

Provided by DSpace@MIT



MIT Sloan School of Management

MIT Sloan School Working Paper 4686-08 1/1/2008

Can Healthcare IT Save Babies?

Amalia R. Miller and Catherine E. Tucker

© 2008 Amalia R. Miller and Catherine E. Tucker

All rights reserved. Short sections of text, not to exceed two paragraphs, may be quoted without explicit permission, provided that full credit including © notice is given to the source.

This paper also can be downloaded without charge from the Social Science Research Network Electronic Paper Collection: http://ssrn.com/abstract=1089132

Can Healthcare IT Save Babies?

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

January 1, 2008

Abstract

The US has a higher infant mortality rate than most other developed nations. Electronic medical records (EMR) and other healthcare information technology (IT) improvements could reduce that rate, by standardizing treatment options and improving monitoring. We empirically quantify how healthcare IT improves neonatal outcomes. We identify this effect through variations in state medical privacy laws that distort the usefulness of healthcare IT. We find that adoption of healthcare IT by one additional hospital in a county reduces infant mortality in that county by 13 deaths per 100,000 live births. Rough cost-effectiveness calculations suggest that healthcare IT is associated with a cost of \$450,140 per infant saved.

^{*}Economics Department, University of Virginia, Charlottesville, VA

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

[‡]We thank HIMSS for providing the data used in this study and seminar participants at the University of Virginia and the NBER Health Care Meetings for helpful comments. All errors are our own.

1 Introduction

About four million babies are born in the United States each year. 6.9 out of every 1,000 of these babies die within the first year of life. This gives the US the second worst infant mortality rate in the developed world, after Latvia. For African-Americans, the mortality rate is twice the national rate, with 14.1 infant deaths per 1,000 births. Several European countries, along with Japan and South Korea, have low infant mortality rates and are also international leaders in the adoption of healthcare IT (Bristol (2005)). As pointed out by Wilson (2007), one of the reasons why 79% of Australian, 89% of British, and 98% of Dutch physicians use electronic medical records is because of substantial coordination and spending by centralized health administrations. The low 28% percent adoption rate of US physicians may therefore be partially explained by the fragmented nature of the healthcare system in the US and the lack of centralized coordination of standards and interoperability. In this paper, we assess whether increased use of healthcare IT in the US, replacing paper records with electronic records, can improve the country's grim infant mortality statistics.

The US Department of Health and Human Services has made the diffusion of healthcare IT a key policy because it believes that creating an electronic interface between patients and healthcare providers can improve healthcare quality. However, as of yet, there has been little empirical research to support its assumption. In this paper, we ask whether electronic medical records can improve neonatal mortality rates. This is an area of medicine where there is an established body of literature emphasizing the importance of careful monitoring and record-keeping for ensuring successful outcomes (Nielson, Thomson, Jackson, Kosman, and Kiley (2000)). It is precisely this accurate record keeping and automated monitoring that healthcare IT is designed to ensure.²

¹Save the Children Report, 2006. According to the CDC, the US was ranked 28th in the world for infant mortality in 1998. The year 2004 saw 4.1 million births and 28,000 infant deaths in the US.

²Bernstein, Farinelli, and Merkatz (2005) finds that electronic obstetric records improve communication among providers, by reducing the incidence of missing charts (16% for paper records and 2% for electronic).

Although there is a substantial body of research that explores what promotes technology diffusion among healthcare providers, there has been less research by economists into how technology affects health outcomes.³ Previous research that investigates the production function for neonatal health outcomes highlights the role of a variety of medical interventions. Examples include Harris (1982) on prenatal care, Miller (2006) on midwives, and Bitler and Currie (2005) and Walters (2007) on nutritional programs for pregnant women. When exploring technology's effect on neonatal outcomes, the focus has been on evaluating technologies specific to neonatology, such as neonatal intensive care units (NICUs) (Corman, Joyce, and Grossman (1987), Baker and Phibbs (2002)). By contrast, this paper explores a technology that is not designed specifically for neonatal outcomes. Rather, healthcare IT systematizes care throughout a hospital. Using the particular example of infant mortality, we can detect the presence of quality improvements that may extend to other health outcomes.

Our empirical work focuses on two major healthcare IT innovations for hospitals: Enterprise Electronic Medical Records (EMR) and Radiology Information Systems (RIS). EMR is a software system that allow hospitals to record and monitor a patient's progress electronically rather than using paper. This is useful for diagnosing conditions, such as pre-eclampsia, that require careful monitoring of expectant mothers' blood pressure. RIS is used by radiology departments to store, manipulate and distribute patient radiological data and imagery. This aids cross-ultrasound comparisons that allow the diagnosis and management of dangerous conditions in fetuses, such as hydrops.

First, we present results that show a negative association between county-level adoption of healthcare IT and neonatal deaths. We include county and year fixed effects, but it is

Missing charts can be especially detrimental when dealing with emergency labor and delivery situations. Section 3 discusses the channel for quality improvements in more detail.

³An important exception is Athey and Stern (2002)'s work on the effects of E911 adoption. Studies of the effects of IT adoption on productivity outside of healthcare include Brynjolfsson and Hitt (2003), Hubbard (2003), and Bartel, Ichniowski, and Shaw (2007). For examples of the health technology diffusion literature, see Baker and Phibbs (2002), Spetz and Baker (1999), Hill and Wolfe (1997), Baker (2001)), Acemoglu and Finkelstein (2006), Lenzo (2005), Hamilton and McManus (2005) and Schmidt-Dengler (2006).

still problematic to interpret this relationship causally if there are potentially unobserved and confounding changes in county or hospital characteristics over time. 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. 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.

To overcome these identification challenges, we exploit variations across states and across time in state health privacy laws that restrict the ability of hospitals to exchange patient information electronically and consequently reduce the attractiveness of healthcare IT. Building on work in Miller and Tucker (2007), we use variation in healthcare IT adoption, explained by the presence or absence of state privacy laws and the spillovers this has on regional health networks, to study the effect of healthcare IT on neonatal outcomes. When we use instrumental variables to identify causal relationships, we find that the effects of these technologies on neonatal outcomes are larger than the correlations would suggest.

Our results imply that EMR adoption by one additional hospital in a county reduces that county's annual neonatal mortality rate by 5 deaths per 100,000 live births, or a 1 percent reduction. RIS adoption reduces neonatal mortality by 8 deaths per 100,000 live births, or 0.6%. Increased adoption of each of these technologies between 1994 and 2004 can separately explain about 14% of the decline in infant deaths during the period. Rough cost-effectiveness calculations suggest that healthcare IT is associated with a cost of \$450,140 per infant saved.

To explore the mechanism that drives this effect, we also break down our analysis for counties that have higher and lower rates of ultrasound use during pregnancy. We find that RIS adoption matters more in counties with above-average ultrasound use, where medical records contain more radiology-based content. The estimated effect of RIS in such counties is an order of magnitude larger than it is in counties with below-average ultrasound use.

Finally, we build on research such as Currie and Gruber (1996b) and Currie and Gruber (2001) that explorers whether interventions (in their case an expansion of the Medicaid program) can reduce disparities in birth outcomes. When we allow the effects of healthcare IT to vary by race, we find significantly larger gains for African-Americans than for Whites, with gains for African-Americans being more than twice as large.

The paper is organized as follows. Section 2 sets out the data we use in this study. Section 3 outlines the medical basis for how healthcare IT can improve neonatal outcomes. Section 4 discusses how we exploit state variation in privacy regulation as an identification strategy. Section 5 reports our results, demonstrates their robustness and presents cost-effectiveness estimates. Section 6 investigates heterogenous effects. In Section 7, we discuss the implications of our findings.

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 1994-2004. We obtain maternal and pregnancy characteristics from birth certificate data, covering the universe of births registered in the US. The Center for Disease Control and Prevention's National Center for Health Statistics (NCHS) receives these data as electronic files, prepared from individual records processed by each registration area, through the Vital Statistics Cooperative Program.

Mortality data are obtained from CDC Compressed Mortality Files, representing the universe of death certificates for the continental US. We examine two types of mortality: neonatal death in the first month of life, and infant death that occurs within the first year.

Fetal deaths and maternal deaths are not studied.

The analysis that follows estimates the effect of local area IT adoption on childbirth outcomes, and employs an aggregated county-year level of analysis. Data from birth and death certificates are linked by county and year of occurrence. Since the healthcare IT data are for hospitals, we use the location of healthcare delivery or county of occurrence rather than the county of residence for mother and infant.⁴ Privacy concerns limit geographic information for both deaths and births, and identification is available only for counties and cities of 100,000 or larger. Births and deaths that take place in smaller counties are grouped together within each state. Since these counties may be geographically distant, and there is no natural way to link them to local hospital IT adoption, we limit our analysis to births and deaths with identified counties. This restriction means that our results should be interpreted strictly as applying to more densely populated areas and may not apply to rural areas.

The Vital Statistics data contain a rich set of information regarding live births and deaths, including maternal characteristics such as age. We supplement the dataset using a state-year level measure of Medicaid coverage rates for women aged 15 to 50 based on CPS March Supplement files.

Table 1 displays the overall rates of infant and neonatal mortality (measured as deaths per 1,000 live births) on the sample of counties used in the main analysis for 1989-2004. Our data cover the tail-end of a period when health outcomes for neonates and infants have shown dramatic improvement (Corman and Grossman (1985), Singh and Yu (1995)). Infant mortality, or deaths of babies under one year of age, dropped from 26.00 per 1,000 live births in 1960 to 6.9 per 1,000 live births in 2000.

⁴Among births for which we can identify both county of residence and county of occurrence, the two match in 87% of cases.

2.2 Healthcare IT Data

We use data from the 2005 release of the Healthcare Information and Management Systems Society (HIMSS) Dorenfest database. The 2004 release of this data has been used to study the diffusion of EMR technology in three RAND studies: Fonkych and Taylor (2005), Hillestad, Bigelow, Bower, Girosi, Meili, Scoville, and Taylor (2005) and Bower (2005).

We study two major and interlinked IT innovations. Enterprise Electronic Medical Records (EMR) is the backbone software system that allows healthcare providers to store and exchange patient health information information electronically. Radiology Information Systems (RIS) refers to IT systems that allow hospital radiology departments to store and transfer radiological data and images electronically. Though in this paper we focus on how these healthcare IT systems improve patient outcomes, there are other potential benefits for both EMR and RIS systems, such as lower administrative costs.

The HIMSS 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 of healthcare systems. Also, hospitals that were in operation during the sample period but that closed or merged before 2005 are not in the database. Ultimately, we have data on 4,010 hospitals across the nation. By 2005, 1,888 of those hospitals reported having an enterprise-wide EMR system and 3,106 reported having RIS. The effect of adoption is identified for hospitals who expanded their IT during the sample period between 1994 and 2004: 1,317 hospitals for EMR and 1,972 for RIS.⁵

We aggregate the hospital-level data into a county-level panel on IT adoption by summing the total number of hospitals with each technology by the end of the previous calendar year. This generates our primary variables of interest: CountyEMRAdoption and

⁵These values exclude hospitals who reported IT adoption dates before the sample period and those who did not report the timing of their adoption.

CountyRISAdoption. These data are then linked to the county-year level aggregated birth and death certificates. Table 1 provides summary statistics describing the data. Comparing adoption rates in 1994 and 2004 confirms that healthcare IT spread substantially during the sample period. By 2004, diffusion was still incomplete. On average, a county has 5.2 hospitals, of which 2 have EMR and 3.3 have RIS.

3 The Link between IT and Infant Outcomes

Most women in the US have a low-risk pregnancy and will see a regular obstetrician, doctor or midwife at an off-site clinic at relatively infrequent intervals throughout their pregnancy. They will receive at most two ultrasounds prior to giving birth at term. Our focus is women who fall into a high-risk category, and consequently see high-risk perinatologists in specialized maternal-fetal medicine departments within hospitals. Some women, who have a history of three or more pregnancy losses, diabetes, cancer, or a history of an incompetent cervix, start their pregnancy treatment with these departments. Other women, who are found to have multiple-order pregnancies, problems with placentas, umbilical cords or membranes, or other fetal abnormalities, are transferred there by their regular obstetrician or doctor who does not have the specialized knowledge to deal with their particular case. Our focus on the use of technology by hospitals rather than ambulatory facilities, reflects the sad reality that such "high-risk" cases account for more than 70 percent of fetal deaths (Smulian, Ananth, Vintzileos, Scorza, and Knuppel (2002)).6

We want to study whether the healthcare IT available at hospitals that may see these high-risk pregnancies can improve neonatal outcomes. Nielson, Thomson, Jackson, Kosman, and Kiley (2000) describes how electronic medical records can be used, and describes the development and implementation of a new electronic record system (known as STORC, for

⁶In 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%.

Standard Obstetric Record Charting) to track antepartum, intrapartum and postpartum care. However, this study does not describe precisely the conditions that such systems improve. Using the maternal-fetal medicine literature, we find many conditions where medical experts prescribe the need for careful monitoring of patients, consistent record-keeping and frequent ultrasounds. These include pre-eclampsia (Walker (2200)); vasa previa (Oyelese, Turner M, and Campbell (1999)); other problems with the umbilical cord and placenta, like placenta previa, placental abruption, and abnormal cord insertions or lengths (Chou, Ho, and Lee (2000)). Healthcare IT can be useful in abating the serious risks associated with multiple pregnancies. On average, twins are six times more likely to die than singletons before 40 weeks, while triplets are 26 times more likely to die (Kahn, Lumey, Zybert, Lorenz, Cleary-Goldman, D'Alton, and Robinson (2003)). Easy access to accurate records of estimated fetal weight can help to diagnose conditions such as IUGR (restricted growth) that are more common in multiple births (Ott (2002)). 15 to 20 percent of monochorionic (identical) twins develop twin-to-twin transfusion syndrome, which is fatal in 90 percent of cases without treatment prior to birth (Fisk and Galea (2004)). Diagnosis requires 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, Windrim, Barrett, and Ohlsson (2001)).

Table 2 displays the top five causes of neonatal death, by race. The two categories of interest for our study are maternal complications of pregnancy and prematurity since prematurity is highly linked to the maternal complications discussed above.⁷ An important

⁷ "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, McDuffie, and Lyons (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."

implication of this table is that healthcare IT should produce larger absolute gains for African Americans than for Whites. This is shown to be the case in Section 6.2.

4 Identification

The potential benefits to hospitals from IT adoption consist of stand-alone benefits that are independent of others' adoption choices, and network benefits that increase with local area adoption. Stand-alone benefits are reduced administrative costs and improved quality of care from better monitoring and case management. Network benefits stem from the greater ability of providers to quickly access relevant information from a patient's medical history that was accumulated elsewhere. When a greater share of patients' medical information is available from other hospitals in electronic format, the benefits from adopting healthcare IT are higher.

A correlation between healthcare IT adoption and county level neonatal health does not necessarily imply a causal relationship. Instead, a positive correlation could reflect unobserved heterogeneity, such as higher hospital revenues at hospitals serving richer patients who receive better nutrition. Similarly, a negative correlation could mean that hospitals that operate in areas with many high-risk patients are more likely to invest in healthcare IT. We address the identification challenge in two stages. First, we employ a full set of state and year fixed effects to absorb cross-sectional differences and national trends in mortality rates, along with a rich set of control variables, including maternal characteristics and pregnancy risk factors. Second, we exploit exogenous variation in privacy laws and nearby IT adoption as instrumental variables for county level healthcare IT. This IV strategy builds on Miller and Tucker (2007), which documents how state privacy laws limit the network benefits of healthcare IT, making hospitals less likely to invest in the technologies.

Our source for changes in state privacy regulation over time is a series of surveys of health

privacy statutes produced by the Health Privacy Project at Georgetown University: Pritts, Choy, Emmart, and Hustead (2002), Pritts, Goldman, Hudson, Berenson, and Hadley (1999) and Gostin, Lazzarini, and Flaherty (1996). They classify state privacy laws by examining state statutes governing medical privacy. This approach excludes refinements to privacy law stemming from case law or administrative law. The state variation that we exploit in this paper is from changes in privacy protection above and beyond federal rules.

These regulations vary in how much they limit the disclosure of medical information, the range of covered organizations, the rules for obtaining consent, the exemptions from disclosure rules, and the penalties for violations. We distinguish between the substantial variations in the strength and content of these laws across states. Our main instrument, HospitalPrivacyLaw, is an indicator for whether a county is located in a state with a privacy law covering hospitals. Hospitals in these states have explicit statutory requirements to protect the confidentiality of patient medical information, and are restricted in their ability to disclose such information to outside parties without express prior authorization from the patient. Hospitals in other states are not explicitly covered by state statute governing the privacy of medical information.

During the sample period, we observe 19 changes in laws: 4 changes to increase privacy protection and 15 to decrease it. Figure 2's display of privacy regulations in 1996 shows the difference compared to the 2002 privacy laws in Figure 3. Figure 3 shows that in 2002 about half of the states in the US have laws that cover hospital behavior. Coverage is geographically dispersed, and each of the nine census divisions includes at least one state with and one without hospital coverage. States with hospital privacy laws are significantly larger and more populous than other states, but have statistically indistinguishable population densities and numbers of hospitals.

Healthcare IT in general, and EMR and RIS in particular, can enhance the ability of hospitals to exchange information from medical records. These inter-hospital benefits are likely negligible for the case of childbirth since second opinions and emergency admissions are rare, but may amplify the gains from IT adoption for other types of hospital visits. Since adoption of EMR is a hospital-wide decision, the network effects for other conditions still provide useful variation for studying infants.

State privacy laws, however, can impede this exchange of medical information. Miller and Tucker (2007) estimate that hospitals in states without privacy laws are 6% more likely to adopt EMR after another hospital in their local Health Services Area has adopted. The effect of other hospital adoption in states with privacy laws is negligible. Privacy laws are estimated to reduce overall EMR adoption by up to 25 percent. These results are robust to the inclusion of state fixed effects, controls for average state income and managed care penetration, and hospital-level controls for size, age and ownership. Further concerns about the potential endogeneity of the enaction of state privacy laws are addressed with an instrumental variables strategy exploiting cross-sectional variation in sign-ups to the federal Do Not Call list as a proxy for tastes for privacy. The IV estimates support a similar conclusion: privacy laws reduce EMR adoption by about 29 percent.

In addition to the state privacy law variable, HospitalPrivacyLaw, we also exploit variation in IT adoption in nearby counties as a measure of the level of cross-county network benefits that hospitals can expect to enjoy from adopting healthcare IT. We capture the network benefits from each of these technologies with two installed base variables for hospitals in nearby counties: OtherEMRAdoption and OtherRISAdoption. As in Miller and Tucker (2007), we use the 815 Health Service Areas to determine relevant local healthcare markets. The sample in this paper includes data from 300 HSAs. The typical HSA contains two counties. We also use interactions between the presence of health privacy laws and the installed base measures of technology adoption as instrumental variables. These interactions allow the within-HSA correlations in hospital adoption to vary by state privacy regime. Finally, we interact the installed base measures with the number of hospitals in the county. This

allows larger counties to increase adoption more in response to similar changes in installed base.

5 Effects of IT Adoption on Infant Mortality

5.1 Fixed Effects

We start with a fixed effect panel data framework and estimate the relationship between hospital IT adoption and rates of infant and neonatal deaths at the county-year level. We control for multiple maternal characteristics and pregnancy risk factors included in the birth certificate data. We include a full set of county fixed effects to capture unobservable local variation in health and behavior and a set of year fixed effects to capture nationwide 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 sample of 4,526 county-year observations on 450 counties.⁸

Table 3 reports the results for adoption of Electronic Medical Records. Fixed-effect estimates are reported in columns 1 and 3 for infant and neonatal death rates per 1,000 live births, respectively. There is a negative association between increased EMR adoption and county-year mortality rates, which is statistically significant for infant deaths: Each additional hospital that adopts EMR is associated with a decline of about 4 infant deaths per 100,000 live births. Mortality rates are substantially higher in counties with increasing shares of African-American mothers, but do not vary significantly with changes in the age

⁸The dataset is a balanced panel of 4,950 observations of 450 counties over 11 years. The estimation sample is reduced due to missing information on medical risk factors for certain state-year combinations. For example, Texas does not report genital herpes or uterine bleeding. Estimation on the full sample of 4,950 observation with the reduced set of risk factors yielded similar results.

or educational attainment of mothers. Consistent with Currie and Gruber (1996a), we find that increases in the Medicaid coverage rates for women aged 15 to 50 are associated with significant declines in infant mortality. The table also reports coefficients for key risk factors for infant mortality found in birth certificate data: previous cesarean sections, multiple births (twins or higher), pre-eclampsia, previous infant pre-term or small for gestational age, and other medical risks. 10

Table 4 reports the results for adoption of RIS. Again, adoption is associated with large declines in mortality, this time significant for both neonates and infants: each new RIS adopter is linked with 3 fewer infant deaths and 2 fewer neonatal deaths per 100,000 live births. The main control variables reported in Table 4 show similar effects to those in the previous table.

5.2 Endogenous Technology Adoption

In columns 2 and 4 of Tables 3 and 4, we report IV results that address the potential endogeneity of technology adoption. The county fixed effects included in all regressions account for permanent county characteristics, such as the technological sophistication of patients or stable traits of local hospitals. Nevertheless, we may be concerned that adoption is endogenous, in that hospitals are more likely to invest in new information technology when they are in a better financial state or if their patient load is growing. These factors may themselves affect the quality of care provided at hospitals, and may lead to bias in the basic fixed effects estimates of the impact of technology adoption. As described in Section 4, we use a set of instrumental variables, based on the state legal environment and actions

⁹This variable captures actual Medicaid coverage and is potentially endogenous. Estimated effects of hospital IT are not sensitive to removing this variable.

¹⁰The regression model includes the following additional medical risk factors: anemia, cardiac disease, lung disease, hydramnios/oligohydramnios, hypertension, diabetes, genital herpes, hemoglobinopathy, incompetent cervix, previous infant 4000 grams or larger, renal disease, Rh sensitization, and uterine bleeding. These factors are not generally statistically significant, and coefficients are suppressed from the tables for readability.

of hospitals in other nearby counties, to predict adoption.

As above, the coefficients for healthcare IT are negative for each of the technologies, indicating lower mortality rates. The magnitudes of the effects are non-trivial. A single additional hospital adopting EMR in a county reduces neonatal deaths by 5 per 100,000 births, or 1%. RIS adoption by a single hospital reduces neonatal deaths by 0.6%. During the sample period from 1994 to 2004, EMR use increased by 1.8 hospitals per county and RIS by 2.6 hospitals per county. Separately, these can explain 18.2% and 16.9% of the decline in neonatal deaths during the period. For infant deaths, the estimates are larger. A single hospital adopting EMR reduces deaths by 8 per 100,000 births and RIS reduces deaths by 5 per 100,000 births. Increased use of the technologies can separately explain 14.5% and 13.7% of the infant mortality improvements during the period. Switching to the IV framework leaves the coefficient estimates for other control variables qualitatively unchanged.

The IV estimates are generally larger in magnitude than the OLS estimates. This may imply that IT adoption is correlated with worsening health outcomes, as predicted by the unobserved components of the model. Alternatively, measurement error in the IT adoption variables may be biasing the fixed-effect estimates towards zero.

5.3 Robustness

This section assesses the validity of the instrumental variables strategy and demonstrates the robustness of the main results to changes in other medical investments and alternative definitions of the key IT adoption variables.

First, we test the strength of the instrumental variables as predictors of the endogenous IT variables. Table 5 reports results from the first-stage regressions. Increased IT adoption by hospitals in neighboring counties within the same HSA tends to promote IT adoption, with a greater impact in counties with more hospitals. Privacy laws significantly inhibit

adoption of EMR and RIS. They also diminish the responsiveness of RIS adoption to EMR adoption in nearby counties. An F-test on the joint significance of the instruments strongly rejects zero for each of the technologies. Hence, the instruments satisfy the first necessary condition for validity.

We explored three avenues to ensure that the second condition on the instruments is fulfilled - that is that they themselves are exogenous. A potential source for a spurious negative correlation between IT adoption and adverse health outcomes is if changes in privacy laws lead hospitals to simultaneously to embark on technological upgrades of both their IT systems and other neonatal technologies. We explore this directly using data from the American Hospital Association. First, we find that the availability of hospital ultrasound did not spread during the period. Although high-level NICU diffusion had leveled off by the early 1990s (Baker and Phibbs (2002)), diffusion of mid-level NICUs continued. Given previous research emphasizing the role of NICUs, one possibility is that hospital IT penetration may be positively correlated with NICU availability. Using 1994-1998 data from the American Hospital Association on the number of hospitals in a county with any neonatal intensive or intermediate care beds, we assess the importance of this concern. Rather than finding significant positive relationships in hospital investments, the correlations are negative for EMR and insignificant for RIS. Furthermore, when NICU counts are included in the main regressions, they have only minor effects on the estimated coefficients for IT.

There are also concerns that the installed base measure for neighboring counties may be directly related to improved outcomes if the transferability of electronic medical records improve outcomes for mothers who receive care in multiple counties. To address these concerns, we repeated the main IV estimation with a reduced model that uses only privacy laws to instrument for IT adoption and includes only county fixed effects as controls. The qualitative results are unchanged, although coefficient estimates and standard errors are

 $^{^{11}}$ Rather, it was stable at about 78% of hospitals reporting "ultrasound hospital or subsidiary".

inflated.¹² Finally, we test the over-identification restrictions implied by the full IV model. The Hansen J-statistic and its associated P-value are reported below each of the main IV results in the tables. These tests fail to reject the null hypothesis that the instruments are valid, under the assumption that at least one is exogenous.

Another concern is that the technology adoption is related to unobservable changes in maternal risk factors that are correlated with changes in the EMR network installed base. Comfortingly, regressions on the installed IT base variable variables for other county adoption on the full set of controls indicate that this is not the case. The IT adoption instrumental variables are negatively correlated with own-county share of African-Americans, ¹³ but they are not significantly related to any of the rich set of observed medical risk factors. ¹⁴ The lack of correlation with observed risk factors provides some reassurance that the adoption instruments are not correlated with omitted risk factors.

The benefit of using the number of hospitals with each technology as the key the measure of adoption is that coefficient estimates have a natural interpretation: the effect of a single additional hospital adopting healthcare IT on the county-level mortality rate. However, one drawback is that adoption decisions at all hospitals are constrained to influence neonatal health in the same way. This seems inappropriate for hospitals without maternity wards. In our first robustness test of the IT variables, we recreate the hospital IT database, but exclude all hospitals with no births reported in the AHA database for the base year of 1994. This eliminated under 10% of the hospitals in HIMSS, and left the main results essentially unchanged. We also created a new set of IT adoption measures that counted

¹²The IV impact of EMR adoption is -0.358 (s.e. of 0.20) and of RIS adoption is -0.232 (s.e. of 0.13). Coefficient estimates using only privacy laws to instrument and with the full set of controls are very similar in magnitude but not statistically significant.

¹³Section 6.2 reports results separately by race.

¹⁴For each of the three technologies, T-tests on each of the individual coefficients failed to reject zero, as did joint F-tests on all of the coefficients.

 $^{^{15}}$ This process required matching the AHA and HIMSS databases by hospital. Unfortunately, due to differences in the coding of hospital names, the match was imperfect.

adoption only in hospitals designated as Obstetric Level III.¹⁶ These are the hospitals that provide antepartum, intrapartum and postpartum care to the full range of maternity patients, including complicated and high-risk pregnancies and emergencies. The estimated effects of IT adoption were qualitatively unchanged, but much larger in magnitude.¹⁷ This evidence supports the robustness of the main findings and suggests that the mechanism for the effect is as described in Section 3. Additional indirect evidence supporting the mechanism is provided in Section 6 below.

5.4 Cost-Effectiveness Analysis

Using the IV estimates presented in Tables 3 and 4, we are able to make some rough calculations for how many babies healthcare IT can save, and compare these gains to the likely costs. Multiplying the IV coefficients for county-year infant death rates by the number of babies born in the average county (6,419 per year) suggests that EMR in 1 hospital saves 0.51 babies per year, or 1 every 2 years. RIS saves .34 babies per year.

The costs of installing either EMR or RIS include upfront costs of software and hardware installation, training of medical and support staff, and ongoing maintenance. The pricing scheme for RIS and EMR systems is complicated by the initial upfront costs being subsidized by vendors who hope to recoup from high support fees. A 2007 American Hospital Association survey put the median capital spending per bed for healthcare IT at \$5,556. For operating costs, the median amount per bed was \$12,060.¹⁸ The median cost per bed of \$17,616 translates to annual costs of \$3,188,496 for an average hospital in our data that has 181 beds. Of course not all these beds are devoted to patients who give birth. According to

¹⁶This information was obtained from the AHA data. Unmatched hospitals and those with missing information regarding their level of obstetric service were excluded.

¹⁷For EMR adoption, the IV estimates for infant and neonatal mortality were -0.187 (standard error of 0.085) and -0.0907 (s.e. of 0.055), respectively. For RIS, they were -0.174 (s.e. of 0.055) and -0.0848 (s.e. of 0.042).

¹⁸Continued Progress: Hospital Use of Information Technology, American Hospital Association, 2007

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 \$382,619 a year on health IT for maternity beds.¹⁹

Using the calculation that on average adoption of EMR and RIS by one hospital in a county leads to a saving of 0.85 infants each year, that suggests saving the life on one infant by spending on healthcare IT costs \$450,140. This is likely to be a lower bound on the benefits of healthcare IT spending. First, the healthcare IT spending costs used for this calculation includes spending on other technologies that we do not study, such as computerized physician order entry. Also, this figure does not capture improvements in maternal mortality and maternal or neonatal morbidity. There also may be additional administrative cost savings. For example, it has been estimated that RIS systems can save \$500,000 in film costs per year. 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.

6 Further Exploration by Prenatal Care and Race

6.1 Ultrasound Use and Prenatal Care

Prenatal ultrasound is not universal in the US. The rate is only about 66 percent, and there is substantial variation across counties. Ultrasound imaging is essential for for the referral of high-risk patients, such as those with problematic umbilical cords and placental conditions, to the specialized hospital units that we study. An initial ultrasound provides the basis

¹⁹Data on number of hospital beds devoted to specialities from the UK supports this assumption. In Wales, 14 percent of hospital beds are devoted to maternity patients (Hospital Activity 2003-04 Volume 1: Bed use and in-patients, Statistical Directorate for Wales, 2005).

for referral that allows the group of patients to receive regular ultrasound and monitoring. Storing and managing these images are central features of RIS systems. Counties where ultrasound use is more prevalent overall should experience greater improvements in outcomes when their hospitals adopt RIS systems.

To test this potential falsification hypothesis, we stratified our sample of counties into those with average rates of ultrasound use during the sample period above and below the average for the median county in the sample. Our aim is to distinguish between counties where there is a high likelihood of referral to hospitals of high-risk patients who will benefit from intensive ultrasound use, and counties where there is a low likelihood of referral due to limited ultrasound use. Counties with above median rates are designated as "High Ultrasound Use" and the rest are designated as "Low Ultrasound Use."

The main estimation for RIS adoption (in Table 4 for all counties) is repeated separately for each set of counties. This method produces a substantially reduced sample size for each regression. Nevertheless, the results in Table 6 show an effect of RIS on high ultrasound use counties that decreases neonatal mortality by a statistically significant amount. Low ultrasound use counties exhibit a far smaller (close to an order of magnitude smaller, in some cases) benefit from RIS adoption which is statistically indistinguishable from zero. This pattern is consistent across the dependent variables and estimation methods. Together, these results confirm that RIS adoption in hospitals matters more when general ultrasound use in the surroundings is higher, and suggest that IT is in fact improving outcomes by improving the flow of relevant health information.

The logic of this test implies additional falsification tests that would involve stratification of the sample according to reported risk factors such as rates of multiple births and pre-eclampsia. Unlike ultrasound use, however, there is insufficient variation in these variables across counties to estimate meaningful differences.

To further confirm the results, we conduct a falsification test on the sub-sample of women

who reported receiving no prenatal care during their pregnancies. This is 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. In order to identify this group, it is necessary to use the individual linked birth and death certificates. This reduces the estimation sample size considerably to 1,375 with fewer than 200 counties for the period 1994 to 2002.²⁰ For women who had no prenatal visits, IT adoption has inconsistent and insignificant effects on infant mortality. The coefficients vary in sign and the lowest P-value is 0.358. It is worth noting that on this limited sample, we do observe significant gains from EMR and RIS adoption for women who received adequate prenatal care. The fixed effect estimates are negative and statistically significant at 5%, and the IV estimates are negative and statistically insignificant. Together, these results suggest 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.

6.2 Can Technology Equalize Outcomes?

Infant and neonatal mortality rates are substantially higher for African-Americans than for Whites. The two categories with the most striking racial disparity are prematurity (short gestation) and maternal complications of pregnancy. In particular, the statistics in Table 2 suggest that African-Americans 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.

A far-reaching overview of the literature on racial disparities in health is provided by Smedley, Stith, and Nelson (2003). This Institute of Medicine report emphasizes that racial

²⁰This is because fewer counties are identified in the linked data, and the more recent years are not yet available to researchers.

disparities exist in many areas of medical care, after controlling for health and insurance coverage, but that the source of this disparity is unclear; discrimination by doctors and different levels of patient assertiveness are discussed as potential causes. These trends within neonatal care at the national level have been extensively documented by Singh and Yu (1995). They find that the long-term downward trend in US infant mortality has not benefited African-Americans and Whites equally. The disparity in infant mortality has not only persisted but increased over time, and is not expected to diminish in the near future. Such findings have led institutions such as the Center for Disease Control to emphasize that infant health and mortality should be a "priority" for CDC's Reach 2010 initiative.²¹

There is some initial evidence that the disparity may partly arise from discretion over treatment options in the face of clinical uncertainty. This contention is supported in a recent random experiment conducted by (Schulman, Berlin, Harless, Kerner, Sistrunk, Gersh, Dube, Teleghani, Burke, Williams, Eisenberg, Escarce, and Ayers 1999) to explore the role of race in differential health care treatment. They hired actors to portray patients with different characteristics of chest pain. Doctors were asked to diagnose and recommend treatment. They found that women and African-Americans were less likely to be referred for cardiac catheterization. One of the aims of EMR and RIS systems is to systematize treatment, and ensure that best practices are always pursued. If African-American expectant mothers are the victims of treatment discretion (or lack of patient assertiveness), the imposition of EMR and RIS systems should improve outcomes for them more than for other women. That could also happen if there are other factors making African-American mothers more high-risk, which a more systematic EMR-based treatment protocol would be more likely to pick up. Though our study is silent about the precise mechanism by which healthcare IT improves outcomes more for African-American mothers, this section provides evidence that reducing

health disparities is another positive spill-over from encouraging the diffusion of healthcare ${\rm IT}.^{22}$

Therefore, we extend our analysis to investigate the differential impact of IT adoption on mortality rates by race. We separate births and deaths by race, keeping only Whites and African-Americans, and construct a new panel dataset with a county-year-race unit of observation. We estimate the effects of technology using a pooled sample. We interact the measure of technology adoption, as well as each of the instrumental variables separately, with the indicator variable for African-American.

The results presented in Table 7 show that healthcare IT technology adoption leads to greater reductions in mortality rates for African-Americans than for Whites. For neonatal death rates, the differential racial impacts of healthcare IT adoption consistently favor African-Americans, and are statistically significant for each of the technologies. One hospital's adoption of EMR reduces mortality for Whites by 2 deaths per 100,000 births and by 8 deaths per 100,000 births for African-Americans. Relative to the average mortality rates for each race, these figures represent a 0.5% decline for Whites, but a 0.7% decline for African-Americans. RIS adoption reduces White neonatal deaths by 1 per 100,000 births, and African-American deaths by 3 per 100,000 births. For infant death rates, the IV estimates of the heterogenous treatment effects are again negative but not statistically significant. Since the baseline neonatal mortality rates are substantially higher for African-Americans, we conclude that IT investments have an equalizing effect on healthcare delivery and outcomes.

The results in this section reveal an important benefit from healthcare IT in standardizing care and reducing racial disparities in health. In addition, the racial divergence in the impact of IT adoption provides additional support for the underlying mechanism proposed in this paper. African-American women are far more likely to suffer from maternal complications,

²²The IOM report concludes with a discussion of "needed research", in which it lists "assessing the effectiveness of intervention strategies." This paper contributes toward redressing that research deficit.

and thus constitute an exogenously pre-determined population with "high-risk" pregnancies. Since IT should matter more for women with these types of pregnancies, our model predicts larger gains for them.

7 Conclusion

The US has the highest infant mortality rate among developed nations except for Latvia. This is despite one of 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 systematized approach to the adoption of health care IT in other comparable industrialized nations. Electronic medical records (EMR) and other healthcare IT improvements offer a potential way to reduce this death rate, by standardizing treatment options and improving monitoring. We explore empirically whether healthcare IT improves neonatal outcomes. We use variation in state privacy laws that curtail the network benefits of healthcare IT technologies as an exogenous source of variation in order to identify a causal relationship. Our estimates suggest that adoption of healthcare IT by an additional hospital in a county reduces infant mortality in that county by 13 deaths per 100,000 live births. Rough cost-effectiveness calculations suggest that healthcare IT is associated with a cost of \$450,140 per infant saved.

We also find that adoption of radiological information systems in particular matters more in counties with above-average ultrasound use. This finding underlines that combining technologies is effective in improving healthcare outcomes. We also find that adoption of healthcare IT by hospitals in a county significantly reduces infant mortality rates in that county, and that the gains are significantly larger for African-Americans. These findings provide an empirical basis for quality concerns regarding the slow diffusion of healthcare IT.

References

- Acemoglu, D. and A. Finkelstein (2006). Input and technology choices in regulated industries: Evidence from the health care sector. Technical report, NBER Working Paper No. 12254.
- Allen, V. M., R. Windrim, J. Barrett, and A. Ohlsson (2001). Management of monoamniotic twin pregnancies: a case series and systematic review of the literature. *BJOG:*An International Journal of Obstetrics and Gynaecology 108(9), 931–936.
- Athey, S. and S. Stern (2002, Autumn). The impact of information technology on emergency health care outcomes. *RAND Journal of Economics* 33(3), 399–432.
- Baker, L. C. (2001, May). Managed care and technology adoption in health care: evidence from magnetic resonance imaging. *Journal of Health Economics* 20(3), 395–421.
- Baker, L. C. and C. S. Phibbs (2002, Autumn). Managed care, technology adoption, and health care: The adoption of neonatal intensive care. *RAND Journal of Economics* 33(3), 524–548.
- Bartel, A., C. Ichniowski, and K. Shaw (2007, November). How Does Information Technology Affect Productivity? Plant-Level Comparisons of Product Innovation, Process Improvement and Worker Skills. *Quarterly Journal of Economics* 122(4), 17211758.
- Bernstein, P., C. Farinelli, and I. Merkatz (2005, March). Using an Electronic Medical Record to Improve Communication Within a Prenatal Care Network. Obstetrics & Gynecology 105(3), 607–612.
- Bitler, M. and J. Currie (2005). Does WIC Work? The Effects of WIC on Pregnancy and Birth Outcomes. *Journal of Policy Analysis and Management* 24(1), 73–91.
- Bower, A. G. (2005). The Diffusion and Value of Healthcare Information Technology. RAND.

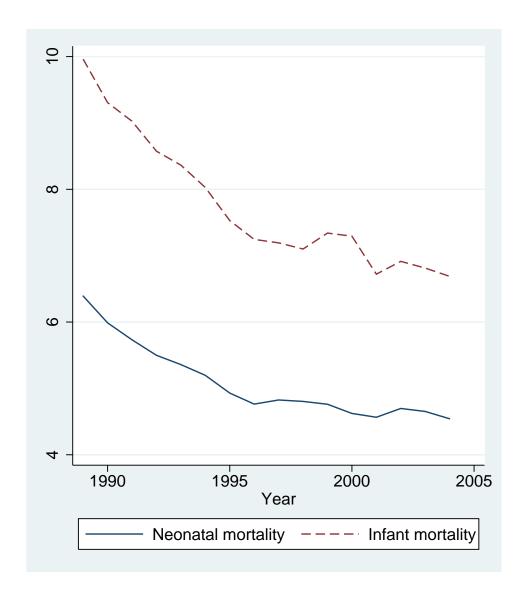
- Bristol, N. (2005, May). The Muddle of US Electronic Medical Records. *The Lancet 365* (9471), 1610–1611.
- Brynjolfsson, E. and L. Hitt (2003, November). Computing Productivity: Firm-Level Evidence. *Review of Economics and Statistics* 85(4), 793–808.
- Chou, M., E. Ho, and Y. Lee (2000). Prenatal diagnosis of placenta previa accreta by transabdominal color Doppler ultrasound. *Ultrasound in Obstetrics and Gynecology*.
- Corman, H. and M. Grossman (1985, September). Determinants of neonatal mortality rates in the u.s.: A reduced form model. *Journal of Health Economics* 4(3), 213–236.
- Corman, H., T. J. Joyce, and M. Grossman (1987, Summer). Birth Outcome Production Functions in the U.S. *Journal of Human Resources* 22(3).
- Currie, J. and J. Gruber (1996a, May). Health Insurance Eligibility, Utilization of Medical Care, and Child Health. *The Quarterly Journal of Economics* 111(2), 431–466.
- Currie, J. and J. Gruber (1996b, December). Saving babies: The efficacy and cost of recent expansions of medicaid eligibility for pregnant women. *Journal of Political Economy* 104(6), 1263–1296.
- Currie, J. and J. Gruber (1997). The Technology of Birth: Health Insurance, Medical Interventions, and Infant Health. Technical report, NBER Working Paper No. 5958.
- Currie, J. and J. Gruber (2001). Public health insurance and medical treatment: the equalizing impact of medicaid expansions. *Journal of Public Economics* 82, 63–89.
- Fisk, N. and P. Galea (2004). Twin-twin transfusion—as good as it gets? New England Journal of Medicine 351(2), 182–4.
- Fonkych, K. and R. Taylor (2005). The state and pattern of health information technology adoption. Technical report, RAND.

- Gostin, L., Z. Lazzarini, and K. Flaherty (1996). Legislative Survey of State Confidentiality Laws, with Specific Emphasis on HIV and Immunization. Technical report, Report to Centers for Disease Control and Prevention.
- Hamilton, B. and B. McManus (2005). Technology Diffusion and Market Structure: Evidence from Infertility Treatment Markets. Mimeo, Washington University.
- Harris, J. E. (1982, July). Prenatal medical care and infant mortality. NBER Reprints 0281, National Bureau of Economic Research, Inc. available at http://ideas.repec.org/p/nbr/nberre/0281.html.
- Hill, S. C. and B. L. Wolfe (1997, June). Testing the hmo competitive strategy: An analysis of its impact on medical care resources. *Journal of Health Economics* 16(3), 261–286.
- Hillestad, R., J. Bigelow, A. Bower, F. Girosi, R. Meili, R. Scoville, and R. Taylor (2005, Sep-Oct). Can electronic medical record systems transform health care? Potential health benefits, savings, and costs. *Health Affairs* 24(5), 1103–17.
- Hubbard, T. (2003, November). Information, Decisions and Productivity: On-Board Computers and Capacity Utilization in Trucking. *American Economic Review* 93(4), 1328–1353.
- Kahn, B., L. H. Lumey, P. A. Zybert, J. M. Lorenz, J. Cleary-Goldman, M. E. D'Alton, and J. N. Robinson (2003). Prospective Risk of Fetal Death in Singleton, Twin, and Triplet Gestations: Implications for Practice. Obstet Gynecol 102(4), 685–692.
- Lenzo, J. (2005). Market Structure and Profit Complementarity: The Case of SPECT and PET. Mimeo, Northwestern University.
- Lynch, A., R. McDuffie, and E. Lyons (2007). Perinatal loss among twins. *The Permanente Journal*.
- Miller, A. (2006). The Impact of Midwifery-Promoting Public Policies on Medical In-

- terventions and Health Outcomes. Advances in Economic Analysis & Policy 6(1), 1589–1589.
- Miller, A. and C. Tucker (2007). Privacy Protection and Technology Diffusion: The Case of Electronic Medical Records. SSRN eLibrary.
- Nielson, P. E., B. A. Thomson, R. B. Jackson, K. Kosman, and K. C. Kiley (2000, December). Standard Obstetric Record Charting System: Evaluation of a New Electronic Medical Record. *Obstetrics & Gynecology* 96(6), 1003–1008.
- Ott, W. (2002, May). Diagnosis of intrauterine growth restriction: Comparison of ultrasound parameters. *American Journal of Perinatology* 19(3), 133–137.
- Oyelese, K., L. C. Turner M, and S. Campbell (1999). Vasa previa: an avoidable obstetric tragedy. *Obstet Gynecol Surv* 54, 13845.
- Pritts, J., A. Choy, L. Emmart, and J. Hustead (2002). The State of Health Privacy: A Survey of State Health Privacy Statutes. Technical report, Second Edition.
- Pritts, J., J. Goldman, Z. Hudson, A. Berenson, and E. Hadley (1999). The State of Health Privacy: An Uneven Terrain. A Comprehensive Survey of State Health Privacy Statutes. Technical report, First Edition.
- Quintero, R. (2003). Stage-based treatment of twin-twin transfusion syndrome. American Journal of Obstetrics and Gynecology, 188(5), 1333–1340.
- Schmidt-Dengler, P. (2006). The Timing of New Technology Adoption: The Case of MRI. Mimeo, LSE.
- Schulman, K., J. Berlin, W. Harless, J. Kerner, S. Sistrunk, B. Gersh, R. Dube, C. Teleghani, J. Burke, S. Williams, J. Eisenberg, J. Escarce, and W. Ayers (1999, Feb.). The Effect of Race and Sex on Physicians' Recommendations for Cardiac Catheterization. New England Journal of Medicine 340(8), 618–626.

- Singh, G. and S. Yu (1995). Infant Mortality in the United States: Trends, Differentials, and Projections. *American Journal of Public Health* 85(7), 957–964.
- Smedley, B. D., A. Y. Stith, and A. R. Nelson (Eds.) (2003). *Unequal Treatment: Confronting Racial and Ethnic Disparities in Health Care*. Institute of Medicine. National Academies Press.
- Smulian, J. C., C. V. Ananth, A. M. Vintzileos, W. E. Scorza, and R. A. Knuppel (2002). Fetal Deaths in the United States: Influence of High-Risk Conditions and Implications for Management. *Obstet Gynecol* 100(6), 1183–1189.
- Spetz, J. and L. Baker (1999). Has managed care affected the availability of medical technology? Technical report, PPIC.
- Walker, J. (2200, Oct). Pre-eclampsia. *Lancet* 7(356), 1260–5.
- Walters, C. (2007). The Effects of the WIC Program on Infant Birth Outcomes. Mimeo, University of Virginia.
- Wilson (2007, March). Lessons for Health Care Could be Found Abroad. *Annals of Internal Medicine* 146(6), 473–476.

Figure 1: Trends in Neonatal and Infant Mortality Rates: Selected Counties



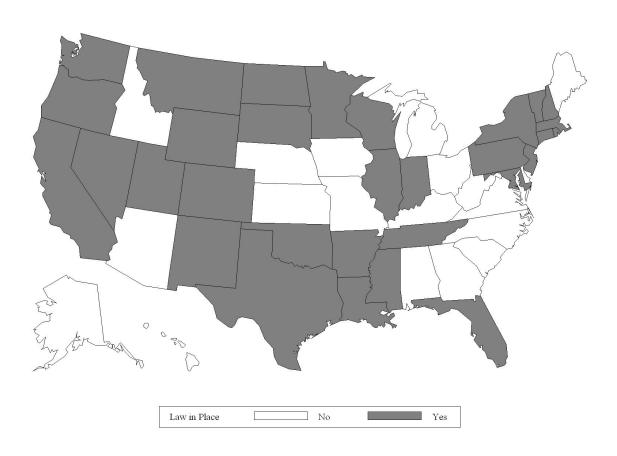


Figure 2: Map of States with Hospital Privacy Laws: 1996

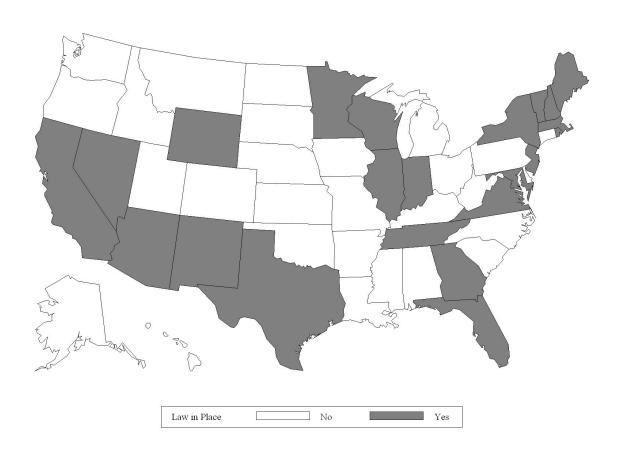


Figure 3: Map of States with Hospital Privacy Laws: 2002

Table 1: Summary Statistics

Variable	Mean	Std. Dev.	N
Variable	Mean	Stu. Dev.	11
Infant Death Rate	7.286	2.612	4950
Neonatal Death Rate	4.833	1.965	4950
African-American Mother	0.133	0.135	4950
White Mother	0.828	0.139	4950
Teen Mother	0.117	0.043	4950
High School Graduate	0.806	0.090	4950
College Graduate	0.174	0.123	4950
Medicaid Coverage	0.167	0.046	4950
Previous C-section	0.111	0.023	4950
Multiple Birth	0.029	0.01	4950
Eclampsia Risk	0.003	0.005	4950
Preterm Risk	0.013	0.013	4839
Other Medical Risks	0.181	0.128	4839
Hospitals in county	5.217	7.072	4950
Year = 1994:			
Hospitals in county adopting EMR	0.207	0.600	450
Hospitals in county adopting RIS	0.716	1.431	450
Year = 2004:			
Hospitals in county adopting EMR	2.031	2.700	450
Hospitals in county adopting RIS	3.309	4.288	450

Table 2: Infant Deaths and Mortality Rates for the Five Leading Causes of Infant Death

Cause of Death	All Races	Non-Hispanic White	Non-Hispanic Black
All Causes	677.6	566.1	1,359.6
Congenital malformations, deformations,	137.1	129.3	167.4
and chromosomal abnormalities Disorders related to short gestation and low birth weight, not classified elsewhere	112.1	77.1	297.2
Sudden Infant Death Syndrome	54.6	54.0	110.9
Newborn affected by maternal complica-	41.5	32.2	103.1
tions of pregnancy Accidents	25.6	25.6	46.8

United States, 2004 linked birth-death file. Rates per 100,000 live births. Vital Statistics Reports, Vol 55, No 14 May 2007

Table 3: Electronic Medical Records Adoption and Local Mortality

		(-)	(-)	
	(1)	(2)	(3)	(4)
Dependent Variable	Infant Death Rate		Neonatal Death Ra	
	OLS	IV	OLS	IV
County EMR Adoption	-0.0390*	-0.0783**	-0.0168	-0.0463**
County EMIX Adoption	(0.023)	(0.031)	(0.018)	(0.021)
A.C.: A .: D.T. (1)	` /	9.200**	, , , ,	,
African-American Mother	10.44**		8.632**	8.306**
	(4.31)	(4.30)	(3.44)	(3.44)
White Mother	2.962	2.380	1.456	1.425
	(3.19)	(3.20)	(2.64)	(2.64)
Teen Mother	-1.023	-0.155	-1.806	-1.472
	(3.97)	(3.80)	(2.57)	(2.53)
High School Graduate	-1.280	-2.104	-1.399	-1.727
	(1.94)	(1.85)	(1.52)	(1.50)
College Graduate	0.219	0.158	0.0222	-0.008
9	(0.70)	(0.68)	(0.58)	(0.57)
State Medicaid	-2.681**	-2.709**	-2.372**	-2.314**
	(1.30)	(1.28)	(1.05)	(1.04)
Previous C-section	4.571*	4.483*	4.262**	4.388**
	(2.66)	(2.63)	(2.09)	(2.07)
Multiple Birth	14.68**	15.76**	8.760	9.313*
•	(6.56)	(6.40)	(5.43)	(5.34)
Eclampsia Risk	21.91**	22.19**	13.36	13.10
•	(10.9)	(10.8)	(8.55)	(8.48)
Pre-term Risk	8.423*	9.258**	1.367	2.456
	(4.58)	(4.49)	(3.91)	(3.85)
Other Medical Risks	1.205**	1.275**	1.100***	1.192***
	(0.51)	(0.50)	(0.40)	(0.40)
Observations	4526	4526	4526	4526
Counties	450	450	450	450
Over-identification test of instrumental variables				
Hansen J statistic		3.363		3.718
P-value		0.762		0.715

Robust standard errors, clustered at the county level, in parentheses.

County-year unit of observation. Death rates per 1,000 live births.

Coefficients for fixed effects and additional risk factors suppressed for readability.

^{***} p<0.01, ** p<0.05, * p<0.1

Table 4: Radiology Information System Adoption and Local Mortality

Dependent Variable		(2) eath Rate		(4) Death Rate
	OLS	IV	OLS	IV
County RIS Adoption	-0.0340** (0.015)	-0.0510*** (0.019)	-0.0215* (0.012)	-0.0298** (0.014)
African-American Mother	10.31**	9.189**	8.410**	8.381**
	(4.30)	(4.32)	(3.45)	(3.44)
White Mother	2.863 (3.19)	2.398 (3.20)	1.304 (2.64)	1.454 (2.63)
Teen Mother	-1.103	-0.368	-1.823	-1.606
reen Mother	-1.105 (3.98)	-0.308 (3.81)	(2.57)	(2.53)
High School Graduate	-1.280	-2.141	-1.356	-1.778
	(1.93)	(1.84)	(1.51)	(1.49)
College Graduate	0.215	0.158	0.0243	0.0158
	(0.70)	(0.68)	(0.58)	(0.57)
State Medicaid	-2.689**	-2.704**	-2.383**	-2.273**
	(1.30)	(1.29)	(1.06)	(1.04)
Previous C-section	4.601*	4.454*	4.325**	4.268**
	(2.66)	(2.63)	(2.09)	(2.06)
Multiple Birth	14.40**	14.98**	8.636	9.031*
	(6.54)	(6.37)	(5.42)	(5.32)
Eclampsia Risk	21.29*	21.02*	13.00	12.45
	(10.9)	(10.9)	(8.58)	(8.54)
Pre-term Risk	8.618*	9.281**	1.529	2.584
	(4.57)	(4.49)	(3.90)	(3.84)
Other Medical Risks	1.188**	1.211**	1.084***	1.192***
	(0.50)	(0.50)	(0.40)	(0.40)
Observations	4526	4526	4526	4526
Counties	450	450	450	450
Over-identifica	ation test of		l variables	
Hansen J statistic		3.387		3.950
P-value		0.759		0.683

Robust standard errors, clustered at the county level, in parentheses.

County-year unit of observation. Death rates per 1,000 live births.

Coefficients for fixed effects and additional risk factors suppressed for readability.

^{***} p<0.01, ** p<0.05, * p<0.1

Table 5: First Stage Regressions: Predicting Healthcare IT Adoption using HSA Network Adoption and Privacy Laws

	(1)	(2)
	EMR Adoption	RIS Adoption
Hospital Privacy Law	-0.132**	-0.161**
	(0.053)	(0.072)
EMR adoption elsewhere in HSA	-0.0628***	-0.216***
	(0.021)	(0.028)
Other EMR adoption * Number of hospitals	0.0386***	0.0485***
	(0.0014)	(0.0018)
Other EMR adoption * Hospital privacy law	-0.00190	-0.0788**
	(0.023)	(0.031)
RIS adoption elsewhere in HSA	-0.0629***	-0.0156
	(0.015)	(0.020)
Other RIS adoption * Number of hospitals	-0.000915	0.00853***
	(0.0013)	(0.0018)
Other RIS adoption * Hospital privacy law	0.0190	0.0414**
	(0.014)	(0.019)
Observations	4526	4526
Counties	450	450

Robust standard errors in parentheses.

^{***} p<0.01, ** p<0.05, * p<0.1

Table 6: Use of Ultrasound and Effects of Technology Adoption

	(1)	(2)	(3)	(4)	
Dependent Variable	Infant Death Rate		Neonatal Death Rate		
	OLS	IV	OLS	IV	
High	ı Ultrasour	nd Use Cour	nties		
		ia ose coai	10100		
County RIS Adoption	-0.0620*	-0.107***	-0.0551*	-0.0839**	
•	(0.036)	(0.038)	(0.031)	(0.033)	
Observations	2288	2288	2288	2288	
Counties	228	228	228	228	
Low Ultrasound Use Counties					
County RIS Adoption	-0.0173	-0.0302	-0.00635	-0.0109	
	(0.017)	(0.025)	(0.013)	(0.016)	
Observations	2238	2238	2238	2238	
Counties	222	222	222	222	

Robust standard errors, clustered at the county level, in parentheses.

County-year unit of observation. Death rates per 1,000 live births.

All regressions include the full set of control variables and fixed effects.

^{***} p<0.01, ** p<0.05, * p<0.1

Table 7: Technology Adoption and Infant Mortality by Race

-	(1)	(2)	(3)	(4)
Dependent Variable	Infant Death Rate		Neonatal Death Rate	
	OLS	IV	OLS	IV
County EMR Adoption	-0.0307**	-0.0483**	-0.00885	-0.0197*
	(0.012)	(0.024)	(0.0078)	(0.012)
Black * EMR Adoption	-0.0667	-0.0528	-0.0653**	-0.0614**
	(0.044)	(0.038)	(0.031)	(0.030)
Observations	7486	7486	7446	7446
Counties	450	450	450	450
County RIS Adoption	-0.0226***	-0.0288*	-0.00988**	-0.0123*
	(0.0087)	(0.015)	(0.0043)	(0.0073)
Black * RIS Adoption	-0.00897	-0.000483	-0.0192**	-0.0154*
	(0.013)	(0.011)	(0.0091)	(0.0090)
Observations	7486	7486	7446	7446
Counties	450	450	450	450

Robust standard errors, clustered at the county level, in parentheses.

County-year-race unit of observation. Death rates per 1,000 live births.

All regressions include the full set of control variables and fixed effects.

^{***} p<0.01, ** p<0.05, * p<0.1