes made it impossible to examine rare events or estimate mortality effects. Studies with larger samples involving multiple hospitals find some positive associations between computerization and quality of care or outcomes measures. For example, Amarasingham et al. (2009) finds lower mortality rates in a cross-sectional correlation in Texas, and DesRoches et al. (2010) associates computerized decision support with improved quality in a national cross-section. However, these estimates will not capture the impact of IT adoption if early adopters differ from other hospitals along other quality-enhancing dimensions.

Two studies have used 4-year hospital panels to study healthcare IT (Parente and McCullough, 2009; McCullough et al., 2010). Since a typical EMRs implementation takes 2 years, these studies found it hard to find precise measures of outcomes. Perhaps because of this short time frame they also, unlike this study, did not find any evidence of other forms of healthcare IT (such as digitized archival systems) improving outcomes. They did, however, find some hopeful correlations between EMRs adoption and improvements in process measures for pneumonia care and lower rates of medical infection. By contrast, Agha (2010), found no precise effect from healthcare IT on outcomes for Medicare inpatients. Jones et al. (2010) hypothesized that their mixed results associating EMRs with various hospital quality measures may be caused by the limitations of those measures, especially ceiling effects.

Relative to the existing literature, our study has several practical advantages for the analysis of quality impacts of healthcare IT. First, the population for the at-risk sample is clearly and objectively defined based on live births and data available for the full population at risk. This is unlike hospital admissions data, which is conditional on an adverse health event that leads to the visit and may be affected by healthcare IT. Second, our sample is not limited to patients with a particular type of insurance coverage. Third, we have a very large sample size of about 4 million births per year, which is necessary to detect effects for rare events. Fourth, we have an unusually rich amount of information about demographic, health and specific pregnancy risk factors, including medical history, that can be included as controls. Using our geographic unit of analysis, we can also control for insurance coverage and income, and our hospital data allows us to control for other technology or quality factors that might be correlated with IT adoption. Fifth, we study an outcome that is a commonly-used measure for assessing the quality of a nation's healthcare system and is important in its own right. Finally, this is the first paper that uses instrumental variables to address the potential endogeneity of IT adoption. Instead of cataloguing associations between IT adoption and all available measures of quality, we focus on a particular measure of quality where the benefits may be important, even from simple IT systems. We also provide evidence in our exploration of heterogeneity that the effects are not present for cases where IT should not be expected to matter (for deaths from congenital anomalies or women without prenatal information), and we also find larger effects for disadvantaged populations.

In sum, this paper offers evidence that suggests cautious optimism about the potential value of healthcare IT and EMRs in improving neonatal health outcomes and current health policy that is directed towards increasing the spread of these technologies.

2 Data

2.1 Childbirth and Infant Mortality Data

Our primary health data are derived from administrative records of births and deaths in the US during the period 1995-2006. The Center for Disease Control (CDC) and Prevention's National Center for Health Statistics (NCHS) receives this data as electronic files, prepared from individual records processed by each registration area, through the Vital Statistics

Cooperative Program. These cover the universe of birth and death certificates for the continental US. Our primary outcome of interest is the neonatal death rate, defined as the number of deaths within 28 days per thousand live births. We also examine infant mortality within the first day and first week of life, as well as the rates of stillbirth and maternal death.

We use the confidential version of the linked birth and death certificate dataset, which allows us to match individual births and deaths occurring in the US and to identify the state and county for all observations.[2] Because we study hospital technology adoption, we limit the sample to records stemming from births that took place in a hospital. In the US, childbirth itself occurs almost exclusively in hospitals. Across the sample period, the rate of hospital birth for all women was consistently over 98%. The confidential geographic data also enable us to include smaller and less urban counties with fewer hospitals in the analysis.[3]

The analysis that follows primarily employs an aggregated county-year level of analysis. This is because the smallest geographic area identified in the national birth certificate data is the county. In a robustness test, we limit the sample to counties where there was a single hospital providing obstetric care. For that sample, any births that took place in a hospital in a particular country would have taken place in a single identifiable hospital with a specific IT regime.

Table 1 displays the county-year average rates of neonatal mortality (measured as deaths per 1,000 live births) for the sample of births used in the main analysis for 1995-2006. The average value of 5.21 deaths per 1,000 live births is higher than the national rate of 4.58 deaths because of elevated mortality rates in less populated counties with fewer births.

The Vital Statistics data contain a rich set of information regarding live births and deaths, including maternal and pregnancy characteristics, that we include as controls in our anal-

[2] We coded independent cities in the state of Virginia as part of their adjacent counties.

[3] The 2007 working paper version of this paper finds similar effects of EMRs adoption on neonatal mortality rates using publicly available birth and death data up to 2004. Privacy concerns limit geographic information in those files and county identification is available only for counties of 100,000 or larger until 2004. Starting in 2005, all county-level information is purged from the public use files.

ysis. We also supplement this individual information with data from the annual American Hospital Association Surveys that provide information on hospital resources, including size and NICU status, as well as patient insurance coverage, that are lacking in Vital Statistics birth certificates data. We control for changes in income at the state level using Gross State Product statistics from the US Bureau of Economic Analysis Regional Accounts data. We control for changes in county income levels using the average payroll wages per birth event as recorded by the Census's County Business Patterns for that year.

2.2 Healthcare IT Data

We use technology data from the 2007 release of the Healthcare Information and Management Systems Society (HIMSS) Analytics^{TM} Database (HADB). This describes hospital technology adoption decisions up to 2006, which is the year the survey was conducted.

We focus on the adoption of Electronic Medical Records (EMRs) by hospitals. These are the backbone software system that allows healthcare providers to store and exchange patient health information electronically. Clinical benefits from a basic EMRs system would mainly flow from the improved data repository and access to relevant patient information. As discussed in detail in section 3.3, better flow of timely information can be especially important for childbirth and neonatal outcomes. Hospital EMRs are potentially particularly important for women who fall into a high-risk category, and consequently see high-risk perinatologists in specialized maternal-fetal medicine departments within hospitals. These high-risk cases account for more than 70 percent of fetal and neonatal deaths (Smulian et al., 2002). Nielson et al. (2000) describes how electronic medical records can be used in such cases to track and improve antepartum, intrapartum and postpartum care.

The HADB database covers the majority of US hospitals, including about 90 percent of non-profit, 90 percent of for-profit, and 50 percent of government-owned (non-federal) hospitals. However, it excludes hospitals that have fewer than 100 beds and are not members

Table 1: Summary Statistics for Full Sample

Dependent Measures	Mean	Std Dev
Neonatal Death Rate	5.21	47.0
Death Rate 7 Days	4.39	44.0
Death Rate 1st Day	3.19	37.4
Stillborn Rate	1.23	21.5
Maternal Death Rate	0.016	0.11
Death Rate for No Prenatal Care	12.0	62.9
Death Rate for Premature	19.3	64.7
Death Rate from SIDS or Accidents	0.11	5.77
Death Rate from Congenital	0.72	10.7
Death Rate from Perinatal Complications	3.99	43.3
Premature Birth Rate	100.2	135.1
IT Measures	**Mean**	**Std Dev**
EMR Adoption	0.10	0.28
EMR+OB IT Adoption	0.018	0.12
Advanced EMR Adoption	0.011	0.092
Maternal Controls	**Mean**	**Std Dev**
Mother Black	0.095	0.20
Mother White	0.66	0.40
Mother Teenager	0.13	0.13
Mother >40 yrs	0.071	0.23
Mother College Graduate	0.13	0.13
Mother High School Graduate	0.63	0.32
Married Mother	0.52	0.28
Hospital Controls	**Mean**	**Std Dev**
Staffed Beds	125.4	135.7
Admissions (000)	4.90	6.40
Inpatient Days (000)	28.1	35.9
Medicare Inpatient Days (000)	12.6	16.5
Medicaid Inpatient Days (000)	5.97	9.46
Births per hospital	621.9	921.1
Total Operations (000)	3.93	5.22
No. Doctors	9.05	28.7
No. Nurses	142.7	205.1
No. Trainees	7.93	39.2
Non-Medical Staff	415.4	555.0
PPO	0.59	0.46
HMO	0.45	0.47
System Member	0.38	0.45
NICU	0.17	0.34
GSP (000,000)	31914.1	5015.5
County Payroll per Birth (000)	8.13	44.9
Medical Risk Controls	**Mean**	**Std Dev**
Vaginal Birth	0.66	0.29
Forceps	0.017	0.034
Vacuum	0.046	0.059
Induction of labor	0.17	0.14
Stimulation of labor	0.12	0.13
Multiple Birth	0.017	0.036
Anemia	0.020	0.058
Maternal Cardiac issues	0.0028	0.014
Acute or Chronic Lung Disease	0.0062	0.024
Maternal Diabetes	0.024	0.042
Genital Herpes	0.0056	0.016
Hydramnios/Oligohydramnios	0.0080	0.019
Maternal Hemoglobinopathy	0.00046	0.0069
Chronic Hypertension	0.0071	0.024
Pregnancy Associated Hypertension	0.037	0.048
Pre-Eclampsia	0.0028	0.015
Incompetent cervix	0.0016	0.011
Previous infant 4000+ Grams	0.010	0.028
Previous Preterm or Underweight	0.014	0.047
Renal disease	0.0023	0.014
Rh sensitization	0.0062	0.029
Uterine bleeding	0.0054	0.030
Other Medical Risk Factors	0.13	0.17
Observations	30300	

Death and premature birth rates are measured as per thousand live births.

of healthcare systems. We merge the HADB with annual American Hospital Association (AHA) survey data to collect information about the services available at the hospital, as well as costs and staffing. We limit our hospital sample to those providing some obstetric care that did not open or shut during the 12 year panel, which leaves us with 3,764 hospitals in 2006.

Hospitals are coded as having an EMRs system in the calendar year after the system is expected to be fully installed and operational, or 2 years after their initial contract date with that IT vendor. This is based on 2007 HADB survey data for 144 hospitals that suggests that on average implementation occurs 2.03 years after the initial contract date. For hospitals that report having multiple healthcare IT systems in place, but with missing data on the contract year for one component, we assigned the contract year for the missing component to match the most recent contract year in the data. By the end of our sample, 1,430 HADB hospitals have an enterprise-wide EMRs system, which is about 38 percent of the hospitals. Adoption rates are far lower for EMRs and obstetric IT (539) and advanced EMRs (366). In our fixed effect framework, the impact of IT adoption is identified for hospitals who expanded their IT during the sample period: 1,301 hospitals for basic EMR, 534 for obstetric IT and 363 for advanced EMR.

We aggregate the hospital-level data into a county-level panel on IT adoption by computing the share of deliveries in that county that took place in hospitals with healthcare IT. We compute this by taking the average value of our hospital adoption variables, weighting by the number of births reported in the AHA data for that hospital. We use the median instead of annual number of births to create a measure of IT availability that is not affected by patients endogenously choosing to switch hospitals because of healthcare IT. For counties with a single hospital that provides obstetric care, this average is an indicator for IT adoption at that hospital. These data are then linked to the county-year level aggregated birth and death certificates. Table 1 also provides summary statistics that cover this IT data.

3 Results from Panel Data with Fixed Effects

3.1 Effects of EMRs Adoption on Neonatal Mortality

In order to estimate the impact of healthcare IT adoption on county-level neonatal death rates, we begin with a panel data framework. We control for multiple maternal characteristics and pregnancy risk factors included in the birth certificate data, as well as county and hospital characteristics. Notwithstanding the richness of our dataset, it is possible that unobserved factors that affect neonatal health are varying between counties or over time. Hence, in all of our estimation, we employ a full set of county fixed effects to absorb cross-sectional differences and year fixed effects for non-linear national trends in mortality rates not directly associated with electronic medical records. In all of the tables, robust standard errors are reported, clustered at the county-level. This allows for arbitrary within-county correlation in errors, but assumes that the errors are independent across counties. The main estimates are reported for a balanced panel of 30,300 observations of 2,525 counties over 12 years.

Table 2 reports the results for adoption of Electronic Medical Records and neonatal mortality rates, measured as deaths per 1,000 live births. There is a negative association between increased EMR adoption and neonatal death, which is statistically significant across all specifications. The first column reports estimates from the fixed effects model with no additional controls. Column 2 adds controls for county-level average maternal background variables, showing an increased mortality for white mothers relative to non-white (Asian) mothers that is further elevated for black mothers. The increased mortality associated with teenage mothers is greater than that associated with mothers above the age of forty. Maternal education, measured by college completion, and marriage are both associated with lower death rates, but these relationships are not statistically significant at conventional levels. The next two columns add controls for hospital and pregnancy characteristics in turn. Higher (non-medical) staffing is associated with lower mortality, as is membership

Table 2: EMRs Adoption and Neonatal Mortality

	All Counties				Single Hospital counties
	(1)	(2)	(3)	(4)	(5)
	All	All	All	All	All
EMR Adoption	-2.406***	-2.661***	-2.669***	-2.581***	-3.415**
	(0.865)	(0.864)	(0.956)	(0.899)	(1.359)
Mother Black		20.06**	13.89	1.904	0.234
		(9.293)	(9.330)	(9.972)	(11.68)
Mother White		10.77***	8.208***	1.425	-1.668
		(3.034)	(2.859)	(3.016)	(3.623)
Mother Teenager		20.60*	18.06*	10.16	17.92
		(10.62)	(10.76)	(11.00)	(12.88)
Mother >40 yrs		3.055	2.053	0.131	2.809
		(2.392)	(2.443)	(2.460)	(2.981)
College Graduate		-11.33	-8.751	-4.079	-4.620
		(7.914)	(8.229)	(8.303)	(10.21)
Mother High School Graduate		10.18	6.994	-2.739	9.679
		(7.509)	(7.540)	(8.060)	(8.839)
Married Mother		-6.016	-8.843	-16.64**	-14.80*
		(7.256)	(7.321)	(7.887)	(8.738)
Staffed Beds			0.00360	0.00242	-0.000707
			(0.00647)	(0.00661)	(0.0143)
Admissions (000)			-0.115	-0.101	-0.252
			(0.132)	(0.140)	(0.336)
Inpatient Days (000)			0.0351	0.0366	0.0702
			(0.0228)	(0.0240)	(0.0463)
Medicare Inpatient Days (000)			-0.0132	-0.0240	0.00585
			(0.0193)	(0.0218)	(0.0368)
Medicaid Inpatient Days (000)			0.0164	-0.00776	0.0192
			(0.0285)	(0.0257)	(0.0416)
Births per hospital			-0.000226	-0.000553	-0.00241
			(0.000391)	(0.000605)	(0.00229)
Total Operations (000)			-0.0427	-0.0182	-0.0395
			(0.0403)	(0.0461)	(0.111)
No. Doctors			-0.00210	-0.00162	-0.00433
			(0.00222)	(0.00282)	(0.00795)
No. Nurses			-0.000905	-0.00100	0.00164
			(0.00250)	(0.00261)	(0.00538)
No. Trainees			-0.000587	0.00240	0.0172
			(0.00365)	(0.00421)	(0.0144)
Non-Medical Staff			-0.00140*	-0.000831	-0.00172
			(0.000722)	(0.000779)	(0.00214)
PPO			-0.231	-0.388	-0.401
			(0.654)	(0.635)	(0.786)
HMO			0.498	0.595	0.850
			(0.837)	(0.773)	(0.997)
System Member			-1.143**	-0.940*	-1.030
			(0.567)	(0.566)	(0.779)
NICU			-1.058	-0.715	-1.509
			(1.169)	(0.713)	(1.374)
GSP (000,000)			-0.0000789	-0.0000414	0.000147
			(0.000307)	(0.000291)	(0.000449)
County Payroll per Birth (000)			0.139***	0.112***	0.150***
			(0.0370)	(0.0358)	(0.0493)
Vaginal Birth				22.01***	9.344
				(7.008)	(7.584)
Induction of labor				-10.63***	-12.36**
				(4.021)	(5.197)
Stimulation of labor				-12.47***	-10.33*
				(4.688)	(5.994)
Multiple Birth				115.8**	154.7**
				(48.30)	(67.63)
County and Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Other Risk Factors	No	No	No	Yes	Yes
Observations	30300	30300	30300	30300	17862
R-Squared	0.0999	0.112	0.121	0.153	0.156

Ordinary Least Squares (OLS). Dependent variable is number of neonatal deaths per 1000 live births. Robust standard errors clustered at the county level. * $p < 0.10$, ** $p < 0.05$,*** $p < 0.01$.

in a multi-hospital system. Unassisted vaginal delivery rates are associated with higher infant mortality, though deliveries with forceps or vacuum extraction are not (coefficients not reported), and artificially induced or stimulated labor rates are associated with lower mortality. The most significant single predictor of neonatal death rates in our model is the rate of multiple births (twins or higher), which has a coefficient of over 100. Other risk factors reported on the birth certificate and included in the model for Column 4 are: anemia, cardiac disease, lung disease, hydramnios/oligohydramnios, hypertension, pre-eclampsia, diabetes, genital herpes, hemoglobinopathy, incompetent cervix, previous infant 4000 grams or larger, previous infant preterm or small for gestation age, renal disease, Rh sensitization, uterine bleeding and other medical risks. With the exception of anemia and lung disease, both of which are associated with lower neonatal mortality rates, these additional risk factors are not individually statistically significant. The coefficients are omitted from the table for readability.

Although there is some variation in the exact point estimate for EMRs adoption across the columns, there is no systematic pattern to the direction of the change (some controls increase it while others decrease it), and the changes are small. The magnitude of the estimates, ranging from -2.4 to -2.7, imply that a 10 percent increase in the share of births occurring in hospitals with EMRs in place would lead to a decline in neonatal mortality of about 26 deaths per 100,000 live births. This is a substantial effect, on the scale of about 5 percent of neonatal mortality during the sample period (521 deaths per 100,000 live births).

The steps taken to protect patients' privacy in the birth certificate database make it impossible for us to the match all births with particular hospitals or IT systems, which may produce measurement error for IT exposure. However, for a subset of counties in the AHA data, there is only one hospital providing obstetric care. In those cases, our EMRs adoption variable should apply equally to all births. Column 5 of Table 2 reports estimates from the model with the full set of fixed effects and controls (also used in Column 4) on the sub-sample of 17,862 observations from single-hospital counties. Again, EMRs adoption is associated with large declines in mortality. The point estimate of -3.4 is somewhat larger, which may reflect improved measurement of IT adoption or larger gains for women living in counties with more limited medical resources.

We also checked the robustness of our results to alternative dependent measures. These are reported in Table A-1 in the appendix. The results suggest that EMRs adoption is associated with relative declines in mortality within the first week and first day of life. The magnitudes of these effects suggest that the majority of the gains in neonatal survival are due to improved outcomes within the first seven days after birth. This pattern of the largest gains occurring soon after the time of birth is consistent with medical care at the hospital playing an important role in the observed variation in health outcomes. We also find a decline in the stillbirth rate (measured as a share of live births). This suggests that the analysis of neonatal mortality, which is conditional on having a live birth, may understate the gains from healthcare IT. This is especially true if the marginal infants who are born alive because of healthcare IT are at an elevated mortality risk within their first month of life. We looked at the association between EMRs adoption and maternal mortality. We were unable to estimate a precise relationship, perhaps because maternal death is exceptionally rare: the average county-level maternal death rate in our sample, reported in Table 1, is fewer than 4 deaths per 100,000 live births. We found that EMRs adoption was not systematically related to the rate of preterm births (with gestation periods shorter than 37 weeks). This is consistent with the medical literature. Although prematurity is a key risk factor for our mortality outcomes, surprisingly little is known about its causes and prevention. This lack of medical knowledge means that healthcare IT has a limited potential to affect premature birth rates (Behrman and Butler, 2007).

3.2 Analysis of Alternative Technologies

In this section, we estimate the impact of different forms of hospital IT on neonatal mortality. In Table 3, we estimate the model with the complete set of fixed effects and controls using our two alternative measure of healthcare IT adoption. The results in Table 2 consider a hospital to have EMRs if they have installed any Enterprise EMRs system, including those only capable of the most basic data storage and retrieval functions. As highlighted by Jha et al. (2009) and DesRoches et al. (2010), and reflected in the "meaningful use" criteria developed by the Office of the National Coordinator for Health Information Technology, simply having a basic EMRs system is not likely to produce a comprehensive transition to an entirely digital workflow if other pieces of healthcare information are still in paper form. Therefore, we also study what happens when this 'barebones' EMRs system is combined with two other classes of technologies: obstetric data systems, and technologies that increase the digitization of clinical decision making.

The essential IT components to ensure that obstetric data is digitized include a radiology information system for managing ultrasound images and a dedicated obstetrics information system. Ultrasound images allow healthcare providers to observe a fetus in the mother's womb safely and detect potential risk factors or concerns before the birth. Radiology Information Systems are general IT systems that allow hospital radiology departments to store and transfer these images electronically. Obstetrics Information Systems are the information systems designed to record data that are specific to the practice of obstetrics. In addition to storing fetal ultrasound data, these systems often have components that automatically record fetal heart rates and how they respond to maternal contractions during labor. In Column 1, we test the prediction that having a designated obstetric IT system to collect and manage obstetric information on top of an EMRs foundation will lead to larger benefits than EMRs alone. We find a coefficient of -5 in Column 1 for a combined EMRs and obstetric IT system, which represents a substantially larger mortality drop than the estimate of -2.6 for any EMRs system. This is consistent with our hypothesis that the information management features of EMRs would be most important when there is more specifically obstetric clinical information available in digital form.

In addition to these specifically obstetric IT developments, there have also been further developments more generally in healthcare IT devoted to streamlining and managing the way that healthcare providers interact with digital data. These include computerized practitioner order entry, clinical data repositaries, clinical decision making support software, and systems designed to digitize physician documentation. We designate EMRs with these enhancements as 'advanced EMR.' In 2006, the advanced EMRs adoption rate is under 6 percent for our sample. Therefore our definition is still less restrictive than the 'comprehensive' electronic-records system concept used by Jha et al. (2009), who report only 1.5 percent of hospitals having such a system in place by 2008. These advanced features are especially important for standardizing care, managing drug prescriptions for patients with multiple conditions and preventing medical errors. Column 2 reports the estimate for adoption of EMRs that include advanced features. The coefficient of -4 is again larger in absolute value than that for basic EMRs, which suggests that these additional features have a role in improving health outcomes. However, this need not be the case if the advanced EMRs are also better in their basic features, which would be the case if systems with many add-ons also had better user interfaces or were more stable.

In the third column of the table, we report estimates from a single model that includes all three measures of healthcare IT adoption. The -1.6 estimate for EMRs adoption should be interpreted as the effect of a basic system alone. This is lower than in Table 2, suggesting that some of its measured effect of EMRs reflected complementary IT improvements. However, the effect is still economically significant since it suggests that a 10 percent increase in births at hospitals with a basic EMRs in place would lead to a decline in neonatal mortality of about 16 deaths per 100,000 live births. This corresponds to about 3 percent of the mean

Table 3: Alternative Measures of Health IT

	(1) Neonatal Death Rate	(2) Neonatal Death Rate	(3) Neonatal Death Rate
EMR Adoption			-1.592**
			(0.683)
EMR+OB IT Adoption	-5.037**		-3.562*
	(2.138)		(1.952)
Advanced EMR Adoption		-3.958**	-1.250
		(1.913)	(1.839)
County Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Hospital controls	Yes	Yes	Yes
Maternal Controls	Yes	Yes	Yes
Medical Controls	Yes	Yes	Yes
Observations	30300	30300	30300
R-Squared	0.153	0.153	0.153

Ordinary Least Squares. Dependent variable as noted. All controls from Column 4, Table 2 included but not reported to improve readability. Robust standard errors clustered at the county level. * $p < 0.10$, ** $p < 0.05$,*** $p < 0.01$.

and 0.3 percent of the standard deviation of neonatal mortality in our sample.

The negative coefficients for EMRs plus obstetric IT and Advanced EMRs represent additional incremental gains for additional IT investments beyond basic EMR. Although the EMRs plus obstetric IT coefficient is significant at the 10 percent level, the estimate for Advanced EMRs is not. Unfortunately, the large standard errors likely result from low adoption rates of advanced EMRs in our sample, preventing a more definitive interpretation.[4]

3.3 Analysis by Cause of Death and Falsification Checks

In this section, we explore variation in the effects of healthcare IT adoption on mortality rates based on medical factors associated with the birth or death. Specifically, we investigate whether EMRs adoption is indeed associated with declines in mortality for causes of death where technology should have a role, but not for other types of death. Each column of the table reports separate estimates relating EMRs adoption to deaths from different underlying

[4]Estimates for these two types of information technology advances that echo subsequent analysis in the paper are available from the authors. In general they echo closely the patterns exhibited by basic EMRs.

causes.

The first column of Table 4 reports estimates for "Certain conditions originating in the perinatal period." For many of these conditions, medical experts prescribe the need for careful monitoring of patients, consistent record-keeping and frequent ultrasounds. These include pre-eclampsia (Walker, 2000), vasa previa (Oyelese et al., 1999), and other problems with the umbilical cord and placenta, like placenta previa, placental abruption, and abnormal cord insertions or lengths (Chou et al., 2000). Easy access to accurate records of estimated fetal weight can help to diagnose conditions such as IUGR (restricted growth) (Ott, 2002). Similarly, diseases of the placenta such as twin-to-twin transfusion syndrome, which is fatal in 90 percent of cases without treatment prior to birth require careful weekly monitoring for signs of advancing fluid discordancy, abnormal dopplers, and renal failure (Quintero, 2003). For mono-amniotic twins (who share a sac), access to a complete series of records documenting evidence of cord entanglement is essential for the most expeditious timing of delivery (Allen et al., 2001). As expected, we find that EMRs adoption is associated with a significant declines in neonatal mortality from perinatal complications (coefficient of -1.7, significant at the 5% level)

In the second column, we also investigate how EMRs affect deaths that result from prematurity. "Prematurity" is somewhat analogous to the euphemism "heart failure" used to describe a range of conditions that might lead a heart to stop for adults. This was documented by Lynch et al. (2007), who found in a small study of twin death certificates in Colorado that "In all of the cases of neonatal death that we attributed to cervical incompetence, placenta previa, placental abruption, preterm premature rupture of the membranes, or preterm labor by our review, the death certificate listed prematurity as the cause of death." Therefore, given its overlap with conditions evolving in the perinatal period, it is not surprising that we find a similarly large and negative effect of EMRs adoption (coefficient of -2.8, significant at the 5% level).

We then turn, in the spirit of a falsification check, to look at causes of death where medical intervention or easy access to documentation are unlikely to change the outcome. These include deaths due to "Congenital malformations, deformations and chromosomal abnormalities" and deaths due to accidents or SIDS. If we are simply picking up differences in the accuracy of birth certificates or similar unobserved heterogeneity associated with technology adoption, then these types of deaths would be similarly affected. In both cases these have smaller estimates that are not statistically significant.

In a similar spirit, the final two columns of Table 4 show results from falsification tests using death rates for neonates that are unlikely to be affected by hospital IT adoption. The dependent variable in Column 5 is the neonatal mortality rate for deaths that occurred outside of a hospital. These deaths are more likely to occur later in the neonatal period and less likely to be associated with healthcare IT at the hospital. The small, positive and statistically insignificant coefficient estimate implies no relationship between EMRs adoption and deaths outside of the hospital. This is reassuring that there was no general trend in parental out-of-hospital behavior that was correlated with hospitals adopting healthcare IT that can explain our finding.

The estimate for EMRs adoption is similarly positive and insignificant for the second falsification check reported in Column 7. Here we limit the samples of births (in the denominator) and deaths (numerator) to the sub-sample of women whose birth certificates do not report them as having received prenatal care at any point during their pregnancies. This sample is likely to suffer negative selection as the subset of women who seek no prenatal care are likely to less diligent about their medical care in other ways and may be more likely to engage in risky behaviors during pregnancy or have worse access to medical facilities which perhaps explains the high mortality rate for infants born after pregnancies with no prenatal care (12 deaths per 1000 births, compared to 5 deaths per 1000 births in the total population). This is also not a pure test, since it is possible that IT adoption increases hospital efficiency and reduces waiting times for admission. However, that channel seems at best secondary. The primary benefits of improved record-keeping and monitoring of pregnancy will not apply to these selected women. For women with no prenatal care, we find no evidence of health improvements associated with healthcare IT adoption, in the form of basic EMRs or more advanced technologies. The point estimates are positive and statistically insignificant. These results suggest that the gains from IT adoption are limited to women who received some prenatal care, and hence had medical records created prior to their hospital admissions for labor and delivery.

Table 4: EMRs Adoption and Mortality by Condition

	Cause of Death				Falsification	
	(1)	(2)	(3)	(4)	(5)	(6)
	Perinatal Complications	Prematurity	Congenital	SIDS+Accident	Not Hospital Death	No Prenatal Care
EMR Adoption	-1.734**	-2.821**	-0.239	-0.155	0.0102	2.008
	(0.799)	(1.368)	(0.195)	(0.171)	(0.140)	(2.603)
County and Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Medical Controls	Yes	Yes	Yes	Yes	Yes	Yes
Hospital controls	Yes	Yes	Yes	Yes	Yes	Yes
Maternal Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	30300	30300	30300	30300	30300	21055
R-Squared	0.154	0.148	0.0874	0.0860	0.0947	0.225

Ordinary Least Squares. Dependent variable as noted. All controls from Column 4, Table 2 included but not reported to improve readability. Robust standard errors clustered at the county level. * $p < 0.10$, ** $p < 0.05$,*** $p < 0.01$.

4 Endogenous Technology Adoption

4.1 Identification using Privacy Laws

In Section 3, the impact of healthcare IT on mortality rates is identified using county and year fixed effects to isolate within-county variation over time and controls for a rich set of observable variables that could be correlated with IT adoption and mortality rates. Although the decision of a hospital to invest in healthcare IT is clearly not taken at random, it is not obvious in what direction this selection might bias the initial panel estimates. The OLS estimates may overstate the benefits from IT adoption, for example, if the counties with increasing healthcare IT adoption have populations that are becoming more health-conscious. These individuals may come to value technology investment at hospitals and also be more diligent with their nutrition and health behaviors during pregnancy. Alternatively, the fixed-effects estimates may understate the value of healthcare IT if hospitals tend to invest in more computer technology when they expect an increase in the complexity of their case-mix and health risks of their patients.

In this section, we address the identification challenge by exploiting variation in state regulation designed to protect the privacy of patient data. This identification strategy builds on Miller and Tucker (2009a) who document empirically that hospitals are less likely to convert to electronic records if they are located in a state that has enacted a privacy rule for hospital use of health information.

States enact health privacy rules to address patients' concerns about the handling of their sensitive medical information. The enactment of these laws reflect growing patient concerns about their medical privacy. Westin (2005) found that 69% of survey respondents stating that they are very concerned or somewhat concerned that digital health records may lead to "more sharing of your medical information without your knowledge" and 65% of respondents were concerned that digital health records would make it more likely that others would not disclose sensitive but necessary information to doctors and other healthcare providers because of worries that it would go into computerized records.

However, this well-intentioned regulation also imposes burdens on hospitals that wish to use electronic medical data. The regulation imposes substantial costs, since hospitals have to develop or purchase new software and specialized filters to comply with it, as well as establishing protocols for authorization and limits on permitted data distribution. In a recent survey conducted by the American Hospital Association (released in May 2009 and described by Miller and Tucker (2009b)), 48 percent of hospitals reported that the risk of improper disclosure of medical information was an impediment to EMRs adoption. The laws are also particularly onerous for hospitals that wish to share electronic data. These data exchanges occur between healthcare providers for patient transfers and new admissions and between hospitals and insurance companies for billing In the May 2009 AHA survey, 56% of hospitals with EMRs in place report sharing data with other hospitals in their hospital system and 18% share information with other hospitals outside their system. The increased regulatory burden associated with information exchange may eliminate what would otherwise be a relative advantage of electronic records, the ability to transfer information quickly and cheaply.

Our initial source of information on state privacy regulation over time is a series of surveys of health privacy statutes produced by the Health Privacy Project at Georgetown University: Pritts et al. (2002), Pritts et al. (1999) and Gostin et al. (1996). They classify state privacy laws by examining state statutes governing medical privacy. Their approach excludes refinements to privacy law stemming from case law or administrative law. Following the effective compliance date for the federal Privacy Rule component of the Health Insurance Portability and Accountability Act (HIPAA) in April 2003, all healthcare providers are subject to a common minimum standard for privacy and security of health information. We do not exploit variation from the enactment of HIPAA since it is national in scope and is

Table 5: Instrumental Variables Summary Statistics

	Mean	Std Dev
Any Disclosure Rule	0.73	0.44
Limits on Redisclosure	0.20	0.40
Any Exceptions to Disclosure	0.35	0.48
Exception for Audits	0.13	0.34
Exception for Quality	0.15	0.36
Patient Access Right	0.69	0.46
Disclosure Rule for HMOs	0.67	0.47
HMO Disclosure and PPO	0.40	0.47
Insurance Disclosure and PPO	0.20	0.39
Insurance Disclosure and HMO	0.16	0.35
Special Rules for HMOs	0.47	0.50
Disclosure Rule for non-HMO Hospitals	0.24	0.43
Any Disclosure and Admissions (000)	3.62	6.02
Any Disclosure and Hospitals in Area	1.35	2.70
Disclosure and Hospital System Member	0.085	0.26
Observations	30300	

therefore absorbed into the year fixed effects. However, federal law provides only a binding floor. The state variation that we exploit in this paper derives from changes in privacy protection above and beyond federal rules. Building on the three snapshots provided in the Health Privacy Project surveys, we used Lexis-Nexis to track the date of enactment of each law and its content.

The privacy regulations vary in how much they limit the disclosure of medical information and the range of covered organizations. To distinguish between the substantial variations in the strength and content of these laws across states, we constructed a state panel regulatory database that includes a variety of privacy rule components and each component's effective date. There was considerable change in the laws in the period we study. For example, 11 states enacted rules requiring patient authorization before the disclosure of personal medical information during the 12-year period.

Table 5 summarizes these variables in our county-year panel. Rules that limit disclosure of patient data are the most common state requirement (73%). These are followed by patient access rules (69% of observations) which give patients the right to access their own medical records. We also account for the presence of statutory exceptions to disclosure limits (for any reason, for audits or for quality assessments), as these may lessen the impact of disclosure limits. We interact the presence of disclosure rules (that may hamper information exchange) with three variables aimed at capturing the latent value to the hospital of exchanging patient information. The first interaction is with size (measured by the number of staffed beds). This captures how size mediates the effect of disclosure laws. For example, hospitals that offer many services within their organization are less likely to value ease of obtaining data from other healthcare entities (Miller and Tucker, 2009b), and consequently may find disclosure laws less off-putting. The second interaction is with the number of other hospitals in the county. This reflects how the scope of potential healthcare organizations the hospital could obtain patient data from affects hospitals responses to disclosure laws. The main effect of number of hospitals is captured in the county fixed effect as we only include hospitals that did not close or open in the period in our data. The third interaction is an interaction with system membership, based on our expectation that disclosure rules have a smaller effect on members of multi-hospital systems if they are still able to exchange information internally. The hospital-level variables are aggregated to the county-level using the same weighting scheme, based on share of births, described above for the technology variables. These variable constitute our core set of instruments for the analysis that follows.

These disclosure laws also vary with respect to patients' insurance status. To reflect this we constructed variables that are indicators for rules that apply to HMOs, to non-HMO hospitals or to insurance companies, as well as interactions between these scope variables and relevant information about the hospital's insurance contracts from the AHA data. For example, HMO disclosure rules are expected to have a smaller impact on non-HMO hospitals (with PPO contracts) and insurance disclosure rules can affect all hospitals but may have a smaller deterrence effect on HMO hospitals that are vertically integrated with their insurance companies. Since these are primarily to do with the exchange of data between a hospital and insurance carriers, we expect that these aspects of policy regime will affect hospital EMRs adoption decisions less directly, so we exclude them from the core set of instruments.

However, repeating the estimating including these extra instruments does not change the results and marginally increases precision.

Table 6: First Stage Results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	EMR Adoption			EMR+OB IT Adoption			Advanced EMR Adoption		
Any Disclosure Rule	-0.0505***	-0.0394***	-0.108***	-0.0193***	-0.0149**	-0.0465***	-0.0152***	-0.00590	-0.0117
	(0.0110)	(0.0128)	(0.0318)	(0.00592)	(0.00628)	(0.0171)	(0.00447)	(0.00442)	(0.0147)
Any Disclosure and Admissions (000)	0.0128***	0.0127***	0.0127***	0.00627***	0.00622***	0.00614***	0.00383***	0.00377***	0.00369***
	(0.00144)	(0.00145)	(0.00146)	(0.000882)	(0.000892)	(0.000898)	(0.000601)	(0.000608)	(0.000616)
Any Disclosure and Hospitals in Area	-0.00279**	-0.00266**	-0.00259**	-0.000869	-0.000881	-0.00110	-0.000799*	-0.000742*	-0.000827*
	(0.00132)	(0.00128)	(0.00128)	(0.000598)	(0.000603)	(0.000679)	(0.000458)	(0.000442)	(0.000472)
Disclosure and Hospital System Member	0.0100	0.00828	0.00471	-0.0103	-0.0107	-0.0161*	-0.00954	-0.00889	-0.0107
	(0.0138)	(0.0140)	(0.0145)	(0.00778)	(0.00784)	(0.00839)	(0.00698)	(0.00711)	(0.00746)
Patient Access Right		-0.00507	-0.00569		-0.00416	-0.00664*		-0.00843***	-0.00923***
		(0.0100)	(0.0101)		(0.00407)	(0.00399)		(0.00246)	(0.00253)
Limits on Redisclosure		0.0469*	0.0386		-0.00397	-0.000801		-0.00177	0.00132
		(0.0268)	(0.0242)		(0.00831)	(0.00884)		(0.00640)	(0.00667)
Any Exceptions to Disclosure		-0.00824	0.0124		0.00204	-0.0113		-0.00683	-0.0156
		(0.0202)	(0.0258)		(0.0110)	(0.0122)		(0.00432)	(0.00984)
Exception for Audits		0.0157	0.0184		-0.000427	0.00884		0.00416	0.00803
		(0.0189)	(0.0207)		(0.0103)	(0.00935)		(0.00582)	(0.00578)
Exception for Quality		-0.0164	-0.0397		-0.0110	-0.0000339		-0.00573	0.00441
		(0.0187)	(0.0249)		(0.0105)	(0.0119)		(0.00542)	(0.0104)
Disclosure Rule for HMOs			0.0312			0.0282**			0.00987
			(0.0219)			(0.0127)			(0.0101)
HMO Disclosure and PPO			0.0165**			0.00772*			0.00479*
			(0.00816)			(0.00434)			(0.00252)
Insurance Disclosure and PPO			-0.0124			-0.00337			-0.00555
			(0.0123)			(0.00567)			(0.00405)
Insurance Disclosure and HMO			0.0148			0.0135**			0.00675*
			(0.0116)			(0.00574)			(0.00372)
Special Rules for HMOs			0.0356			-0.00165			-0.00848
			(0.0245)			(0.0103)			(0.0103)
Disclosure Rule for non-HMO Hospitals			-0.0108			0.0454*			0.0219
			(0.0377)			(0.0241)			(0.0157)
County Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	30300	30300	30300	30300	30300	30300	30300	30300	30300
R-Squared	0.160	0.161	0.162	0.0854	0.0858	0.0883	0.0561	0.0574	0.0581

Ordinary Least Squares. Dependent variable is the birth-weighted proportion of hospitals who have adopted that type of technology. Robust standard errors clustered at the county level. $p < 0.10$, ** $p < 0.05$,*** $p < 0.01$.

To be successful instruments the enactment of these privacy laws must not be be related in unobserved ways to neo-natal outcomes. Generally, hospitals in states with no disclosure laws do tend to have smaller staffs with fewer beds and operations though are otherwise similar. Coverage of these laws is geographically dispersed, and each of the nine census divisions includes at least one state with and one without a disclosure law. One lingering concern is that the enactment of these laws is endogenous to other forces within the state which may also be associated with improved neo-natal outcomes. For example, it would be problematic if these laws reflected to a greater attention to healthcare issues in that state by policy-makers in the state that led to other unobserved policies which improved healthcare outcomes. However, regressions reported in Miller and Tucker (2009a) suggest that these laws do not reflect any political tendencies within the state. This is because the laws could be prompted either by more left-wing concerns about insurance companies and employers gaining access to private medical data or by more right-wing concerns relating to distrust of surveillance.

Table 6 reports how these different aspects of privacy protection related to hospital technology adoption for each of our measures of healthcare IT. For each technology, we first report results for a limited set of privacy variables linked solely to the disclosure law, followed by results using our core set of privacy variables that excludes rules related to insurance status, and, last, results using the full set of privacy variables that includes rules connected to insurance status.

The largest single predictor of EMRs adoption among the full set of instrumental variables is the presence of a rule limiting the disclosure of patient information, with a coefficient ranging from -0.11 to -0.04 (in Columns 1 to 3, significant at the 1 percent level). This makes sense because this is a type of privacy safeguard which intentionally tries to prevent the type of easy flow of patient information that the digitization of health records is meant to promote. There is also evidence in Columns 1 to 3 of significant variation in the impact of disclosure rules by hospital size and competition. For the typical county in our sample, the combined effects of these three variables in Column 3 imply a reduction in EMRs use of 5% associated with any disclosure rule. This pattern is confirmed in separate estimation of simplified models with only the disclosure rule instrument (and no interactions). The impact of the law is negative and significant for counties with 4 or more hospitals but positive and insignificant for those with 3 or fewer hospitals. In areas where information sharing is less important, the net effect of privacy rules may be to make EMRs more useful. There is also some evidence that the scope of the rule matters in the fact that rules limited to HMOs have a 1.6% smaller impact on adoption when the hospital is not an HMO. The signs on the patient access right and insurance disclosure interaction with HMO status are consistent with our predictions, but not statistically significant in the EMRs model.

The next six columns report estimates for adoption of EMRs with obstetric IT and advanced EMRs using the full and more parsimonious sets of privacy instrumental variables in turn. The set of privacy law variables has a strong predictive value for each of the technologies, and F-tests on their joint significance consistently and strongly reject zero (see Column 1 in Tables 7). Nevertheless, it is important to note that the predictive value (measured by R-squared, for example) of the instruments is strongest for basic EMRs adoption and is weaker for EMRs combined with obstetric IT or with decision support and computerized ordering capabilities. This is consistent with privacy laws mattering most for the exchange of information between hospitals (or between hospitals and other entities), rather than the flow of information within hospitals. Since obstetric information is rarely shared electronically between providers, choices regarding this additional feature are less likely to be affected by the regulations we study. Similarly, the decision to adopt advanced systems designed to digitize workflow, such as clinical decision support software, is less likely to be affected by restrictions on patient data disclosure. For this reason, the IV analysis that follows will focus on the results for basic EMRs adoption.[5]

4.2 Main Results from Instrumental Variables Estimation

The results in this section use the variation in privacy laws described in Section 4.1 to instrument for potentially endogenous technology adoption. County fixed effects are included in all regressions to account for permanent local characteristics, such as the technological sophistication of patients or stable traits of local hospitals. We also include the full set of controls from Column 4 of Table 2 as well as a full set of year fixed effects.

Column 1 of Table 7 reports our main IV estimate for the overall impact of EMRs adoption on neonatal mortality. As in the OLS model in Table 2, the estimate is negative and statistically significant, indicating that EMRs adoption reduces infant deaths. However, relative to the OLS estimate, there is a substantial increase in the magnitudes of the main coefficient of interest as well as its associated standard error. The larger estimate in the IV model may be the result of an upward bias in the OLS model, where hospitals adopt EMRs as they specialize in more complicated cases and consequently experience higher mortality rates. It may also be the result of heterogeneous effects of EMRs adoption on health outcomes. Specifically, the larger estimates may be caused by the *local* average treatment effect of EMRs adoption being largest for hospitals whose adoption is most influenced by the privacy regime in place. The IV point estimate of -43.4 and standard error of 18.65 imply that the 95 percent confidence interval for a 10 percent increase in healthcare IT would be a reduction of between 7 and 80 neonatal deaths per 100,000 live births. This wide range includes effects that are very large and one should be cautious about using the exact IV point estimate for predictions outside the sample. Nevertheless, the IV estimate provides strong support for the main OLS finding that EMRs adoption can improve neonatal health outcomes.

[5] The full set of instrumental variable results for the alternative technologies are available from the authors.

Table 7: Instrumental Variables Results

	All	Cause of Death				Falsification	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	All	Perinatal Complications	Prematurity	Congenital	SIDS+Accident	Not Hospital Death	No Prenatal Care
EMR Adoption	-43.38**	-27.70*	-31.09	-0.788	-5.331	-0.0567	-23.72
	(18.65)	(15.50)	(20.94)	(2.956)	(5.324)	(1.785)	(34.95)
County and Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Medical Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hospital controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Maternal Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	30300	30300	30300	30300	30300	30300	19200
ID stat	37.49	37.49	37.49	37.49	37.49	37.49	24.47
ID P-value	0.0000215	0.0000215	0.0000215	0.0000215	0.0000215	0.0000215	0.00362
OverID Test	8.453	6.189	11.95	7.016	1.543	5.895	10.25
OverID P-value	0.390	0.626	0.153	0.535	0.992	0.659	0.248

Instrumental Variable Results. Dependent variable is as shown. Robust standard errors clustered at the county level. * $p < 0.10$, ** $p < 0.05$,*** $p < 0.01$.

The remaining columns in Table 7 repeat the investigation into how EMRs affect different causes of neonatal death and various falsification checks, described for the basic panel model in Section 3.3. Although the instrumental variables estimates are less precise, the effects of EMRs adoption are again largest for the causes of death most likely related to healthcare IT, perinatal complications (Column 2, significant at the 10 percent level) and prematurity (Column 3). The estimates are smaller and less statistically significant for other causes less directly related to hospital care, such as congenital and chromosomal defects (Column 4) and SIDS and accidents (Column 5). Similarly, there is no measured effect of healthcare IT on neonatal mortality outside of the hospital (Column 6) or to women with no prenatal care (Column 7).[6] These results provide additional support for the validity of the estimation approach taken in this paper, and suggest that the mechanisms of primary importance are related to hospital care and management of information that is revealed during the prenatal period.

In each of the IV tables, the P-value from an F-test on the joint significance of the instruments is reported beneath the coefficient estimates. For each of the technologies, a zero effect of the privacy laws is strongly rejected, indicating that the instruments satisfy the first necessary condition for validity. We also test the over-identification restrictions implied by using multiple instruments for a single endogenous regressor and report the Hansen J-statistic and its associated P-value in the tables. These tests consistently fail to reject the null hypothesis that the instruments are valid, under the assumption that at least one is exogenous.

Though these over-identification tests are reassuring, we ran further checks to ensure that the span of the instruments is not driving the effect. In Appendix Table A-2, we explore the separate contributions of different subsets of the privacy law instruments for estimation

[6] In the companion estimates for more advanced forms of IT, the estimates for deaths outside of the hospital and no prenatal care remain statistically insignificant, and the coefficient for no prenatal care reverses in sign.

relative to the estimates for our core instruments reported in Column 1 of Table 7. Though sometimes insignificant the sign is always in the expected direction. We also show that this result is not driven by ignoring important variation in the indirect effects from insurance privacy laws.[7]

4.3 Healthcare IT and Health Disparities

In addition to having relatively high rates of neonatal mortality, the US also has large disparities in mortality between different types of mothers. Babies born to black mothers are twice as likely to die within their first 28 days of life than as born to white mothers (MacDorman and Mathews, 2008). Death rates are also higher for infants born to unmarried and less educated mothers. In this section, we explore the implications of healthcare IT for disparities by education, marital status, race and ethnicity.

It is not obvious *a priori* whether healthcare IT would favor women whose socioeconomic backgrounds are relatively advantaged or disadvantaged. On the one hand, technological innovation in healthcare has often disproportionately benefited those with higher education and more resources (Glied and Lleras-Muney, 2008). On the other hand, the relatively elevated mortality rates for disadvantaged groups imply a larger potential role for improvement from IT adoption.

Furthermore, if some of the disparities in health outcomes result from differences in the treatment behavior of physicians and other healthcare providers (rather than differences in population health behaviors or geographic availability of medical resources), then healthcare IT can play an additional role in reducing disparities by standardizing care and ensuring that best practices are pursued in all cases. For example, Hamvas et al. (1996) finds that the diffusion of surfactant therapy to treat premature infants with respiratory distress syndrome

[7] In a separate regression, we also confirm the negative IV estimate using only the privacy law instrument (with no interactions) on the sample of counties with more than 3 hospitals, where privacy laws alone were significant in the first stage. The estimate is -4.7 with a standard error of 3.9.

Table 8: Inequality: Instrumenting for Electronic Medical Records Adoption

	(1) High School Dropout	(2) College Graduate	(3) Unmarried	(4) Married	(5) Black	(6) Hispanic	(7) White
EMR Adoption	-39.38*	1.427	-57.01**	5.852	-137.8**	-23.29	-13.52
	(21.37)	(7.679)	(27.84)	(7.346)	(57.13)	(15.95)	(18.74)
County and Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Medical Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hospital controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Maternal Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	24397	22996	24907	24428	17301	21641	27704
ID stat	22.77	19.86	23.00	23.13	23.05	21.20	36.56
ID P-value	0.00674	0.0188	0.00619	0.00590	0.00608	0.0118	0.0000316
OverID Test	7.679	12.00	7.103	11.18	5.927	13.84	5.459
OverID P-value	0.465	0.151	0.526	0.192	0.655	0.0860	0.708

Instrumental Variable Results. Dependent variable is number of neonatal deaths per 1000 live births, for that demographic group. All controls from Column 4, Table 2 included but not reported to improve readability. Robust standard errors clustered at the county level. * $p < 0.10$, ** $p < 0.05$,*** $p < 0.01$.

improved survival rates for low-birthweight white infants but not for black infants. If such treatment were standardized across races, there might be further improvements in death rates. There are also concerns that physicians and other practitioners may provider better medial care to richer white and non-Hispanic patients. This contention is supported in a randomized experiment conducted by Schulman et al. (1999) that finds racial differences in health care treatment.[8] This suggests that clinical uncertainty combined with physician discretion may lead to variation in treatment decisions that harms certain populations. To the extent the healthcare IT systems reduce this variation, they may improve outcomes for black and Hispanic mothers more than for whites. Previous studies of other technological innovations (such as the spread of NICUs) on infant mortality have found an important role for medical advances in reducing deaths overall, but a general failure to reduce socioeconomic disparities (Gortmaker and Wise, 1997).

The results in Table 8 show which groups of mothers are most affected by technology adoption. Each column presents estimates for the impact of EMRs adoption on different

[8]They hired actors to portray patients with different characteristics of chest pain. Doctors were asked to diagnose and recommend treatment. Women and Blacks were less likely to be referred for cardiac catheterization.

sub-samples of births and deaths in which the mother belongs to the group listed above the estimate. Counties in which there were no births for that sub-sample of mothers are naturally excluded, leading to varying sample sizes that are lower than the full 30,300.

We start by comparing outcomes by maternal education. Column 1 reports an estimate of -39 for low-education mothers with less than a high school degree reported on their babies' birth certificates. These women represent about 22 percent of the sample and have a slightly elevated neonatal death rate compared to all births in the same subsample of county observations. This improvement associated with EMRs adoption, significant at the 10 percent level, is similar to the overall estimate for all births of -43 reported in Column 1 of Table 7. By contrast, the result in Column 2 shows a positive and insignificant estimate for women with college degrees. These women represent 10 percent of the sample and have similar neonatal mortality rates to average women in their same counties, though these counties have substantially lower rates than the rest of the country.

We find a similar pattern of EMRs having a potentially equalizing effect on health care quality in Columns 4 and 5, when we split the sample of births based on the mother's marital status, as reported on the birth certificate. The average county in our sample has nearly half of its infants born to unmarried mothers. Those infants face substantially higher neonatal death rates than infants born to married mothers. The estimated impact of EMRs adoption is -57 for unmarried women, substantially larger than the overall estimate. For married women, the estimate is positive and statistically insignificant for basic EMR.

In the remaining columns, we estimate different effects of EMRs adoption on neonatal mortality rates by maternal race and ethnicity. Columns 5 and 7 of Table 8 report the estimated effects of EMRs adoption on neonatal mortality for black and white mothers. The coefficient for Blacks is -138, which is more than three times the size of the overall estimate of -43 and ten times the size of the point estimate for whites of -13.5. The estimate for black mortality is statistically significant at the 5% level, while the estimate for whites is not statistically different from zero.

To interpret these differences, it is useful to note both the overall racial differences in neonatal mortality as well as the differences by cause of death. Average black neonatal mortality is 7.9, while the overall rate in counties with black births is 5.2. white mortality rates are 4.0, compared to 4.3 overall in counties with white births. Furthermore, MacDorman and Mathews (2008) indicate that the two categories with the most striking racial disparity are prematurity (short gestation) and maternal complications of pregnancy. This suggests that Blacks suffer three times as many neonatal deaths from maternal complications of pregnancy of the kind that may be improved by careful monitoring and sequential ultrasound records. The larger gains for Blacks from EMRs and obstetric IT are therefore consistent with the mechanisms proposed in the medical literature for how healthcare IT could improving infant outcomes.

The estimate for Hispanic mothers, reported in Column 6 of Table 8, is also substantially larger and more significant than those for Whites. Although not statistically significant, the larger estimate for Hispanics is suggestive of the potential for relative gains for another disadvantaged group.

What is interesting about Hispanic births in this context is that their mortality rates are actually lower than average. In counties with Hispanic births, the average neonatal death rate for Hispanics is 3.4, while the overall rate is 3.6. The fact that gains are present for this group with a relatively depressed health risk could be due to substantial heterogeneity within the Hispanic group (for example, death rates are higher for Puerto Rican infants but lower for Mexican and Cuban Americans). It could also be that Hispanics more often face linguistic barriers to obtaining high-quality medical care, and difficulty in ensuring the accuracy and completeness of their paper records. In that case, there may be an especially important role for healthcare IT for that population.

Overall, the IV results in this section suggest a potential benefit from EMRs adoption in standardizing care across patients and reducing some disparities in health outcomes. We should note, however, that the OLS point estimates for separate demographic subgroups tend to be smaller than IV estimates and are not always statistically significant. The relative magnitudes of the OLS and IV estimates are the same for groups defined by education and marital status. For race and ethnicity, the OLS estimates are statistically identical for Whites and Blacks, both of which are larger than for Hispanics. This means that the result that EMRs reduce racial as well as educational disparities, rests on the plausibility of the instrumental variable strategy. Taken together, these results show no evidence that EMRs increase socioeconomic disparities in infant mortality.

5 Cost-Effectiveness

In this section, we compare the estimated health benefits associated with healthcare IT to the costs of adopting and maintaining EMRs. These back-of-the-envelope calculations are by no means definitive, as they rely on simplifying assumptions and predictions about impacts outside of the observed data. We are also deliberately conservative. We focus on the lower estimates for basic EMRs adoption, and use the lower coefficients from the OLS panel.

Using the OLS coefficient presented in Column 3 of Table 3 that captures purely the effect of EMRs rather than complementary technologies, we are able to make some rough calculations for the number of babies that could be saved by widespread diffusion of healthcare IT. The estimated impact of basic EMRs adoption is a reduction of 1.6 deaths per 1000 live births. This implies that a complete national transition from paper to computer records could save as many as 6,400 infants per year in the US, out of about 4 million births.

The costs of adopting healthcare IT include the upfront costs of software and hardware installation, training of medical and support staff, and ongoing maintenance. The pricing scheme for EMRs is complicated by the initial upfront costs being subsidized by vendors who expect to recover these subsidies through high support fees. Laflamme et al. (2010) puts the installation costs for EMRs at \$80,000 to \$100,000 per bed for the required project planning, software, hardware, implementation and training. For operating costs, the median amount per bed was \$12,060 (AHA, 2007). Over a 5-year time-horizon, with a 5 percent discount rate this would translate to roughly a cost of \$150,000 or an annualized cost of \$30,000 per bed. This translates to annual costs of \$3.75 million for an average hospital in our data that has 125 beds. Of course not all these beds are devoted to patients who give birth. According to the 2004 National Hospital Discharge Survey published by the National Center for Disease Control and Prevention, 12.1% of all discharges were women who had delivered babies. If this discharge rate is reflected in the number of beds allocated to maternity beds, then this roughly suggests that hospitals are spending \$454,000 a year on EMRs for maternity beds. These cost estimates can be scaled nationally by multiplying by 944,277, the total number of staffed hospital beds in the US, leading to a total cost of \$3.4 billion. Combining the two estimates yields a cost-effectiveness calculation that each infant life saved by spending on EMRs costs about \$531,000. This is likely to be a lower bound on the benefits of EMRs spending. It does not capture improvements in neonatal morbidity. There may also be administrative cost savings if healthcare IT allows hospitals to streamline their record-keeping or reduce duplicate testing. It is, however, possible that improved diagnosis and identification of risk factors from healthcare IT leads to some increased spending on health services, such as costly transfers to neonatal intensive care units.

These costs per baby saved are substantially lower than the costs of Medicaid expansions estimated in Currie and Gruber (1997). The targeted changes were more cost-effective, but still cost \$840,000 per infant life saved (over \$1.1 million, after adjusting for inflation). Our estimates are also marginally lower than the local cost estimates of saving a baby near the very low birthweight threshold of \$550,000, reported in Almond et al. (2010) using the treatment discontinuity created by the threshold. By comparison, the median estimated value attributed to a statistical life was about \$7 million in 2000 dollars (Viscusi and Aldy, 2003). The Office of Management and Budget endorses values between \$1 million and \$10 million for a statistical life (Circular A-4, issued on September 17, 2003) in cost-benefit evaluations of regulation required by Executive Order 12866. This suggests that investing in healthcare IT may be a relatively cost-effective way of improving neonatal health outcomes.

6 Conclusion

The US has one of the highest infant mortality rates among developed nations, despite the largest per-capita expenditures on healthcare. One potential explanation for this disparity is that coordination efforts by centralized health authorities have led to a more systematized approach to the adoption of health care IT in other comparable industrialized nations. Electronic medical records (EMRs) and other healthcare IT improvements offer a potential way to reduce this death rate, by improving access to patient records, standardizing treatment options and improving monitoring. We explore empirically whether EMRs improve neonatal outcomes in a panel setting. We also use variation in state privacy laws that impose costs on using and acquiring patient data as an exogenous source of variation in order to identify a causal relationship.

Our panel estimates suggest that a 10 percent increase in the adoption of basic EMRs can reduce infant mortality by 16 deaths per 100,000 live births. We also find that the drop in neonatal deaths is driven by a reduction in deaths from diseases originating in the perinatal period. These conditions require careful monitoring and may be improved by increased access to data. We find no effect on deaths due to either SIDS or chromosomal abnormalities - both conditions for which there is less established evidence about how to use process-based medicine to prevent adverse outcomes. We find further evidence that healthcare IT adoption has the most beneficial effects for birth outcomes for historically disadvantaged groups and there is no evidence that the gains to EMRs are focused on women from higher socio-economic backgrounds. Rough cost-effectiveness calculations suggest that healthcare IT is associated with a cost of $531,000 per infant saved. These findings provide an empirical basis for government policy intervention to hasten the diffusion of healthcare IT.

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Table A-1: Alternative Dependent Variables

	(1) Death Rate 7 Days	(2) Death Rate 1st Day	(3) Stillborn Rate	(4) Maternal Death Rate	(5) Premature Birth Rate
EMR Adoption	-2.250***	-1.702**	-0.808**	0.00458	0.518
	(0.798)	(0.663)	(0.336)	(0.00944)	(2.714)
County Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Hospital controls	Yes	Yes	Yes	Yes	Yes
Maternal Controls	Yes	Yes	Yes	Yes	Yes
Medical Controls	Yes	Yes	Yes	Yes	Yes
Observations	30300	30300	30300	20200	30300
R-Squared	0.151	0.142	0.101	0.225	0.366

Ordinary Least Squares. Dependent variable as noted. All controls from Column 4, Table 2 included but not reported to improve readability. There are no observations for maternal deaths after 2002 because of a change in the way they were recorded by the CDC. Robust standard errors clustered at the county level. * $p < 0.10$, ** $p < 0.05$,*** $p < 0.01$.
Data on maternal mortality rates from the compressed mortality data from the CDC by underlying cause of death, county and year. Unfortunately for this analysis, and unlike for neonatal deaths, the definition of maternal deaths are less clear-cut and have been inconsistent over time. Improvements in recording maternal deaths on standard death certificates starting in 2003 are cited as a cause of increased official statistics for maternal mortality in the US (Hoyert, 2007). Since these changes did not affect all states equally, and there is no obvious correction available, we limit our analysis of maternal mortality to 2002 and earlier and present the exploratory estimates as a supplement to our main analysis of neonates.

Table A-2: Estimation Using Different Sets of Privacy Law Instruments

	Additional Insurance IV (1) Neonatal Death Rate	Disclosure Rule (2) Neonatal Death Rate	Exceptions (3) Neonatal Death Rate
EMR Adoption	-31.93**	-29.61**	-90.09
	(14.42)	(14.16)	(70.21)
County and Year Fixed Effects	Yes	Yes	Yes
Medical Controls	Yes	Yes	Yes
Hospital controls	Yes	Yes	Yes
Maternal Controls	Yes	Yes	Yes
Observations	30300	30300	30300
ID stat	50.74	27.94	4.305
ID P-value	0.00000912	0.0000128	0.230
OverID Test	17.00	4.905	4.314
OverID P-value	0.256	0.179	0.116

Instrumental Variable Results. Dependent variable as noted. All controls from Column 4, Table 2 included but not reported to improve readability. Robust standard errors clustered at the county level. Column 1 uses the full set from Column 1 of Table 6. Column 2 uses disclosure laws and interactions with the exogenous hospital characteristics (size, number of local hospitals, and system membership). Column 3 uses exceptions to disclosure laws (any, for audits and for quality). * $p < 0.10$, ** $p < 0.05$,*** $p < 0.01$.

Online Appendix for 'Can Healthcare IT Save Babies?'

Amalia R. Miller* and Catherine E. Tucker‡

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Abstract

This electronic appendix provides details of additional empirical analysis. These include additional results for the more advanced forms of EMRs. They also include the results when we use the full set of instruments.

*University of Virginia, Charlottesville, VA and RAND Corporation, Arlington, VA.

†MIT Sloan School of Management, Cambridge, MA.

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Contents

1 Further Data Descriptives

This section presents additional tables of descriptive information.

Table 1: Summary Statistics by whether below or above median EMRs (which is zero)

	No EMR Mean	Std Dev	Some EMR Mean	Std Dev
Neonatal Death Rate	4.71	43.0	4.88	26.4
Death Rate 7 Days	3.85	39.3	4.14	26.4
Death Rate 1st Day	2.60	31.0	3.30	26.4
Stillborn Rate	0.89	13.6	0.88	1.20
Maternal Death Rate	0.013	0.10	0.044	0.13
Death Rate for No Prenatal Care	15.2	72.3	23.1	54.0
Death Rate for Premature	18.5	62.5	26.0	34.2
Death Rate from SIDS or Accidents	0.069	0.55	0.076	0.37
Death Rate from Congenital	0.68	7.99	0.84	1.07
Death Rate from Perinatal Complications	3.65	41.4	3.66	26.4
Premature Birth Rate	96.0	135.3	112.9	69.0
EMR Adoption	0	0	0.62	0.37
EMR+OB IT Adoption	0	0	0.041	0.18
Advanced EMR Adoption	0	0	0.020	0.12
Mother Black	0.099	0.21	0.14	0.18
Mother White	0.72	0.37	0.81	0.20
Mother Teenager	0.15	0.14	0.14	0.080
Mother >40 yrs	0.012	0.036	0.017	0.010
Mother College Graduate	0.12	0.12	0.20	0.12
Mother High School Graduate	0.63	0.32	0.77	0.16
Married Mother	0.53	0.29	0.64	0.15
Staffed Beds	113.6	123.4	246.0	173.7
Admissions (000)	4.15	5.50	10.7	8.38
Inpatient Days (000)	24.6	31.6	59.0	49.2
Medicare Inpatient Days (000)	11.0	14.6	26.5	21.3
Medicaid Inpatient Days (000)	5.28	8.69	11.0	13.0
Births per hospital	523.5	777.4	1419.9	1348.7
Total Operations (000)	3.33	4.62	8.39	6.66
No. Doctors	6.90	20.8	23.3	56.9
No. Nurses	117.9	169.3	307.9	279.6
No. Trainees	5.34	28.1	30.0	83.2
Non-Medical Staff	350.6	468.4	886.7	796.1
PPO	0.57	0.46	0.69	0.39
HMO	0.44	0.47	0.62	0.41
System Member	0.33	0.44	0.56	0.41
NICU	0.14	0.32	0.35	0.41
GSP (000,000)	30773.3	4489.2	31972.0	6028.4
County Payroll per Birth (000)	7.67	40.5	2.08	14.4
Vaginal Birth	0.68	0.30	0.75	0.11
Forceps	0.021	0.039	0.022	0.028
Vacuum	0.049	0.064	0.056	0.049
Induction of labor	0.16	0.14	0.22	0.11
Stimulation of labor	0.13	0.13	0.18	0.12
Multiple Birth	0.016	0.036	0.026	0.013
Anemia	0.022	0.062	0.024	0.043
Maternal Cardiac issues	0.0029	0.014	0.0055	0.0086
Acute or Chronic Lung Disease	0.0063	0.028	0.011	0.020
Maternal Diabetes	0.021	0.041	0.030	0.022
Genital Herpes	0.0057	0.015	0.0089	0.024
Hydramnios/Oligohydramnios	0.0082	0.020	0.013	0.013
Maternal Hemoglobinopathy	0.00039	0.0023	0.00078	0.0036
Chronic Hypertension	0.0061	0.019	0.0087	0.014
Pregnancy Associated Hypertension	0.037	0.048	0.043	0.024
Pre-Eclampsia	0.0030	0.015	0.0039	0.0072
Incompetent cervix	0.0015	0.0067	0.0025	0.0030
Previous infant 4000+ Grams	0.012	0.029	0.012	0.017
Previous Preterm or Underweight	0.015	0.052	0.014	0.014
Renal disease	0.0024	0.013	0.0026	0.0054
Rh sensitization	0.0064	0.029	0.0087	0.029
Uterine bleeding	0.0063	0.032	0.0059	0.024
Other Medical Risk Factors	0.13	0.16	0.18	0.14

Table 2: Summary Statistics by whether there is a disclosure rule or not

	No Disclosure Law		Disclosure Law	
	Mean	Std Dev	Mean	Std Dev
Neonatal Death Rate	4.82	43.7	4.69	40.8
Death Rate 7 Days	4.09	41.7	3.78	36.5
Death Rate 1st Day	3.05	37.0	2.48	27.1
Stillborn Rate	0.73	9.37	0.96	14.4
Maternal Death Rate	0.018	0.095	0.015	0.11
Death Rate for No Prenatal Care	16.0	74.2	15.8	69.1
Death Rate for Premature	18.0	61.4	19.8	60.1
Death Rate from SIDS or Accidents	0.055	0.39	0.077	0.59
Death Rate from Congenital	0.60	1.80	0.74	9.15
Death Rate from Perinatal Complications	3.94	43.7	3.52	38.4
Premature Birth Rate	103.3	145.5	94.9	122.9
EMR Adoption	0.045	0.18	0.064	0.23
EMR+OB IT Adoption	0.0049	0.062	0.0034	0.053
Advanced EMR Adoption	0.0015	0.034	0.0020	0.038
Mother Black	0.094	0.19	0.11	0.21
Mother White	0.72	0.37	0.73	0.36
Mother Teenager	0.15	0.15	0.14	0.13
Mother >40 yrs	0.012	0.035	0.013	0.034
Mother College Graduate	0.11	0.11	0.14	0.12
Mother High School Graduate	0.60	0.31	0.66	0.30
Married Mother	0.53	0.29	0.55	0.28
Staffed Beds	123.4	130.2	127.3	136.6
Admissions (000)	4.88	5.95	4.71	6.21
Inpatient Days (000)	26.2	32.4	28.6	36.3
Medicare Inpatient Days (000)	12.3	15.0	12.5	16.5
Medicaid Inpatient Days (000)	4.77	7.51	6.32	10.0
Births per hospital	642.5	897.3	591.3	881.6
Total Operations (000)	3.76	4.82	3.82	5.18
No. Doctors	7.08	18.3	9.07	29.9
No. Nurses	133.9	180.3	136.6	195.4
No. Trainees	6.76	30.8	8.08	40.4
Non-Medical Staff	393.7	500.9	404.4	545.7
PPO	0.59	0.45	0.58	0.46
HMO	0.48	0.46	0.44	0.47
System Member	0.36	0.43	0.35	0.44
NICU	0.18	0.34	0.15	0.33
GSP (000,000)	31249.7	5074.7	30714.4	4453.8
County Payroll per Birth (000)	8.78	43.9	6.37	36.2
Vaginal Birth	0.67	0.30	0.69	0.28
Forceps	0.022	0.041	0.020	0.037
Vacuum	0.046	0.061	0.051	0.063
Induction of labor	0.15	0.13	0.17	0.14
Stimulation of labor	0.13	0.13	0.14	0.13
Multiple Birth	0.017	0.044	0.016	0.030
Anemia	0.025	0.072	0.021	0.055
Maternal Cardiac issues	0.0027	0.015	0.0034	0.012
Acute or Chronic Lung Disease	0.0053	0.028	0.0074	0.027
Maternal Diabetes	0.021	0.046	0.022	0.037
Genital Herpes	0.0046	0.011	0.0067	0.018
Hydramnios/Oligohydramnios	0.0084	0.022	0.0087	0.018
Maternal Hemoglobinopathy	0.00025	0.0016	0.00050	0.0028
Chronic Hypertension	0.0057	0.017	0.0066	0.020
Pregnancy Associated Hypertension	0.037	0.049	0.037	0.045
Pre-Eclampsia	0.0034	0.015	0.0030	0.014
Incompetent cervix	0.0016	0.0095	0.0017	0.0043
Previous infant 4000+ Grams	0.010	0.025	0.012	0.029
Previous Preterm or Underweight	0.015	0.057	0.015	0.047
Renal disease	0.0022	0.012	0.0025	0.013
Rh sensitization	0.0068	0.033	0.0065	0.027
Uterine bleeding	0.0062	0.038	0.0064	0.027
Other Medical Risk Factors	0.14	0.17	0.13	0.16

Table 3: Components of 'Certain conditions originating in the perinatal period' used in analysis

Newborn affected by maternal factors and by complications of pregnancy, labor and delivery
Newborn affected by maternal hypertensive disorders
Newborn affected by other maternal conditions which may be unrelated to present pregnancy
Newborn affected by maternal complications of pregnancy
Newborn affected by incompetent cervix
Newborn affected by premature rupture of membranes
Newborn affected by multiple pregnancy
Newborn affected by other maternal complications of pregnancy
Newborn affected by complications of placenta, cord and membranes
Newborn affected by complications involving placenta
Newborn affected by complications involving cord
Newborn affected by chorioamnionitis
Newborn affected by other and unspecified abnormalities of membranes
Newborn affected by other complications of labor and delivery
Newborn affected by noxious influences transmitted via placenta or breast milk
Disorders related to length of gestation and fetal malnutrition
Slow fetal growth and fetal malnutrition
Disorders related to short gestation and low birthweight, not elsewhere classified
Extremely low birthweight or extreme immaturity
Other low birthweight or preterm
Disorders related to long gestation and high birthweight
Birth trauma
Intrauterine hypoxia and birth asphyxia
Intrauterine hypoxia
Birth asphyxia
Respiratory distress of newborn
Other respiratory conditions originating in the perinatal period
Congenital pneumonia
Neonatal aspiration syndromes
Interstitial emphysema and related conditions originating in the perinatal period
Pulmonary hemorrhage originating in the perinatal period
Chronic respiratory disease originating in the perinatal period
Atelectasis
All other respiratory conditions originating in the perinatal period
Infections specific to the perinatal period
Bacterial sepsis of newborn
Omphalitis of newborn with or without mild hemorrhage
All other infections specific to the perinatal period
Hemorrhagic and hematological disorders of newborn
Neonatal hemorrhage
Hemorrhagic disease of newborn
Hemolytic disease of newborn due to isoimmunization and other perinatal jaundice
Hematological disorders
Syndrome of infant of a diabetic mother and neonatal diabetes mellitus
Necrotizing enterocolitis of newborn
Hydrops fetalis not due to hemolytic disease
Other perinatal conditions

ICD-9 codes: 760-779; ICD-10 codes: P00-P9.

Table 4: Number of Changes for Each Law Used as Instrument

	No. of Changes
Right to Access	14
Any Disclosure	11
Other Hospital Disclosure	2
Limitations to Disclosure	3
Special Rules for HMOs	7
Any Exemptions	13
Exemptions for Audit	4
Exemption for Quality	8

Table 5: Alternative Dependent Variables: Obstetric IT and EMR

	(1) Death Rate 7 Days	(2) Death Rate 1st Day	(3) Stillborn Rate	(4) Maternal Death Rate	(5) Premature Birth Rate
EMR+OB IT Adoption	-4.157**	-2.907*	-0.554	-0.0219	1.106
	(1.852)	(1.534)	(0.447)	(0.0283)	(4.099)
County Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Hospital controls	Yes	Yes	Yes	Yes	Yes
Maternal Controls	Yes	Yes	Yes	Yes	Yes
Medical Controls	Yes	Yes	Yes	Yes	Yes
Observations	30300	30300	30300	20200	30300
R-Squared	0.151	0.142	0.101	0.225	0.366

Ordinary Least Squares. Dependent variable as noted. All controls from Column 4, Table 2 included but not reported to improve readability. There are no observations for maternal deaths after 2002 because of a change in the way they were recorded by the CDC. Robust standard errors clustered at the county level. * $p < 0.10$, ** $p < 0.05$,*** $p < 0.01$.

2 Alternative Technologies

This section presents results tables using alternative measures of health IT.

Table 6: Alternative Dependent Variables: Advanced EMR

	(1) Death Rate 7 Days	(2) Death Rate 1st Day	(3) Stillborn Rate	(4) Maternal Death Rate	(5) Premature Birth Rate
Advanced EMR Adoption	-3.625*	-2.687	-0.637	-0.0728*	-3.214
	(1.906)	(1.810)	(0.432)	(0.0426)	(4.585)
County Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Hospital controls	Yes	Yes	Yes	Yes	Yes
Maternal Controls	Yes	Yes	Yes	Yes	Yes
Medical Controls	Yes	Yes	Yes	Yes	Yes
Observations	30300	30300	30300	20200	30300
R-Squared	0.151	0.142	0.101	0.225	0.366

Ordinary Least Squares. Dependent variable as noted. All controls from Column 4, Table 2 included but not reported to improve readability. There are no observations for maternal deaths after 2002 because of a change in the way they were recorded by the CDC. Robust standard errors clustered at the county level. * $p < 0.10$, ** $p < 0.05$,*** $p < 0.01$.

Table 7: By Condition Panel Results for Obstetric IT and EMR

	Cause of Death				Falsification	
	(1)	(2)	(3)	(4)	(5)	(6)
	Perinatal Complications	Prematurity	Congenital	SIDS+Accident	Not Hospital Death	No Prenatal Care
EMR+OB IT Adoption	-3.926**	-5.808**	-0.261	-0.280	-0.0256	0.159
	(1.871)	(2.536)	(0.278)	(0.280)	(0.183)	(4.225)
County and Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Medical Controls	Yes	Yes	Yes	Yes	Yes	Yes
Hospital controls	Yes	Yes	Yes	Yes	Yes	Yes
Maternal Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	30300	30300	30300	30300	30300	21055
R-Squared	0.154	0.148	0.0874	0.0860	0.0947	0.225

Ordinary Least Squares. Dependent variable as noted. All controls from Column 4, Table 2 included but not reported to improve readability. Robust standard errors clustered at the county level. * $p < 0.10$, ** $p < 0.05$,*** $p < 0.01$.

Table 8: By Condition Panel Results for Advanced EMRs Technology

	Cause of Death				Falsification	
	(1)	(2)	(3)	(4)	(5)	(6)
	Perinatal Complications	Prematurity	Congenital	SIDS+Accident	Not Hospital Death	No Prenatal Care
Advanced EMR Adoption	-3.213*	-3.064	-0.292	-0.170	0.0789	2.703
	(1.889)	(1.865)	(0.286)	(0.255)	(0.138)	(2.579)
County and Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Medical Controls	Yes	Yes	Yes	Yes	Yes	Yes
Hospital controls	Yes	Yes	Yes	Yes	Yes	Yes
Maternal Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	30300	30300	30300	30300	30300	21055
R-Squared	0.154	0.148	0.0874	0.0860	0.0947	0.225

Ordinary Least Squares. Dependent variable as noted. All controls from Column 4, Table 2 included but not reported to improve readability. Robust standard errors clustered at the county level. * $p < 0.10$, ** $p < 0.05$,*** $p < 0.01$.

Table 9: Falsification and by Condition Instrumenting for Obstetric IT and EMR

	All	Cause of Death				Falsification	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	All	Perinatal Complications	Prematurity	Congenital	SIDS+Accident	Not Hospital Death	No Prenatal Care
EMR+OB IT Adoption	-55.27*	-33.23	-27.04	0.324	-8.372	-3.480	12.94
	(28.78)	(22.49)	(31.65)	(4.874)	(8.408)	(2.509)	(52.59)
County and Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Medical Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hospital controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Maternal Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	30300	30300	30300	30300	30300	30300	19200
ID stat	27.78	27.78	27.78	27.78	27.78	27.78	18.65
ID P-value	0.00104	0.00104	0.00104	0.00104	0.00104	0.00104	0.0283
OverID Test	10.72	7.408	12.01	6.608	1.919	6.221	10.57
OverID P-value	0.218	0.493	0.151	0.579	0.983	0.622	0.227

Instrumental Variable Results. Dependent variable as noted. All controls from Column 4, Table 2 included but not reported to improve readability. Robust standard errors clustered at the county level. * $p < 0.10$, ** $p < 0.05$,*** $p < 0.01$.

Table 10: Falsification and by Condition Instrumenting for Advanced EMR

	All	Cause of Death				Falsification	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	All	Perinatal Complications	Prematurity	Congenital	SIDS+Accident	Not Hospital Death	No Prenatal Care
Advanced EMR Adoption	-84.98*	-50.38	-98.70	-2.407	-11.80	-11.92	0.855
	(49.37)	(40.17)	(62.71)	(8.293)	(11.86)	(7.793)	(67.81)
County and Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Medical Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hospital controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Maternal Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	30300	30300	30300	30300	30300	30300	19200
ID stat	42.51	42.51	42.51	42.51	42.51	42.51	32.93
ID P-value	0.00000265	0.00000265	0.00000265	0.00000265	0.00000265	0.00000265	0.000137
OverID Test	10.36	7.942	11.50	7.581	2.290	5.398	10.56
OverID P-value	0.241	0.439	0.175	0.475	0.971	0.714	0.228

Instrumental Variable Results. Dependent variable as noted. All controls from Column 4, Table 2 included but not reported to improve readability. Robust standard errors clustered at the county level. * $p < 0.10$, ** $p < 0.05$,*** $p < 0.01$.

Table 11: Inequality: Instrumenting for Obstetric IT and EMR

	(1) High School Dropout	(2) College Graduate	(3) Unmarried	(4) Married	(5) Black	(6) Hispanic	(7) White
EMR+OB IT Adoption	-45.43	3.441	-69.90*	-6.821	-94.13	-64.75**	-22.13
	(29.27)	(12.87)	(39.76)	(10.42)	(111.6)	(32.85)	(57.59)
County and Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Medical Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hospital controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Maternal Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	24397	22996	24907	24428	17301	21641	27704
ID stat	21.61	20.51	22.83	22.65	12.61	19.70	26.40
ID P-value	0.0102	0.0150	0.00660	0.00704	0.181	0.0198	0.00175
OverID Test	9.365	11.78	9.047	10.93	11.90	9.977	5.578
OverID P-value	0.312	0.161	0.338	0.206	0.156	0.267	0.694

Instrumental Variable Results. Dependent variable as noted. All controls from Column 4, Table 2 included but not reported to improve readability. Robust standard errors clustered at the county level. * $p < 0.10$, ** $p < 0.05$,*** $p < 0.01$.

Table 12: Inequality: Instrumenting for Advanced EMRs Technology and EMR

	(1) High School Dropout	(2) College Graduate	(3) Unmarried	(4) Married	(5) Black	(6) Hispanic	(7) White
Advanced EMR Adoption	-57.94	9.773	-99.68*	7.042	-29.36	-82.62**	-59.64
	(45.54)	(22.81)	(57.84)	(18.11)	(102.0)	(41.42)	(73.67)
County and Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Medical Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hospital controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Maternal Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	24397	22996	24907	24428	17301	21641	27704
ID stat	34.40	33.54	36.41	36.06	26.26	33.76	36.47
ID P-value	0.0000761	0.000107	0.0000335	0.0000387	0.00185	0.0000984	0.0000327
OverID Test	9.457	11.95	9.206	10.98	12.57	8.317	4.518
OverID P-value	0.305	0.153	0.325	0.203	0.128	0.403	0.808

Instrumental Variable Results. Dependent variable as noted. All controls from Column 4, Table 2 included but not reported to improve readability. Robust standard errors clustered at the county level. * $p < 0.10$, ** $p < 0.05$,*** $p < 0.01$.

Table 13: By Condition: Instrumenting for EMRs with the Full Set of Instruments

	All	Cause of Death				Falsification	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	All	Perinatal Complications	Prematurity	Congenital	SIDS+Accident	Not Hospital Death	No Prenatal Care
EMR Adoption	-31.93**	-20.53*	-15.73	-0.836	-3.969	-0.182	-6.772
	(14.42)	(12.19)	(17.17)	(2.767)	(3.967)	(1.560)	(32.47)
County and Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Medical Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hospital controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Maternal Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	30300	30300	30300	30300	30300	30300	20901
ID stat	50.74	50.74	50.74	50.74	50.74	50.74	33.35
ID P-value	0.00000912	0.00000912	0.00000912	0.00000912	0.00000912	0.00000912	0.00420
OverID Test	17.00	13.13	20.06	9.267	2.582	9.376	20.95
OverID P-value	0.256	0.517	0.128	0.814	1.000	0.806	0.103

Instrumental Variable Results. Dependent variable as noted. All controls from Column 4, Table 2 included but not reported to improve readability. Robust standard errors clustered at the county level. * $p < 0.10$, ** $p < 0.05$,*** $p < 0.01$.

3 Full Set of Instruments

This section presents the results of instrumental variable estimation using the full set of privacy laws and interactions described in the text.

Table 14: By Condition: Instrumenting for OB IT and EMRs with the Full Set of Instruments

	All	Cause of Death				Falsification	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	All	Perinatal Complications	Prematurity	Congenital	SIDS+Accident	Not Hospital Death	No Prenatal Care
EMR+OB IT Adoption	-63.18**	-45.54*	-45.27	-1.967	-4.813	-3.372	71.08
	(27.88)	(24.02)	(32.24)	(5.023)	(4.807)	(2.602)	(54.62)
County and Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Medical Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hospital controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Maternal Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	30300	30300	30300	30300	30300	30300	20901
ID stat	41.26	41.26	41.26	41.26	41.26	41.26	24.75
ID P-value	0.000292	0.000292	0.000292	0.000292	0.000292	0.000292	0.0535
OverID Test	16.20	11.90	20.29	9.452	4.276	9.472	19.48
OverID P-value	0.301	0.614	0.121	0.801	0.994	0.800	0.147

Instrumental Variable Results. Dependent variable as noted. All controls from Column 4, Table 2 included but not reported to improve readability. Robust standard errors clustered at the county level. * $p < 0.10$, ** $p < 0.05$,*** $p < 0.01$.

Table 15: By Condition: Instrumenting for Advanced EMRs with the Full Set of Instruments

	All	Cause of Death				Falsification	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	All	Perinatal Complications	Prematurity	Congenital	SIDS+Accident	Not Hospital Death	No Prenatal Care
Advanced EMR Adoption	-98.08**	-64.04*	-93.05	-1.713	-10.04	-7.936	39.71
	(45.54)	(37.55)	(57.51)	(6.312)	(10.09)	(5.482)	(68.87)
County and Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Medical Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hospital controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Maternal Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	30300	30300	30300	30300	30300	30300	20901
ID stat	51.91	51.91	51.91	51.91	51.91	51.91	40.99
ID P-value	0.00000585	0.00000585	0.00000585	0.00000585	0.00000585	0.00000585	0.000321
OverID Test	15.26	11.87	19.04	10.44	3.639	7.989	20.95
OverID P-value	0.361	0.617	0.163	0.729	0.997	0.890	0.103

Instrumental Variable Results. Dependent variable as noted. All controls from Column 4, Table 2 included but not reported to improve readability. Robust standard errors clustered at the county level. * $p < 0.10$, ** $p < 0.05$,*** $p < 0.01$.

Table 16: Inequality: Instrumenting for EMRs with the Full Set of Instruments

	(1) High School Dropout	(2) College Graduate	(3) Unmarried	(4) Married	(5) Black	(6) Hispanic	(7) White
EMR Adoption	-30.19*	6.138	-35.89*	9.022	-73.50*	-14.80	-9.210
	(16.08)	(7.091)	(19.74)	(7.582)	(38.53)	(11.70)	(16.70)
County and Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Medical Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hospital controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Maternal Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	24397	22996	24907	24428	17301	21641	27704
ID stat	33.44	30.76	33.19	34.76	28.03	31.40	43.76
ID P-value	0.00408	0.00945	0.00441	0.00266	0.0214	0.00776	0.000120
OverID Test	11.08	18.64	11.22	17.32	14.53	17.54	12.50
OverID P-value	0.679	0.179	0.669	0.240	0.411	0.228	0.566

Instrumental Variable Results. Dependent variable as noted. All controls from Column 4, Table 2 included but not reported to improve readability. Robust standard errors clustered at the county level. * $p < 0.10$, ** $p < 0.05$,*** $p < 0.01$.

Table 17: Inequality: Instrumenting for OB IT and EMRs with the Full Set of Instruments

	(1) High School Dropout	(2) College Graduate	(3) Unmarried	(4) Married	(5) Black	(6) Hispanic	(7) White
EMR+OB IT Adoption	-46.51*	-0.698	-72.37**	-7.720	-80.26	-68.74**	-79.46*
	(26.52)	(13.19)	(35.14)	(15.60)	(77.07)	(33.40)	(46.51)
County and Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Medical Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hospital controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Maternal Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	24397	22996	24907	24428	17301	21641	27704
ID stat	28.82	27.14	29.92	30.06	17.36	26.36	34.51
ID P-value	0.0170	0.0276	0.0122	0.0117	0.298	0.0344	0.00289
OverID Test	11.81	19.05	10.60	18.16	18.65	11.37	10.37
OverID P-value	0.621	0.163	0.717	0.200	0.179	0.657	0.735

Instrumental Variable Results. Dependent variable as noted. All controls from Column 4, Table 2 included but not reported to improve readability. Robust standard errors clustered at the county level. * $p < 0.10$, ** $p < 0.05$,*** $p < 0.01$.

Table 18: Inequality: Instrumenting for Advanced EMRs with the Full Set of Instruments

	(1) High School Dropout	(2) College Graduate	(3) Unmarried	(4) Married	(5) Black	(6) Hispanic	(7) White
Advanced EMR Adoption	-74.73*	-0.0952	-104.3*	-0.995	-86.47	-90.24**	-38.08
	(44.72)	(22.00)	(55.48)	(19.79)	(94.90)	(44.14)	(61.40)
County and Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Medical Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hospital controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Maternal Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	24397	22996	24907	24428	17301	21641	27704
ID stat	41.07	41.24	43.92	42.77	32.68	40.05	42.06
ID P-value	0.000312	0.000294	0.000113	0.000171	0.00519	0.000445	0.000220
OverID Test	11.67	19.35	10.77	18.14	17.93	9.604	11.91
OverID P-value	0.633	0.152	0.704	0.201	0.210	0.791	0.613

Instrumental Variable Results. Dependent variable as noted. All controls from Column 4, Table 2 included but not reported to improve readability. Robust standard errors clustered at the county level. * $p < 0.10$, ** $p < 0.05$,*** $p < 0.01$.