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Managed Care, Technology Adoption, and Health Care: The Adoption of Neonatal Intensive Care

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Abstract

Advances in medical technology have been identified as a major driver of increases in health care costs, but increases in managed care activity may alter the incentives associated with the acquisition of new technologies and with their use. This paper discusses mechanisms by which managed care could influence the adoption of new technologies and empirically examines the relationship between HMO market share and the diffusion of neonatal intensive care, a collection of technologies for the care of high risk newborns. We find that managed care slowed the adoption of mid-level NICUs, but did not influence the adoption of the most advanced units. Slowing the adoption of mid-level units would have generated savings, and could also have benefitted patients, since health outcomes for seriously ill newborns are better in higher-level NICUs and reductions in the availability of mid-level units appear to increase the chance of receiving care in a high-level center. Thus, it may be in this case that slowing the adoption of a new technology is unambiguously welfare improving.

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1. Introduction

Over the past several decades, concern over persistent growth in U.S. health expenditures has kept the cost of health care at the center of the policy agenda. It is widely believed that the majority of the expenditure growth is due to technological change. Analyses by Aaron (1991) and Newhouse (1992) argue that less than half of the growth in medical spending can be attributed to increased moral hazard, higher administrative spending, or changes in other identifiable supply and demand factors, and that the residual is most likely due to technological change, a view shared by most health economists (Fuchs, 1996).

In the past, the range of activities that make up technological change, from basic science research to the development of products for market to the ultimate installation and use of new innovations, were fueled by a reimbursement system that graciously payed health care providers and generously compensated the developers and adopters of new technologies (Weisbrod, 1991). But now managed care appears to be eroding the pillars that supported this system. In particular, managed care has reduced physician and hospital reimbursement in many parts of the United States, often focusing most intently on spending for new high cost technologies at the most advanced institutions. This may influence technological change in a number of ways. Most directly, it could reduce demand for new and expensive innovations, slowing the adoption of new technologies. This in turn could have ripple effects throughout the process of technology development if researchers and developers change their strategies to produce the kinds of technologies that will be valued in markets with strong managed care presences.

One hope of managed care proponents is that it may thus be able to alter the forces that have driven long term expenditure growth, and contribute to significant future savings. Despite these hopes, however, the effects of managed care on technology development and adoption are not well understood. Moreover, the ultimate implications for the patient care and health outcomes, necessary for drawing conclusions about the welfare effects of expanded managed care activity, are also not well studied.

While it appears common to believe that managed care is slowing the rate of technology diffusion, and that this will be harmful to patients, these views are typically not based on strong comprehensive evidence about the effects of managed care growth.

This paper investigates the relationship between managed care activity and the adoption of neonatal intensive care units (NICUs), hospital units that organize a range of technologies and personnel to care more effectively for newborns with low birthweight and other serious health problems. The development of the specific technologies used in NICUs (mechanical ventilation for newborns, for example), as well as the organizational advance of combining these technologies with other staff and infrastructure to create NICUs, together form an important advance in the care for newborns. The first hospitals to set up NICUs did so in the mid to late 1960s and early 1970s, and NICUs diffused slowly over the course of the 1970s. Over time, as the underlying technologies have advanced, NICUs have become differentiated by the level of service they provide. Today there are a relatively small number of very advanced units that specialize in caring for the most seriously ill newborns. Beneath this very advanced level, though, are most of the NICUs in the country. These “mid-level” NICUs have some advanced capabilities, but do not have the equipment or the personnel to handle the most complicated cases. The number of NICUs grew over the course of the 1970s and into the early 1980s, but most early growth was among the most advanced hospitals that set up very advanced units. During the 1980s and 1990s, many hospitals began providing NICU services via mid-level units.

We are particularly interested in the diffusion of mid-level NICUs. Most of the diffusion of these units occur during the time period in which managed care played an important role in the U.S. health care system. Since setting up and using a NICU is expensive, and since managed care plans may attempt to concentrate their use of expensive advanced services in fewer hospitals, growth in managed care could well influence NICU adoption. In addition, these units provide a strong chance to study the implications for patient care. Good data on the care of high-risk newborns is increasingly available, and some research shows that the use of mid-level NICUs relative to higher-level units can lead to worse health outcomes (Phibbs et al, 1996)

We begin in the next section by describing the impacts managed care could have on technology adoption. We then turn to an empirical analysis of the impact of HMO market share on the diffusion of NICUs over the period 1985-1996. We use proportional hazard competing-risk models to separately examine adoption of mid-level and high-level NICUs. We find that hospitals in high HMO areas were less likely to adopt mid-level NICUs over this time period than hospitals in areas with less HMO activity. There is no effect of HMO market share on the adoption of high-level NICUs during this time period. The net impact is that high HMO areas end up in 1996 with fewer mid level NICUs than high HMO areas, and about the same number of high level units.

Reductions in the diffusion of mid-level NICUs would generate significant savings. From a welfare standpoint, though, these savings could be offset if there are reductions in the quality of patient care. The implications reduced mid-level NICUs availability for newborn health outcomes hinges on the care high risk newborns get in the absence of a mid-level NICU. The presence of a mid-level NICU may prevent some newborns from receiving care at a high-level center. On the other hand, some newborns may receive no NICU care at all in the absence of a mid-level center. For high risk newborns, outcomes at larger, more advanced centers are demonstrably better (Phibbs et al, 1996). We use detailed data on all birth in California between 1990 and 1996 to study the impacts of NICU availability on care. We find that reductions in the availability of mid-level units are associated with substantial improvements in outcomes for high risk newborns.

This work builds on other research that suggests the potential for managed care to influence the performance of health care markets broadly. A number of researchers have studied the effects of managed care on spending and insurance premiums (e.g. Baker, 1997, 1999, Baker and Corts, 1996, Feldman *et al.*, 1993, Goldberg and Greenberg, 1979, Wickizer and Feldstein, 1995, Chernew, 1995, Feldman *et al.*, 1986, McLaughlin, 1987, 1988, Noether, 1988, Robinson, 1991, Clement *et al.*, 1992, Welch, 1994). None of these studies discussed the relationship between managed care activity and NICU adoption, although they provide reason to believe that managed care can influence market-level patterns of care and spending, which could contribute to changes in adoption.

Previous work on managed care and technology is limited. Cutler and Sheiner (1998) studied a wide range of hospital-based technologies and found some evidence that hospitals in states with higher HMO market share had slower rates of adoption of some technologies during the 1980s and 1990s. Baker and Spetz (1999), though, used an index of hospital technological advancement and did not find significant evidence of an overall effect on managed care on hospital technology adoption. Some work examines MRI specifically, finding that areas with high HMO market shares adopted MRI more slowly than low market share areas (Baker and Wheeler, 1997; Baker, 2000). A small number of studies have examined the impact of managed care on health care delivery and suggested that managed care can influence the health care patients receive (e.g. Baker, Heidenreich, Geppert, and McClellan 2000).

More generally, the general literature on the adoption and diffusion of technologies is well developed.[1] This literature provides a strong foundation for this study, particularly in that it consistently suggests that changes in the profitability of a new technology and other environmental factors (e.g. regulation) are important determinants of adoption timing and patterns.

2. <u>Managed Care Activity and the Adoption of New Technologies and Services</u>

Before the advent of managed care, health insurers typically paid health care providers using fee-

[1]See, e.g., Mansfield, 1968 and Reinganum, 1989. Examples of other health care technology studies are Anderson and Steinberg, 1984, Baker, 1979, Banta, 1980, Cutler and McClellan, 1996, Fendrick *et al.*, 1994, Globerman, 1982, Hillman and Schwartz, 1985, Hillman *et al.*, 1984, Lee and Waldman, 1985, Romeo *et al.*, 1984, Salkever and Bice, 1976, Teplensky, 1993, and Russell, 1977. Examples of work in other areas using techniques similar to those use here are Rose and Joskow, 1990, Saloner and Shepard, 1995, Levin, Levin, and Meisel, 1987, and Hannan and McDowell, 1984.

for-service reimbursement, exercising very little oversight of the treatment decisions made by patients and their doctors. The desire of patients and physicians for ever more advanced (and costly) health care, coupled with the readiness of third party payers to meet the costs of providing it, generated ample encouragement to developers, adopters, and users of new services and technologies for speedy advancement.

"Managed care" describes a collection of health plan activities designed to reduce the high levels of utilization and spending that accompanied unfettered fee-for-service medicine. Broadly, the activities that fall under the rubric of managed care can be placed in three groups. First, managed care plans attempt to alter financial incentives. Rather than paying on a fee-for-service basis, many managed care plans pay physicians using capitation or other reimbursement schemes that do not directly reward physicians for performing more, and more expensive, treatments. Second, managed care plans often assert control over many of the treatment decisions made for patients. Many managed care plans promulgate guidelines about the use of some services, require authorization before conducting expensive tests and procedures, and monitor the use of resources on a continual basis so that physicians and hospitals can be notified when treatments begin to seem excessive to the health insurer. Some plans use gatekeeper physicians, who must approve all referrals to specialists. Since the belief on the part of plans is typically that fee-for-service medicine was characterized by excessive use of expensive tests and procedures, their utilization control efforts are largely aimed at curbing the use of these kinds of services.

Finally, managed care plans often search for a set of physicians and hospitals with which they desire to contract, negotiate contracts with just these providers, and then restrict their members to use the chosen providers. Typically, managed care plans are thought to search for low-cost providers. This kind of selective contracting allows plans to select only those health care providers that agree to provide care according to the plans' guidelines at a cost the plan can agree to. This also frequently provides plans with considerable leverage over providers in the negotiation of contracts, since in many areas there are more providers in operation and hospital capacity than plans need to form networks. As managed care grows, it becomes increasingly important for providers to have managed care contracts, and thus increasingly easy for plans to win concessions from providers.

Growth in managed care could influence the incentives associated with adopting a new technology in several ways. First, managed care may change the expected profitability of a new technology. Virtually all models of technology adoption suggest that changes in profitability will change adoption timing.[2] In the most straightforward cases, with continuous increasing (expected) profits from possessing the technology and declining adoption costs, firms with higher expectations about profitability will tend to adopt earlier than firms with lower profitability projections. If managed care reduces the expected profitability of a new technology, firms in high managed care areas will tend to adopt later than otherwise identical firms in areas with less managed care, and vice versa.

The effects of managed care on the profitability of a service or technology can be illustrated in a simple framework. Consider a provider that serves *N* patients, N_t of whom are enrolled in HMOs in period *t*, and the remaining $1\text{-}N_t$ of whom are covered by fee-for-service (FFS) insurers. The provider can price discriminate between HMO and FFS patients. In period *t*, a provider who has the technology earns profits:

$$p_t \; = \; p_H N f_t a_H \; + \; p_F N (1 - f_t) a_F \; - \; c(q_t) \qquad (1)$$

where p_H and p_F are the prices that can be charged to HMO and FFS patients for the service supported by the technology (e.g. a NICU day), $''_H$ and $''_F$ are the fractions of HMO and FFS patients who demand the service, *c* denotes the cost function, and $q_t = N[N_t''_H + (1\text{-}N_t)''_F]$ is the total number of service produced in period *t*.

[2]See, e.g., Reinganum, 1989, Stoneman, 1986, or Rose and Joskow, 1990 for discussions.

Increases in HMO market share will tend to affect profits through three channels. First, HMOs are assumed to have highly elastic demand, and bargain aggressively to obtain low prices, while FFS patients often have little incentive to incorporate price into their decisionmaking. Price discriminating providers may thus be expected to set $p_F > p_H \geq c'$, and shifting patients from FFS insurance to HMOs will reduce revenues. Second, α_F need not equal α_H if managed care plans and FFS plans differ in the care they provide to their patients.

Finally, it is possible that $\partial\alpha_F/\partial N$ is negative. Some evidence suggests that HMOs can affect demand by encouraging the spread of practice patterns that are favored by HMOs to other, non-HMO, parts of the market. By imposing guidelines, financial incentives, and other mechanisms designed to encourage physicians working for HMOs to practice in accordance with the organizations' preferences, managed care organizations can change the ways physicians care for managed care patients. These physicians may, in turn, incorporate changed practice patterns into the treatment of their non-managed care patients. Further, if physicians tend to adopt the practice patterns of those around them (e.g. Phelps, 1992), then an increase in HMO activity could contribute to changes in the practice patterns of other physicians throughout the market. Alternately, demand may be shifted through effects of HMOs on FFS insurers. As managed care activity increases, the competitive pressure felt by traditional insurers may also increase. Some studies indicate that traditional insurers adopted some of the practices of managed care organizations once their value in achieving cost savings was demonstrated (e.g., Baker and Corts, 1996, Feldman and Dowd, 1986, Frank and Welch, 1985, Goldberg and Greenberg, 1979).

The implications of growth in HMOs could vary across technologies. In the case of NICUs, it seems likely that growth in managed care would constrain revenues. To the extent that traditional insurers were perceived as overusing NICUs, growth in managed care could also reduce demand for NICU services overall. HMO patients are typically less likely to use expensive tests and procedures than other patients (Miller and Luft, 1997). The effects of managed care growth could differ by type of

NICU. Anecdotal evidence would, for example, suggest that managed care has led to increases in demand for mid-level relative to high-level units.

Beyond simple profitability considerations, there are a number of additional factors that might also influence adoption decisions, and could work in varying directions. First, the arguments advanced above consider only the case of NICU services, but hospitals and other health care providers generally offer a wide range of health care services. Most new technologies are substitutes for some services and complements for others, and a full assessment of the profitability of adoption would incorporate effects on the complete range of services. If managed care organizations choose providers based on the availability of services as well as costs, there may be an incentive to adopt otherwise unprofitable new technologies as "loss leaders" to help win contracts that will bring in additional patients to other services. Services for births are frequently thought to be in this category. Childbirth is a common first point of exposure to a hospital for young families, and hospitals chosen for births tend also to be chosen for other care later.

Some literature also stresses the importance of strategic interactions between firms as a determinant of the speed of adoption of new technologies (e.g. see Vogt, 1997). The specific assumptions and focus of strategic interaction models, and hence their predictions for diffusion processes, vary from model to model, but the importance of these factors is increasingly clear. Most models focus on the returns to being the first adopter in a market and the incentive for a firm to delay after a rival has adopted. It is not difficult to believe that managed care could influence the parameters of strategic interactions between firms, although it is difficult to predict the direction of the effect. If the providers that initially win managed care contracts have an advantage in negotiations in subsequent years, and HMOs value the presence of a new technology in the choice of providers to contract with, growth in managed care could increase the premium associated with first adoption. Rivals of the first adopter might then perceive that they should immediately adopt, leading to an acceleration of adoption in the presence of managed care. On the other hand, rivals could perceive that the opinions of managed care plans with respect to the quality of hospitals will have been formed based on the initial adoption, and that there is little to be gained by subsequent adoption, and choose to postpone adoption, which would raise the mean time to adoption as HMO market share rises. In formal modeling, the specific direction of the strategic effects would depend on the specific assumptions about the preferences of managed care organizations, and the expectations of hospitals about the returns to various adoption scenarios. For NICUs, there is some reason to believe that these incentives could be important. Anecdotally, managed care plans appear to have attempted to reduce the number of NICUs and centralize services in a limited number of hospitals, and, at least in some areas like California, these relationships have been relatively stable over time, which may suggest to other hospitals that the potential benefit to subsequent adoption is small.

In all, the profitability, strategic, and other effects leave the net effect of managed care on NICU adoption patterns ambiguous. The relative impact on mid-level and high-level NICUs is also ambiguous. Both are empirical questions.

3. Neonatal Intensive Care

Neonatal intensive care units are typically units of hospitals set up with their own beds and equipment and staffed by pediatricians with advanced training in neonatology, specialized nurses, and other specialized staff. Any given NICU contains a range of equipment and service capabilities that are typically adopted together and collectively represent the NICU "technology" that a hospital can invest in.

The first units identifiable as NICUs were set up in mid 1960s with the advent of mechanical ventilators. Over time, the capacity of medicine to care for high-risk newborns has improved, and NICUs have developed in response to changing capabilities. Today, it is common to classify hospitals offering care for newborns into one of three groups. Essentially all hospitals that host planned deliveries are equipped with a "well baby nursery" with basic equipment for newborn care like bassinets and warming stations. Hospitals that offer this level of service, caring only for healthy neonates and those with minor medical problems, are classed as level I hospitals. At the other end of the spectrum are level III units (which we also refer to as "high level" units, and some refer to as "regional" or "tertiary" NICUs), which provide a full range of specialized neonatal care for the most seriously ill newborns, including long-term mechanical ventilation, sub-specialty consultants, and surgeries for newborns. Between level I and level III units, level II units provide some of the advanced services of level III units, but not all. Many of these units do not provide mechanical ventilation for extended periods of time. These units also typically do not have the staff and related equipment for treating rare and very serious cases, or the staff and equipment to support complex neonatal surgeries.[3]

Most of the NICU units adopted early on were high-level units put in place by the most advanced hospitals, especially academic medical centers and childrens hospital, which as a group tend to quickly take up most new innovations to their full extent. To some degree, early diffusion was also confined to high level units because of the available technologies made it difficult to install "mid-level" capabilities and hospitals that wanted to offer NICU services had to enter the market with the full complement of then-available services. This focus was also reinforced by a shortage of neonatology specialists, concentrating services at a smaller number of very advanced centers. As capabilities broadened, and the number of trained neonatology specialists grew, adoption of mid-level NICUs became more feasible, and much of the NICU diffusion in the 1980s and 1990s, has been concentrated in these kinds of units.

The advent of NICUs had powerful effects on the prognosis for high risk newborns. In California the perinatal mortality rate dropped dramatically during the 1960s, 70s, and 80s, and virtually all of this decline is attributed to the advent of NICUs (Williams and Chen 1982). Some research suggests that outcomes are better at higher level centers that see higher volumes of patients (Phibbs et al 1996),

[3]In some situations, finer distinctions are made, for example distinguishing a "level II+" between level II and level III, where level II+ units provide quite advanced services like longer term mechanical ventilation, but not all of the services available at level III units like complex neonatal surgeries.

but others argue that lower level centers may be appropriate, and high quality, locations of care for many newborns.[4]

Hospitals that wish to offer NICU services do so by setting up and staffing a NICU in their hospital.[5] The cost of setting up a NICU unit varies with the level of services offered. Observation of some hospitals in the San Francisco area suggests that setting up the equipment and physician plant for a new NICU can cost between $125,000 and $200,000 per bed, depending on the level of services offered and specific circumstances associated with the physical situation. Beyond the cost of installation, the units must be staffed with relatively expensive physicians and staff. Even in the era of managed care, recently trained neonatologists can command salaries of $200,000 or more, for which hospitals typically make salary guarantees. The costs for other staff and administration can also be substantial. The patient charges associated with a NICU stay vary widely depending on the complexity of the conditions and the length of stay required, physician charges, and other variables, but it is not difficult to run up bills of $50,000 or more for a moderate length NICU stay.

Virtually all insurers cover medically indicated NICU care. But, conventional wisdom suggests that managed care plans have been vigilant about the use of NICUs. NICU patients are by far the biggest single group of high cost patients in HMOs today, and a large amount of work suggests that managed care plans devote particular attention to the use of high cost services (Miller and Luft, 1997). Anecdotal evidence also suggests that HMOs may also discourage the use of high level, typically more expensive, units relative to mid-level units.

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[4]For example, the perinatal mortality rate fell from 2.5% in 1960 to 1.3% in 1977.

[5]The specific arrangements can vary from hospital to hospital. Some hospitals develop their NICUs as separately set up and staffed units in the hospital. Other hospitals set up NICU-like services, but do not designate them a separate unit in the hospital. Some hospitals contract with physician groups or others to “own” a unit set up within a hospital. The practical differences between these arrangements are typically small.

In our empirical analysis, we focus on the diffusion of NICUs between 1985 and 1996. During this period, diffusion of NICUs occurred mainly in mid-level units. The majority of leading tertiary referral centers, which quickly adopt most new innovations, had already adopted level III units by this time. But, the growth of mid level units was strong during the 1980s and 1990s. A key factor driving the spread of mid level units during this time was the expanding effort to improve health outcomes among newborns, which expanded the set of conditions that seemingly "required" treatment in a NICU. Today, NICU admissions are 10-12% of births, and at least another 15% of deliveries have obstetric conditions for which the presence of a level II NICU or better is considered a prudent backup capability to have in the hospital at which the delivery occurs (Phibbs et al., 1993). Many obstetricians and pediatricians thus began to argue during this period that keeping an active obstetrics unit operating in an urban area would require a hospital to have a level II NICU or better. Against the backdrop of this diffusion, however, the incentives associated with managed care growth had begun to change the financial and strategic picture associated with adoption.

4. HMO market share and the diffusion of NICUs

4.1 NICU Data

We begin by analyzing hospital adoption of NICUs using data from the American Hospital Association (AHA) annual survey of hospitals. The AHA surveys all hospitals in the United States each year and inquires about a range of hospital characteristics, including the presence of various units and the sizes of those units.[6]

We focus on NICU diffusion over the period 1985-1996, a time period in which managed care played a significant role in the U.S. health care system and a period in which NICUs were diffusing.

[6]In 1982 and earlier, the AHA survey was conducted every other year.

Focusing on this time period does, of course, leave out some diffusion that occurred earlier. High level units in particular had diffused significantly in the period up to 1984. But, if the effect of managed care on diffusion was different, or non-existent, during the earlier years, concentrating on this period will produce the most accurate estimates. (The assumption that the HMO effect changed is testable, as we discuss further below.) Beginning in 1985 is arbitrary, and similar results are obtained if we look at other beginning years between 1984-1997.

To form our main sample, we selected general medical and surgical hospitals and children's hospitals in the continental United States surveyed in 1984 and 1985.[7] Each hospital was assigned a market area, defined as the Health Care Service Area (HCSA) in which it was located. HCSAs are groups of counties constructed to approximate markets for health care services based on Medicare patient flow data (Makuc *et al.*, 1991). In all, there are 802 HCSAs covering the entire continental United States. As an alternative to Metropolitan Statistical Areas, HCSAs provide smaller units of analysis specifically defined to represent health care markets, as well as a more representative set of markets for study. Hospitals in very rural areas may behave quite differently than hospitals in other areas, so we excluded hospitals in areas with populations under 25,000. This left 5,555 hospitals.

Because we wanted to restrict the analysis to hospitals that were candidates for adoption of a NICU, we included hospitals that had an active obstetrics unit in 1984, had at least 50 births in 1984, or

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[7]General medical and surgical hospitals make up 80 to 85 percent of surveyed hospitals in any given year. Excluded hospitals include a range of institutions for the care of specific populations (e.g. psychiatric hospitals, rehabilitation hospitals) and hospitals affiliated with specific institutions (e.g. prisons). To be included, hospitals had to fit in the included group in every year in which they were observed, so a small number of hospitals that switch categories out of the group of general med/surg or children's hospitals are excluded. The restriction that the hospitals had to be surveyed in 1984 eliminates some hospitals that are only observed beginning in subsequent years. The vast majority of these hospitals are the entities that result from hospital mergers.

were a childrens hospital. This excluded 1,199 hospitals.[8] Of the remaining hospitals, 258 had already adopted a mid-level unit by 1984, and 377 had already adopted a high level unit, and so are not candidates for further adoption. Finally, we identified and excluded 114 hospitals for whom the NICU data on the AHA survey was unclear about the presence of a NICU or the year in which it was adopted.[9] Our main analysis sample is thus 3,607 hospitals in HCSAs with populations over 25,000 that were observed in 1984 and 1985 and that appeared to be candidates for adoption, but had not yet adopted a NICU.

We followed each hospital as far as possible by linking subsequent AHA surveys. We identified hospitals that adopted NICUs, the type of NICU adopted, and the year of adoption based on answers to the survey questions about the number of beds the hospital had in a "neonatal intensive care unit" or in a "neonatal intermediate care unit." We classified hospitals as having a high-level NICU if they had at least some "neonatal intensive care" beds and the sum of the beds reported in their "neonatal intensive care" and "neonatal intermediate care" units was more than 10. (The most advanced units tend to be relatively large.) We classified hospitals as having a mid-level NICU if they said they had at least some "neonatal intensive care" beds, but the sum of their "neonatal intensive care" and "neonatal intermediate care" beds was 10 or less, or if they only said that they had "neonatal intermediate care" beds, regardless of the number. We then examined the data over time to identify the year of adoption of a unit, and the type of unit adopted. The details of this process, including cleaning of the (sometimes messy) AHA survey data and identification of adoption year and type adopted, are discussed further in Appendix A.

We believe that this classification will approximate mid-level and high-level units as described above. Large units called "neonatal intensive care units" by the hospital in which they reside are typically

[8] Of these, 45 did go on to adopt mid-level units over 1985-1996, and 12 adopted high level units. We discuss the implications of making this exclusion restriction further below.

[9] This mainly occurred when hospitals provided inconsistent information from year to year, for example sporadically indicating having a NICU over a several year period.

the most advanced units. Mid-level units are typically smaller and are sometimes not termed "neonatal intensive care units" by hospitals. Because the AHA data do not provide detailed information about the capabilities of the units, we are unable to be more specific.

We assign each hospital a single adoption year and type, and we do not attempt to account for hospitals that shut down their unit or change its type. In practice, these are not frequently observed. For example, in California, where we have relatively detailed data on NICU availability by hospital for 1986-1997, we observe no cases of hospitals changing from a mid-level to a high-level unit or vice versa. Two hospitals, out of about 180 with NICUs, were observed to close a unit during this time.

All hospitals in the sample that had not adopted by 1996 were censored at the end of 1996, the end of the study period. We also censored hospitals that closed or merged before they had adopted a NICU.

4.2 HMO Market Share Data

We measure the level of managed care activity in each HCSA using data on HMO market share (i.e. the percent of the population enrolled in HMOs). "Managed care" is not well defined and there are many types of managed care organizations, all of which could conceivably exert influence on technology diffusion processes. We use HMO market share since good geographically detailed data on HMOs is available for the time period under study here and suitable data on other types of managed care plans like PPOs and POS plans are not. We expect that focusing on HMO activity will not strongly bias the results since HMOs were by far the most prevalent form of managed care during much of the time that neonatal intensive care was diffusing, and thus HMO activity probably provides a good proxy for the general level of managed care activity at this time. Even in more recent years, the presence of HMOs is likely a good proxy for the overall presence of strong managed care organizations since HMOs tend to use more stringent utilization management and have been more aggressive in reducing payments to providers than other forms of managed care plans like PPOs.

Conceptually, at any given time, the decision about whether and when to adopt a NICU should be a function of the current level of HMO market share and the expectations about future levels. The observed diffusion patterns for NICUs over 1985-1996 should thus cumulatively be functions of the actual levels of market share in each of these years and the expectations about future levels held at each point during 1985-1996. Measures of the expectations of hospital managers are not available. Data on HMO market shares by HCSA are available beginning in the early 1990s, and we classify areas based on the average market share over the years 1990-1996. We expect this to be a reasonable proxy for actual and expected HMO market shares during 1985-1996 for two reasons. First, areas that had high average 1990-96 HMO market shares also tended to have high market shares in other years. This can be confirmed with MSA-level data available in 1983 and again in 1990-1996. We find, for example, that the correlation between 1990-1996 average market share and 1996 market share is 0.94. Correlations with 1994, 1992, and 1990 are 0.99, 0.98, and 0.96, respectively. The correlation with 1983 market share is 0.62. Second, areas that had high average 1990-96 HMO market shares also tended to have high growth in market share over 1983-1996. The MSA-level correlation between 1990-1996 average market share and changes between 1983 and 1996 is 0.73. Thus we conclude that hospitals in areas with high average 1990-1996 market shares also tended to have higher actual market shares during 1985-1996 than hospitals in areas with low 1990-1996 average market shares. Further, if hospitals were able to forecast HMO growth in their areas with some degree of accuracy, hospitals in areas with high 1990-1996 average market share would also have had higher expected future market share levels at any given time during this time period.

The estimates of market share we use were constructed using data from the Group Health Association of America (now the Association of American Health Plans) and/or Interstudy reports of total enrollment and counties served for all HMOs operating in the United States in each year 1990-1996.

Using this data, county-level estimates were constructed by apportioning the enrollment of each HMO among the counties served, and estimates for HCSAs and MSAs were constructed by aggregating the county-level estimates. The construction of these estimates is described in more detail in Appendix A. The nationwide mean of the 1990-96 average market share, weighted by population, is 17.8%. Across HCSAs in the sample, 1990-96 average market shares range from 0 to 48.3%.

4.3 Trends

Table 1 summarizes NICU adoptions observed in our sample. 517 hospitals adopted mid-level NICUs between 1985 and 1996, 14.3% of the baseline hospitals. Eighty-six hospitals, 2.3% of the baseline sample, adopted high-level units. Counting hospitals that had adopted prior to 1985, 775 had mid-level units by 1996, and 463 had high level units.

Consistent with trends in the hospital industry, we also observe a significant number of closures and mergers, leading to censored observations in our sample. About 13% of the original sample is censored before 1996, when all remaining hospitals are considered censored.

4.4. Competing risk analysis of HMOs and NICU diffusion in hospitals

We now turn to an examination of the effect of HMOs on NICU adoption. In our empirical model, hospitals that did not previously have a NICU may adopt a mid-level NICU ($P_1(t)$), adopt a high-level NICU ($P_2(t)$), or continue without adopting either ($1-P_1(t)-P_2(t)$). Hazard models provide a natural framework for modeling these probabilities (e.g. Rose and Joskow, 1990, Cutler and McClellan, 1995, Baker, 2000). Denoting the cumulative probability that hospital *i* has a NICU of type *j* at time *t* by $F_{i,j}(t)$ and the corresponding density function as $f_{i,j}(t)$, the hazard is defined as the instantaneous probability that hospital *i* acquires a NICU of type *j* at time *t* conditional on not having acquired either up to that point: $8_{i,j}(t)=f_{i,j}(t)/[1-F_{i,j}(t)]$. Following previous literature, we parameterize the hazard using a proportional hazard form: $8_{i,j}(t)=8_{0,j}\ (t) \cdot exp(x_i\text{'}\$_j)$ where x_i denotes covariates that determine the proportionality in the hazard and $8_{0,j}(t)$ is the baseline hazard associated with adoption of NICU type j.

Define $g_j(t) = \ln(\int_{t-1}^{t} l_{0,j}(t)\, dt)$ to be the logarithm of the integrated baseline hazard of adoption from

t-1 to t. Then the cumulative probability of adopting a NICU of type j by time t is given by:

$$F_{i,j}(t) \ = \ 1 - \exp\left[-\sum_{s=1}^{t} \exp(x_i\text{'}\boldsymbol{b}_j + g_j(s)) \right] . \tag{2}$$

Denote by t_i* the first time in which a hospital is observed to have a NICU or is censored. Because of gaps in survey times, the exact timing of adoption for a hospital first observed with a NICU in t_i* can only be known to fall on the interval between time t_i*-1 and t_i*. The probabilities associated with the three outcomes can thus be written:

$$\begin{aligned} P_{i,1} &= \text{Prob[adopt mid-level unit]} = [F_{i,1}\ (t_i^*) - F_{i,1}\ (t_i^*\text{-}1)] \times [1 - F_{i,2}\ (t_i^*)] \\ P_{i,2} &= \text{Prob[adopt high-level unit]} = [F_{i,2}\ (t_i^*) - F_{i,2}\ (t_i^*\text{-}1)] \times [1 - F_{i,1}\ (t_i^*)] \\ P_{i,3} &= \text{Prob[censored]} = [1 - F_{i,1}\ (t_i^*)] \times [1 - F_{i,2}\ (t_i^*)] \end{aligned} \tag{3}$$

Letting $d_{i,1}$=1 for hospitals that are observed to adopt a mid-level NICU and $d_{i,2}$=1 for hospitals that adopt a high-level unit, the likelihood function for the data is given by:

$$L \ = \prod_{i=1}^{N} P_{i,1}^{d_{i,1}} \ P_{i,2}^{d_{i,2}} \ P_{i,3}^{1-d_{i,1}-d_{i,2}} \tag{4}$$

This is a competing risks model with interval-censored data. We maximize the logarithm of this likelihood function using standard techniques.

In addition to measures of HMO market share, we include a set of hospital and other area characteristics as covariates in the models. Included hospital characteristics are the average bed size of the hospital and dummy variables for hospitals affiliated with medical schools, other teaching hospitals, and childrens hospitals. A set of area controls is designed to account for the degree of urbanization and includes the market population, the area population per square mile, and the percent of the population that lives in an urban area. The models also control for a standard set of market demographics reflecting the age, sex, race, education, and income of the population. Finally we include controls for the number of births per 1000 population in the area, and the percent of newborns below 2500 grams. We measure all of the area variables as of 1996 since these levels seem likely to capture both actual levels of these variables over preceding years and the expectations of hospital managers about trends in their marketplace over 1985-1996. Table 2 summarizes the covariates in the regressions.

Table 3 presents estimation results. The first two columns present results from models in which the baseline hazard is assumed to follow a Weibull distribution: $8_{0,j}(t) = "_j \, t^{"j-1}$. The Weibull is convenient in this setting because it allows for (monotonic) variation in the hazard over time, which is empirically observed in the data. Columns 1 and 2 display results from a model in which HMO market share is entered linearly. The market share coefficient for mid-level NICUs is negative and statistically significant, suggesting that increases in market share are associated with reductions in the adoption hazard. The relative hazard for HMO market share is given by exp($) and is shown in brackets. The results indicated that each 10 percentage point increase in the average 1990-1996 market share is associated with about a 15% reduction in the adoption hazard.[10] For high-level units, there is no measurable relationship between HMO market share and adoption. Columns 3 and 4 display results from a model in which HMO market share is categorized into 3 groups: “low” market share (0-10%), “medium” market share (10-20%), and “high” market share (>20%). This grouping serves two purposes:

[10]It is important to note that, although results are reported using the metric of 1990-1996 average market share, the results reflect the effects of HMOs built up over a range of prior years in which the actual market share levels were generally lower, and potentially also reflect the expectations about future levels of HMO market share, which may be higher than the 1990-1996 average.

it will aid in capturing any non-linearities that might exist in the effect of market share, and it will dampen the effects of any measurement error in the market share data. Like those in columns 1 and 2, these results suggest substantial effects of HMO market share on the adoption of mid level units. Hospitals in areas with market shares over 20% had adoption hazards about 34% lower than hospitals in low market share areas. There appears to be some non-linearity in that the strongest effect on adoption hazards is observed in the high market share group. As in column 2, there is no evidence for an effect of HMO market share on high-level NICU adoption.

The estimates of α_1, the Weibull shape parameter for mid level units, are significantly greater than 1, consistent with an increasing adoption hazard. The assumption that the baseline hazard follows a Weibull distribution is, however, arbitrary. To examine this assumption further, columns 5-8 reestimate the hazard model using a non-parametric baseline in place of the Weibull baseline, as suggested by Prentice and Gloeckler (1978) and Meyer (1990). A likelihood ratio test rejects the equality of the two baseline specifications, but substantively there are no important differences between the two sets of estimates. The coefficients on the HMO market share variables are essentially unchanged. In all subsequent analyses we use the Weibull baseline for convenience.

Figure 1 plots the estimated cumulative adoption probabilities from the Weibull and non-parametric baseline models for mid-level units in areas with <10% market share and areas with >20% market share, holding all other covariates fixed at their sample means. (Estimates for areas with 10-20% market share are very similar to those for areas with <10% share.) The Weibull and non-parametric models suggest similar cumulative adoption patterns. Both the Weibull model and the non-parametric baseline model predict that by 1996, the cumulative adoption probability was 8.7% for hospitals in high market share areas, as opposed to 12.6% in medium market share areas and 12.9% for hospitals in low market share areas.

Pre-1985 Diffusion

We focus on the 1985-1996 diffusion patterns because this is the time period in which managed care is likely to have had an effect on diffusion. Implicitly, we assume that managed care did not impact diffusion before 1985. The best way to examine this further is to use a time-varying covariates model, which is in progress. In the mean time, we can learn more about this by examining the relationship between our HMO market share measures and diffusion up to 1984, taking all hospitals to be censored at 1984. Assuming a proportional hazard framework, the likelihood of observing a hospital with a NICU of type j in 1984 is:

$$F_{i,j}(t) = 1 - \exp\left[-\exp(x_i' \boldsymbol{b}_j)\right] . \tag{5}$$

which is just an adaptation of equation (2) where there is only one time period spanning the interval from the initial availability of NICUs to 1984 and this is incorporated into the intercept.

We estimate equation (5) using maximum likelihood using data on 4,242 hospitals that had active obstetrics units in 1984 and whose NICU data were clear enough to discern an adoption date. The results do not suggest an effect of HMO market share on adoption up to 1984. The linear HMO market share coefficient for mid-level units is 0.024, with a standard error of 0.086, much smaller than estimated in the 1985-1996 period and statistically insignificant. For high-level units, the coefficient is 0.007 with a standard error of 0.093. We conclude that there was no relationship between HMO market share and NICU adoption before 1985.

Modeling unobserved heterogeneity

One important difficulty with the results presented above is the potential for bias from unobserved heterogeneity. Providers in some areas may be less prone to adopt new technologies and services than providers in other areas. If these differences are not accounted for by the included covariates, estimates of the effects of HMO market share may be biased. We investigate the possibility of bias from unobserved heterogeneity two ways. First, unobserved heterogeneity can be modeled as an additional source of error in the adoption equations. If unobserved heterogeneity is assumed to take a multiplicative form, the hazard becomes:

$$l_{i,j}(t) = q_{i,j}\ l_{0,j}(t)\exp(x_i' b_j) \tag{6}$$

where $2_{i,j}$ is a random variable that is assumed to be independent of x_i. One approach to estimating (6) is to assume a distribution for 2 and jointly estimate the parameters of the heterogeneity distribution and the hazard model. However, since the assumption of any distributional form is fundamentally ad hoc, Heckman and Singer (1984), extended by Meyer (1990), suggest estimating the distribution of 2 nonparametrically, as a mixing distribution characterized by a set of discrete mass points and the associated probability that a provider falls at each given point. We adopt this approach here.

To implement it, we assume that there are M discrete mass points for each hazard T_1={ $T_{1,1}$, ..., $T_{1,M}$} for mid-level adoptions and T_2={ $T_{2,1}$, ..., $T_{2,M}$} for high level adoptions. The probability of adoption of either type can then be factored into the probability conditional on any set of T's and the probability of each combination of T. The likelihood is thus:

$$L = \prod_{i=1}^{N}\sum_{k=1}^{M}\sum_{l=1}^{M} P_{i,1}^{d_{i,1}}\ P_{i,2}^{d_{i,2}}\ P_{i,3}^{1-d_{i,1}-d_{i,2}}\ \Pr[w_1 = w_{1,k}, w_2 = w_{2,l}] \tag{7}$$

We estimated equation (7) with 2 mass points per equation for a total of four potential probabilities. In practice, all but one of the probabilities were estimated to be zero. This would suggest no heterogeneity. The coefficients produced are thus very similar to those shown in Table 3, which assumed no heterogeneity.

We should note that obtaining estimates from this model was difficult. The likelihood function appeared to have multiple local maxima. It was not possible to obtain consistent estimates with more than

2 mass points. Although these difficulties lead us to place less than complete confidence in these results, those results obtained are consistent with the view that unobserved heterogeneity does not explain the reduced adoption of mid-level units in high HMO areas.

A comparison with the adoption of Cardiac ICUs

The fundamental concern with regard to unobserved heterogeneity is that there is some unobserved characteristic of high market share areas that causes them to be slower adopters of new technologies. Another approach to examining this issue is thus to compare the diffusion of NICUs in 1985-1996 to other technologies that diffused earlier. If there is some fixed characteristic of high market share areas that causes them to adopt new technologies more slowly than other markets, then we would expect to observe a relationship between 1990-96 average HMO market share and the diffusion of other services similar to that observed for NICUs, even those that diffused too early for HMO market share to plausibly play an important role. Observing no relationship between HMO market share and earlier diffusion patterns would be consistent with the view that there are not fixed characteristics of markets that caused the observed relationship between market share and NICU diffusion.

One good technology for comparison is the cardiac intensive care unit (CICU). CICUs are similar to NICUs in that they are typically separate units of hospitals, set up with specialized equipment and staffed with specialized personnel. The diffusion of CICUs occurred primarily during the 1960s and 1970s, so that they were largely diffused by 1984. By 1984, they reached about the same level of diffusion reached by NICUs in 1996. In 1984, 27% of surveyed hospitals had a CICU and this percentage remained roughly constant through 1996, declining some in the mid 1990s with hospital closures.

We obtained data on the presence of CICUs in hospitals in 1984 from the AHA survey, identifying hospitals with CICUs based on their indication that they had CICU beds present in their hospital. Applying the model for NICUs used above, the cumulative probability that a hospital had adopted a CICU by 1984 is

$$F_i(t) = 1 - \exp[-\exp(x_i' b)] \tag{8}$$

which we estimate by maximum likelihood.

Columns 1 and 2 of Table 4 present results from hospital adoption hazard models for CICUs using data from 1984 for all hospitals. We use the same covariates used above, except we replace the percent of the population female age 15-44 with just the percent female, drop the controls for births, and add a control for the proportion of the population over age 65. We use a Weibull baseline. The HMO market share coefficients are not statistically significant, and do not suggest a systematic relationship. Perhaps a fairer comparison would use the same sample of hospitals for the CICU analysis that we used for the NICU analysis. Results are in columns 3-4. The results for CICUs are similar to those in columns 1 and 2, and again do not suggest an impact of HMO market share on CICU adoption.

If hospitals in the areas we deem high market share areas were simply less likely to adopt new units like NICUs, we might have expected to see reductions in the adoption of CICUs as well. This comparison is not perfect–notably we do not distinguish between mid-level and high-level CICUs, but it is again inconsistent with the view that there are unobserved characteristics of areas that explain our findings above. Other related evidence is also consistent with this view. Baker (2000) studied CT scanners, which largely diffused between 1973 and 1983, and found little effect of HMOs. We also observed no relationship between HMO market share and the pre-1985 diffusion of NICUs above.

Non-independent censoring

An assumption of proportional hazard models with censored observations is that censoring is independent of adoption, that is, that *F(t)* is identical for both censored and non-censored observations.

Here, hospitals can be censored because they close or merge, or because they have not adopted by the end of the sample period in 1996. The latter cause of censoring is likely independent of adoption, but it may be that hospitals that close or merge have different adoption hazards than hospitals that do not. If this is the case, estimates could be biased.

We observe hospital closures and mergers regardless of whether or not the hospital has adopted a NICU, which differs from the traditional case of hazard models in which adopters are not followed after adoption to observe subsequent events. We can thus investigate whether or not assuming fixed *F(t)* has a significant impact on the estimates by extending the models above to allow separate hazards for the two groups, estimating equation (4) separately for each group.

Among the 3,607 hospitals in the sample are 3,104 that do not close or merge between 1985 and 1996, of which 475 adopt a mid-level unit and 72 adopt a high-level unit. 503 hospitals close or merge during this time, of which 42 adopt mid-level units and 14 adopt high level units. Estimates using only hospitals that do not close or merge are presented in panel A of Table 5. These results should not be influenced by non-independent censoring, although they may not be generalizable to the population as a whole, and they are consistent with the results observed above. Estimates for hospitals that do close or merge are in the bottom panel of Table 5. As might be expected, adoption hazards are lower for hospitals that close or merge. Hospitals in high market share areas that close or merge are particularly unlikely to adopt. But, adoption hazards also decrease with market share among hospitals that stay open the entire time. Overall, the results do not suggest that non-independent censoring significantly biased the estimates.

Further specification tests

We estimated several alternate specifications to investigate the robustness of the results. Results are shown in Table 6. The specifications examined were: (1) adding controls for the characteristics of the area health care system. These may be endogenous, but they may also control for important determinants of NICU adoption. The specific variables included are the total number of short-term general hospitals, the number of hospitals per 100,000 population, the average number of beds per hospital, the number of generalist physicians, specialists physicians, and pediatricians per 1,000 population, and the average 1990 Medicare AAPCC, a general measure of health care costs and utilization patterns in the HCSA; (2) Including squares of urbanization variables to the possibility of bias from additional urban-rural variation; (3) Including two dummies for the presence of certificate of need legislation applying to hospital purchases over $1 million and under $1 million, which might have impaired the ability of hospitals to adopt a NICU;[11] (4) Including in the sample even those hospitals that did not have an active delivery service in 1984. These hospitals as a group did not appear to be good candidates for adoption, but a small number of them did adopt NICUs during 1985-1996; (5) Including only hospitals in MSAs and measuring HMO market share at the MSA level, since MSAs may be more homogeneous than HCSAs and HMO market share estimates may be better at the MSA level; (6) Including only hospitals in MSAs and measuring HMO market share with Interstudy's 1996 MSA-level estimate of market share, an alternate measure of market share (note this is not available for all MSAs); (7) Including only hospitals in MSAs and measuring HMO market share with an MSA-level estimate of HMO market share available for 51 markets from the 1996 Community Tracking Study household survey. In all of these cases, the results for mid level units are consistent with those presented above. Results are also generally consistent for high-level units, although some of the MSA-level models do produce fairly large (though still insignificant) negative coefficients.

[11]States vary greatly in their use of CON: not all states use it, many states had CON for some period of time but repealed it, and states that have or had CON vary in the provisions of their laws. Thus, defining variables that capture the effects of CON laws is difficult. Here, we include measures of the presence of CON laws in 1986, a time at which the diffusion of NICUs was starting to accelerate and a year for which good data on state CON provisions are available. These data were derived from Simpson (1986). CON typically did not apply to non-hospital providers.

Cost Savings

Since setting up new NICUs is typically very costly, a slowdown in the adoption of mid-level units should generate savings. One way to develop a crude estimate of the savings is to suppose that all areas had remained in the 0-10% HMO market share category over 1985-1996. The estimates in Table 3 suggest that the cumulative adoption probability is was 8.7% for hospitals in high market share areas, 12.6% in medium market share areas and 12.9% for hospitals in low market share areas. In our sample, there are 1065 hospitals in medium market share areas and 740 in high market share areas. If the 12.9% cumulative adoption rate were applied to the medium and high market share hospitals, this would suggest an additional 34 adoptions that did not take place. Setting up and staffing a moderately sized mid level unit can easily cost more that $2 million, with additional operating costs once it is running. Thus, a crude, probably conservative, estimate of savings might be $70-$100 million.

5. The Impact of Mid-Level NICU Availability on Health Outcomes

Cost-saving reductions in NICU adoptions are unambiguously welfare improving if there are not offsetting changes in patient care or health outcomes. To examine the impact of reductions in the availability of mid-level units on health outcomes for newborns, we examine detailed data on births in California during 1990-1996. The availability of NICUs of different types varied across markets and over time, providing an opportunity to study the implications of unit availability on outcomes. We specifically focus on mortality rates for newborns with serious health problems, the group that would be candidates for NICU care. Mortality is a serious risk for these newborns, and is thus a natural outcome to study.

Changes in the availability of mid-level NICUs could impact mortality rates by influencing the type of care newborns receive. We write the probability of death as a function of the level of care received:

$$Pr[Death] = P_L{*}MR_L + P_M{*}MR_M + P_H{*}MR_H \tag{9}$$

where P_L , P_M , and P_H are the probabilities that an infant is treated in a low-level, mid-level, or high-level NICU, respectively, and *MR* denotes the mortality rate associated with treatment in a unit with that level of care. If there are differences in mortality rates *MR* then increases in the availability of mid-level units could impact mortality by moving infants out of low-level centers or by moving infants out of high-level centers. These effects could be offsetting, and could vary with the specific characteristics of infants. For example, caring for very high risk newborns in mid-level units rather than high-level units could worsen outcomes. But, moving some moderately ill newborns to mid-level units from low-level hospitals could potentially improve outcomes.

To examine the impact of NICU availability on outcomes, we examine the impact of level of care received on mortality rates (the *MR* components above) and then the effect of NICU availability on level of care received (the *P* components above).

5.1 Data

We use California hospital discharge data linked to birth certificate data and to detailed mortality records. These data provide the detailed clinical data necessary to analyze mortality rates controlling for important comorbidities and other risk factors (Phibbs et al 1999).[12] Our database includes essentially all singleton births that took place in California between 1990 and 1996, and for each newborn identifies their comorbities and other clinical characteristics, demographics, mortality, and the hospitals at which they were treated, including transfers and readmissions out to one year after birth. There are more than 500,000 births per year in California, and the database altogether contains records for about 4 million births.

To focus on high-risk newborns for whom NICU availability is relevant, we identified a

[12]We focus on California since the detailed linked data we require is only available for California.

subsample of very low birth weight (VLBW) infants, those with birth weight between 500 and 1500 grams. VLBW is the leading cause of neonatal death in the U.S., and American Academy of Pediatric guidelines recommend that all VLBW infants be cared for in high level NICUs.

Some of our analyses use data on the residence area. We defined areas using the California state definition of Health Facility Planning Areas (HFPAs), which are areas defined to approximate roughly self-contained markets for hospital care in California. There are 132 HFPAs in California. To facilitate these analyses, we excluded from our subsamples the small number of births that occurred in areas with <100 births per year total. This leaves 29,430 births in our VLBW sample.

<u>5.2 Level of Care Received and Mortality Rates.</u>

We measure mortality rates using 28-day mortality, which is defined to include all deaths occurring within 28 days of birth as well as any mortality that occurred in the first year of life if the infant remained hospitalized continuously since birth. We include the latter sources of mortality to capture deaths that are delayed beyond the 28 day neonatal period by care in the NICU.

To examine the impact of NICU care level, we classify newborns using the level of care available in the hospital in which they are born. This does not capture post-birth transfers to higher hospitals. We have investigated the effects of including measures of both level of care in birth hospital and levels of care in hospitals reached by transfers and find that including controls or transfers does not substantially impact the main conclusions. Because including these controls is cumbersome, we omit them here. The California data we use stratifies NICUs into 4 levels: levels I, II, II+, and III, and we follow this distinction in the analyses.[13]

[13]This may complicate comparison of the results presented here and results for “mid-level” and “high-level” units presented above, since it is not always clear whether level II+ units are more appropriately classed with level II (“mid level”) or level III (“high-level”) units. In practice, the appropriate classification could depend on the specific clinical characteristics of the newborns they treat.

Mortality rates vary substantially with the level of NICU availability in the hospital of birth. Table 7 summarizes the distribution of births across hospitals with different NICU levels and mortality rates. The data in Table 7 indicate that a large number of very sick newborns are born in relatively low-level centers, and they also show higher mortality at higher level centers. Since the most advanced units are likely to receive the most difficult cases, though, the mortality rates may not indicate the true impact of higher level units on care. To control for case severity, we use logistic regressions of the form:

$$logit(28\text{-}Day\ MORTALITY) = \beta_0 + \beta_1\ LEVEL + \beta_2\ X \tag{10}$$

where *LEVEL* is a series of dummy variables for the level of care received, and *X* is a set of covariates. We include an extensive set of covariates designed to capture variations in mortality risk of the newborns. These include the baby's sex and birthweight interacted (birthweights grouped: 500-750g, 750-1000g, 1000-1250g, 1250-1500g, 1500-2000g, 2000-2500g, 2500-4000g, >4000g), and detailed controls for 23 comorbidities. The comorbidity controls were derived from the clinical variables in the linked data and are based on the risk model for newborns developed in our previous work (Phibbs et al 1996).[14] Together, these variables represent the state of the art in controlling for variations in mortality risk across newborns. In previous work, they have been shown to capture the majority of the total variation in mortality risk. In addition to these variables, we also control for the mothers race and education, the use of prenatal care, and the insurance status of the baby. Since we pool data from 1990-96, we include year dummies. Finally, some models include dummy variables for the HFPA of residence, in order to capture persistent demographic or other geographic variation.

Main results for the level of care variables are shown in Table 8. Complete results are shown in Appendix B. VLBW infants born in higher level centers have better outcomes. Mortality odds are 35-45% lower at hospitals with level II+ and level III units relative to hospitals with level I units. Computing

[14]The comorbid conditions included here are only those that would have been present at birth, and thus the variables in the model should not be influenced by any subsequent care.

around the sample average mortality rate (19.1%), this would translate to reductions of 6-7 percentage points in the overall mortality rate. level II+ and level III units are also do substantially better than level II units, although level II units do better than level I hospitals.

5.3 NICU Availability and Level of Care Received

Given the large variations in outcomes, slower diffusion of mid-level NICUs could have a substantial impact on outcomes by altering the level of care received by high-risk newborns. To investigate this, we characterized the availability of NICU services in each newborn's residence HFPA and examined the relationship between availability and the level of care received. We characterized availability for each HFPA by computing the number of level I, II, II+, and III units in place each year for 1990-1996. To capture variations across areas in population and birth rates, we normalized these measures by the average annual number of births. Table 9 summarizes the data, and suggests that there are substantial variations in availability across areas.

We model the probability of receiving care in level I, II, II+, or III unit as a function of the availability of different units in the HFPA of residence, controlling for the other covariates used in our mortality models.[13] We estimate the probabilities using a multinomial logistic regression:

$$\Pr[LEVEL_i = j] = \frac{\exp(\boldsymbol{b}_j{}' x_i)}{1 + \sum_{k=1}^{3} \exp(\boldsymbol{b}_k{}' x_i)} \tag{11}$$

where j=1, ..., 3 indexes level I, II, and II+ units and level III is the omitted reference group. We characterize the availability of services in each area as follows. First, since many areas do not have level

[13]We do not include HFPA dummies in this model.

III units and those that do typically have a small number,[14] we generated a dummy variable identifying HFPAs with at least one level III unit. We then enter the number of level I, II, and II+ units per 1000 births as main effects, and interacted with the dummy for level III units. To capture relationships between level I, II, and II+ units, we also include a full set of interactions among these variables, and interactions with the level III dummy.

Complete estimation results can be found in Appendix B. For interpretation, we use the results to compute the derivatives of the probability of receiving care in a level I, II, II+, of III unit associated with increasing the number of level I, level II, and level II+ units:

$$\frac{\partial P_j}{\partial A_m} = P_j\left[\delta_{j,m} - \sum_{k=1}^{3} P_k \delta_{k,m}\right] \tag{12}$$

where P_j is the probability of receiving care in a level j NICU; A_m denotes the area-level availability of units of type *m;* and $*_{j,m}$ is the net “coefficient” of the availability of level *m* NICUs on use of a level *j* NICU from the multinomial logit, incorporating all of the interaction terms, evaluated at sample means. The derivatives are shown in Table 10 The top panel shows results for newborns from areas with no level III unit. Here, increases in the area availability of level II units are associated with strong increases in the probability that a VLBW newborn will be born in a level II unit, substantial reductions in the probability of being born in a level II+ or III unit, and only a small reduction in the probability of being born in a level I unit. Some of the probability derivatives may appear large, but note that the dependent variables are number of units per 1000 births. The average newborn is from an area with 11,000 births, so opening an additional level II unit would increase the measure by only 1/11 = 0.09. Scaled by this figure, the results in the second line of the top panel suggest that opening a new level II unit in the average area would increase the percent of newborns in level 2 hospitals by about 10 points, with corresponding

[14]Over 45% of the newborns in our VLBW sample are reside in an area without a level III NICU.

drops of just under 5 points in each of level II+ and level III units and a small drop in the use of level I units.

Increasing the probability of being seen in a level II rather than a level II+ or III NICU would lead to worse birth outcomes. Using the estimates of the reduction in mortality associated with treatment in level II, II+, and III produced by the mortality model above, the derivatives in Table 10 suggest that the addition of one level II unit would increase mortality rates by 0.2%, or about 59 additional deaths in a population of the size of our sample.

Increases in the availability of level II+ units pull some VLBW newborns down from level III, but also pull some up from level I and II units. Evaluated around sample averages, the addition of a level II+ unit would reduce average mortality rates by 0.3%, or 88 deaths in our sample.

Generally similar results are observed for areas with level III units. (The exception is the derivatives for receiving care in level I hospital, but very few high risk newborns are delivered in level I hospitals in areas with level III units available.)

We conclude that the availability of NICUs is an important determinant of the level of care received by high risk newborns, and on outcomes. The ultimate impact of managed care depends on the specific impacts on the adoption of level II and level II+ units. Increases in HMO market share that reduce the availability of level II NICUs could lead to better birth outcomes, but the opposite is true for the supply of level II+ units. We suspect that results from our AHA data analysis above are more likely to apply to level II than II+ units, but verification of this is still in progress.

6. Conclusions

This paper examined the relationship between HMO market share and the adoption of neonatal intensive care units. Our results suggest that increases in HMO activity slowed the diffusion of mid-level NICUs, and did not influence the diffusion of high-level units. Modeling of unobserved heterogeneity and a comparison with the diffusion of cardiac intensive care units suggests that these effects are not due to unobserved heterogeneity. This suggests that the changes in incentives that managed care brings about can influence technology diffusion in health care in at least some cases.

The fact that we observe impacts on mid-level diffusion but not high-level unit diffusion is perhaps not surprising. Much of the high-level diffusion took place during the 1970s, before managed care played a significant role in the U.S. health care system, while the diffusion of mid-level units occurred largely during the 1980s and early 1990s. Moreover, the adoption of high-level units was centered in the most advanced teaching centers that tend to adopt all new advances, often regardless of their costs. The adopters of mid-level units, on the other hand, were typically smaller hospitals for whom the financial and other market incentives associated with acquiring a new technology often play more important roles in decisionmaking.

Extrapolating these results to other technologies should be done with care. Some other technologies are high cost and infrastructure intensive like NICUs, but other technologies may have very different characteristics. For example, new genetic screening procedures have quite different characteristics and may be adopted and used in quite different ways.

Nonetheless, since technology advancement is thought to be one of the most important drivers of health care costs, our results suggest that managed care may be able to affect costs by changing technology diffusion patterns at least in some cases. Further analysis of the effects of managed care on other technologies is needed to more completely understand the overall effects.

Reductions in NICU availability may bring about reductions in health care costs, but it is also important to examine the implications for patient care and outcomes. We used data from California to study the effects of NICU availability on outcomes. Our results suggest that the proliferation of level II units has had deleterious effects on outcomes for VLBW infants, and thus that it is quite possible that HMO-market-share induced-reductions in diffusion could be good for patients. (Further work is needed to draw this conclusion with certainty.)

Appendix A: Additional Details on the Data Sets

AHA Data

Questions on the AHA survey inquiring about the presence of NICUs are consistent over the 1984-1996 time period. On each survey, hospitals were asked to report the number of beds they had set up and staffed in "neonatal intensive care" units and "neonatal intermediate care" units. These questions were asked separately of questions about bassinets for well baby care, and should not include well baby nurseries.

The first step in analyzing this data was examining and "cleaning" hospital responses. We noticed several patterns that appeared to us to be erroneous reporting, and which we adjusted. These cases where primarily of two types: (1) cases where hospitals reported consistent numbers of beds in NICUs over multiple years, but for one or two years reported having the same number of beds in intermediate care units. In these cases, we moved the intermediate beds to the NICUs to make the prevalent series complete. And vice versa. (2) cases where hospitals reported consistent numbers of beds, but failed to provide any data for one or two years. In these cases we filled in the missing years.

With the cleaned data, we identified the presence of high-level or low-level NICUs in each year. Hospitals were classified as having a high-level NICU if they reported having neonatal intensive care unit beds in the AHA survey and the total number of beds reported in neonatal intensive care units and neonatal intermediate care units summed to more than 10. Most truly advanced units are relatively large, so we expect this cutoff to capture all of the advanced units in the country. And, in hospitals that operate multiple levels of nurseries, distinguishing between the lower level and higher level beds for our purposes here seemed artificial. Hospitals are classified as having a mid level NICU if they report having only neonatal intensive care unit and neonatal intermediate care unit beds that sum to 10 or less, or if they only report having neonatal intermediate care beds (and no neonatal intensive care beds) regardless of the number reported. At this stage, we also identified and dropped 114 hospitals for which the data were sufficiently vague that we were unable to satisfactorily identify the types of units present over time.

For each remaining hospital in each year, we have an indicator of whether the hospital has no NICU, a mid-level NICU, or a high-level NICU. With this data, we defined the year of adoption of a unit and the type of unit adopted for each hospital. We experimented with three definitions of adoption year and type adopted:

1. Adoption year is the first year in which the hospital says it has a unit, and the type of unit adopted is the type present in the adoption year.
2. Adoption year is the first year of the first consecutive pair of years, or triple of years with missing information in the middle year, in which the hospitals says it has a unit. The type of unit adopted is the type present in the adoption year. For example, a hospital that said it had a mid level unit in 1985, 1987, and 1988, but not 1986 would be defined to have adopted a mid level unit in 1987. For example, a hospital that said it had a unit in 1985, 1987, and 1989, but said no in 1986 and had missing data in 1988, would be defined to have adopted a mid level unit in 1987. A hospital that said it had a high level unit in 1988 and a mid level unit in 1989, 1990, and following would be defined to have adopted a high level unit in 1988. Forcing hospitals to indicating having a unit twice in a row to signify adoption results in the reclassification of a small number of hospitals that indicate having a unit in one year but then say that they do not have it in surrounding years.
3. Adoption year is the first year of the first consecutive pair of years, or triple of years with missing information in the middle year, in which the hospital says it has a unit, as in 2. But, the type of unit adopted is reclassified from high level to mid level in cases where the hospital indicates having a high level unit in the year of adoption but a mid level unit in the two subsequent years. Our anecdotal experience is that hospitals seldom if ever open full high level units and then quickly scale them back to mid level units.

We believe definition three appears to have the best chance of accurately identifying adoption timing, and it is the definition used in the paper. Results using the other definitions are generally similar, but statistically weaker in the case of definition 1.

HMO Market Share Data

Construction of county-level estimates of HMO market share (which were aggregated to the HCSA and MSA level for analysis) took place in three steps. First, the total enrollment and service area, specified by county, were obtained for each HMO in the United States. The primary sources of information on HMO enrollments and service areas in 1990-1994 is the *National Directory of HMOs*, published annually by the Group Health Association of America (GHAA, various years). For 1995-1996, the primary source is the Interstudy Competitive Edge (Interstudy, various years). Each year, these sources publish the results of surveys of HMOs, reporting, among other things, their total enrollment and their service area. Both of these sources contain essentially all HMOs operating in the U.S. Virtually all of the HMOs in the directories indicated their enrollment. In cases where enrollment was not reported, enrollment was determined by reference to subsequent directories and/or telephone contact. Virtually all HMOs indicated the counties that they served, although some did not provide a clear definition of their market area in terms of counties. For these HMOs, market areas were determined by reference to subsequent Directories and/or telephone contact.

The next step was to distribute the enrollment of each HMO among the counties in its service area. Initially, this was done by simply distributing enrollment proportionally to county population. In addition, since HMO enrollment may be concentrated near HMO headquarters or since HMOs may locate their headquarters in areas where their enrollment is concentrated, estimates that incorporate both county population and distance from HMO headquarters were constructed. The correlation between estimates produced by the two methods is approximately 0.97. Estimates that incorporate both population and distance are used here.

Once enrollments had been distributed over service areas, the total number of enrollees in each county was computed by summing over the set of HMOs serving that county. Using the set of county enrollment estimates, market share estimates were computed as the proportion of the population enrolled in HMOs. These estimates were then aggregated to the HCSA level for analysis.

To assess the quality of the estimates, they were compared to estimates from some other sources. The correlation between the 1990-1996 average market share and 1996 MSA-level estimates from Interstudy (1997), which have been used by a number of other researchers and are widely viewed as reliable, is 0.73. The correlation between the 1990-1996 average and estimates for 51 MSAs based on a 1996 population survey done by the Center for Studying Health Systems Change is 0.83. Finally, the correlation between the 1990-1996 average and MSA-level estimates of the percent of employees enrolled in HMOs based on a 1993 survey of employers in 10 states done by Rand Corporation was 0.68, despite the fact that the 1990-1996 estimates are for the entire population and the employer-survey estimates are only for employed individuals. Given that all of the comparison data sources are themselves estimates and likely subject to measurement error, we view these results as consistent with the validity of the estimates used here.

Appendix Table B1: Complete Results from Mortality models, VLBW sample

	No Area Dummies (1)	Area Dummies (2)
Level II NICU	-0.399	-0.336
	(0.080)	(0.104)
Level II+ NICU	-0.568	-0.460
	(0.066)	(0.090)
Level III NICU	-0.595	-0.444
	(0.068)	(0.101)
Female, 500-750g	3.529	3.557
	(0.090)	(0.091)
Female, 750-1000g	1.770	1.792
	(0.097)	(0.097)
Female, 1000-1250g	0.717	0.724
	(0.105)	(0.105)
Male, 500-750g	4.015	4.056
	(0.091)	(0.091)
Male, 750-1000g	2.224	2.245
	(0.093)	(0.093)
Male, 1000-1250g	1.077	1.081
	(0.097)	(0.098)
Male, 1250-1500g	0.295	0.296
	(0.102)	(0.103)
pncst1	-0.059	-0.057
	(0.149)	(0.150)
Black	-0.290	-0.263
	(0.048)	(0.051)
Mom educ 8	0.035	0.010
	(0.057)	(0.058)
Mom educ911	0.149	0.127
	(0.048)	(0.049)
pda	-0.917	-0.933
	(0.047)	(0.048)
rds	-0.677	-0.678
	(0.041)	(0.042)
big	-0.620	-0.599
	(0.170)	(0.171)
sga	-0.814	-0.808
	(0.079)	(0.080)
hemoly	-0.511	-0.559
	(0.128)	(0.131)
hydram	0.641	0.697
	(0.136)	(0.137)
hydrops	2.322	2.351
	(0.239)	(0.241)
matcon	-0.614	-0.578
	(0.076)	(0.078)
ohrmc	0.889	0.924
	(0.197)	(0.200)
placen	0.444	0.451
	(0.093)	(0.094)
prom	0.023	0.072
	(0.069)	(0.070)

continued

Appendix Table B1: Complete Results from Mortality models, continued

	No Area Dummies (1)	Area Dummies (2)
fetdis	-0.186	-0.151
	(0.065)	(0.066)
cord1	0.416	0.420
	(0.133)	(0.133)
cord2	0.013	0.011
	(0.143)	(0.145)
mas	-0.561	-0.534
	(0.183)	(0.183)
meconium	-0.555	-0.557
	(0.322)	(0.324)
scalp	-0.028	-0.065
	(0.161)	(0.163)
trauma1	0.455	0.489
	(0.195)	(0.195)
trauma2	0.496	0.527
	(0.048)	(0.049)
anom515	-0.124	-0.126
	(0.067)	(0.068)
anom1535	0.266	0.264
	(0.058)	(0.058)
anomlt5	-0.854	-0.843
	(0.095)	(0.097)
anomhr	3.450	3.487
	(0.087)	(0.088)
hmo	-0.168	-0.151
	(0.077)	(0.078)
private	-0.230	-0.243
	(0.083)	(0.086)
selfpay	-0.022	-0.042
	(0.123)	(0.126)
medicaid	-0.151	-0.162
	(0.069)	(0.071)
y91	-0.032	-0.023
	(0.067)	(0.067)
y92	-0.148	-0.144
	(0.067)	(0.068)
y93	-0.378	-0.381
	(0.069)	(0.070)
y94	-0.446	-0.439
	(0.069)	(0.069)
y95	-0.644	-0.639
	(0.074)	(0.075)
y96	-0.585	-0.593
	(0.075)	(0.076)
_cons	-1.985	-2.258
	(0.126)	(0.159)
HFPA dummies	No	Yes

continued

Appendix Table B1: Complete Results from Mortality models, continued

	No Area Dummies (1)	Area Dummies (2)
N	29430	29430
Pseudo R^2	0.337	0.345
Log Likelihood	-9508.27	-9400.91
$P^2[1]$ for H_0: Lev2=Lev3	7.90	2.76
P-val	0.005	0.096
$P^2[1]$ for H_0: Lev2=Lev4	9.87	1.64
P-val	0.002	0.200
$P^2[1]$ for H_0: Lev3=Lev4	0.38	0.05
P-val	0.536	0.820

Note: Robust standard errors in parentheses.

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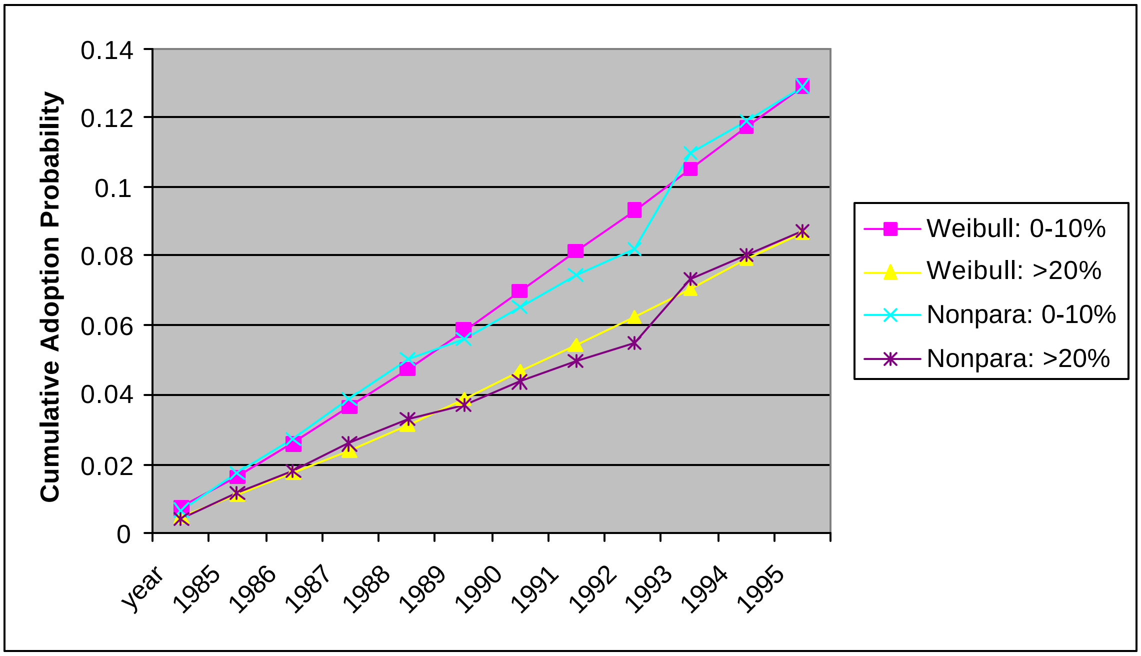
Figure 1 : Predicted Cumulative Adoption Probabilities



Note: Based on estimates in Table 3, column 7.

Table 1 : Summary of NICU Adoption Data

Year	Total Obs	Total Hosps with Mid-Level NICU	Total Hosps with High-Level NICU	Adoptions Mid Level NICU	Adoptions High Level NICU	Censored Yearly	Censored Cumulative
1984	3607	0	0	—	—	—	—
1985	3607	39	12	39	12	29	29
1986	3578	94	23	55	11	43	72
1987	3535	141	36	47	13	54	126
1988	3481	195	46	54	10	40	166
1989	3441	242	50	47	4	53	219
1990	3388	266	54	24	4	44	263
1991	3344	302	59	36	5	55	318
1992	3289	337	63	35	4	39	357
1993	3250	364	69	27	6	34	391
1994	3216	456	79	92	10	40	431
1995	3176	486	80	30	1	55	486
1996	3121	517	86	31	6	3121	3607

Note: The baseline sample is 3607 hospitals observed in 1984 and 1985, in non-rural areas, with active obstetrics services, that had not adopted a unit as of 1984. The number of censored observations is the number of hospitals observed for the last time in the year indicated.

Table 2: Descriptive Statistics for Variables in Hospital Adoption Hazard Models

	Mean (1)	Standard Deviation (2)
HMO Market Share /10	1.247	(1.112)
Low Market Share (0-10%)	0.500	(0.500)
Medium Market Share (10-20%)	0.295	(0.456)
High Market Share (>20%)	0.205	(0.404)
% Pop female age 15-44	22.809	(1.789)
% Pop non-white	17.523	(13.799)
% Pop college graduate	17.533	(5.984)
% Pop high school graduate	73.667	(7.724)
Per capita income /1000	21.899	(4.775)
% Population urban	6.245	(2.278)
Population /100,000	10.047	(19.358)
Population per square mile /100	4.403	(19.234)
1=medical school affiliation	0.122	(0.327)
1=COTH member	0.016	(0.126)
1=children's hospital	0.002	(0.050)
Bed size (1984-96 average)	139.467	(126.783)
Births per 1000 pop	14.107	(2.277)
% births <2500 grams	7.155	(1.416)
N	3607	

Note: Market share refers to 1990-1996 average market share.

Table 3 : Estimates from Hospital NICU Adoption Models

	Weibull Baseline				Non-Parametric Baseline			
	Mid Level (1)	High Level (2)	Mid Level (3)	High Level (4)	Mid Level (5)	High Level (6)	Mid Level (7)	High Level (8)
HMO Market Share /10	-0.163	-0.048	—	—	-0.162	-0.045	—	—
	(0.065)	(0.155)			(0.065)	(0.155)		
	[0.850]	[0.953]			[0.850]	[0.956]		
Medium Market Share	—	—	-0.029	-0.236	—	—	-0.028	-0.234
			(0.145)	(0.391)			(0.145)	(0.389)
			[0.971]	[0.790]			[0.972]	[0.791]
High Market Share	—	—	-0.418	0.051	—	—	-0.419	0.052
			(0.175)	(0.416)			(0.175)	(0.417)
			[0.658]	[1.052]			[0.658]	[1.053]
% pop non-white	0.011	0.029	0.010	0.027	0.011	0.029	0.010	0.027
	(0.007)	(0.018)	(0.006)	(0.017)	(0.007)	(0.018)	(0.006)	(0.017)
% pop female 15-44	0.057	-0.080	0.039	-0.066	0.056	-0.081	0.039	-0.066
	(0.050)	(0.172)	(0.051)	(0.174)	(0.050)	(0.172)	(0.051)	(0.174)
% pop college grad	0.046	0.002	0.054	-0.012	0.046	0.001	0.054	-0.013
	(0.019)	(0.054)	(0.020)	(0.056)	(0.019)	(0.053)	(0.020)	(0.056)
% pop high school grad	-0.031	0.053	-0.034	0.056	-0.030	0.054	-0.034	0.057
	(0.012)	(0.036)	(0.012)	(0.036)	(0.012)	(0.036)	(0.012)	(0.036)
Per capita income /1000	0.029	-0.009	0.023	0.000	0.029	-0.008	0.023	0.000
	(0.018)	(0.042)	(0.018)	(0.044)	(0.018)	(0.042)	(0.018)	(0.044)
% pop urban	0.094	0.048	0.091	0.046	0.093	0.048	0.090	0.046
	(0.042)	(0.103)	(0.043)	(0.102)	(0.043)	(0.103)	(0.043)	(0.102)
Population /100,000	-0.003	-0.002	-0.004	-0.004	-0.003	-0.002	-0.004	-0.004
	(0.003)	(0.006)	(0.003)	(0.006)	(0.003)	(0.006)	(0.003)	(0.006)
Pop per sq. mile /100	-0.007	-0.004	-0.008	-0.003	-0.007	-0.004	-0.008	-0.003
	(0.002)	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)
Med school affiliation	0.068	1.194	0.062	1.215	0.074	1.199	0.068	1.220
	(0.144)	(0.341)	(0.143)	(0.340)	(0.145)	(0.342)	(0.143)	(0.341)
COTH member	-0.491	0.381	-0.522	0.348	-0.505	0.360	-0.534	0.328
	(0.310)	(0.397)	(0.319)	(0.407)	(0.312)	(0.399)	(0.320)	(0.409)
Childrens hospital	-0.043	1.622	-0.057	1.693	-0.058	1.616	-0.073	1.686
	(1.108)	(0.885)	(1.107)	(0.856)	(1.105)	(0.887)	(1.104)	(0.862)
Bed size	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005
	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)
Birth per 1000 pop	0.090	0.152	0.091	0.172	0.091	0.152	0.091	0.172
	(0.034)	(0.073)	(0.033)	(0.073)	(0.034)	(0.073)	(0.033)	(0.074)
% births <2500g	-0.129	-0.016	-0.122	0.026	-0.127	-0.015	-0.121	0.025
	(0.056)	(0.135)	(0.054)	(0.122)	(0.056)	(0.135)	(0.054)	(0.122)
Weibull Baseline Parameter	1.200	1.029	1.198	1.025	—	—	—	—
	(0.053)	(0.118)	(0.052)	(0.118)				
Baseline spec. test χ^2[11]	—		—		90.63		90.86	
N	3607		3607		3607		3607	
Log-Likelihood	-2900.798		-2898.380		-2855.483		-2852.948	

Note: Robust standard errors in parentheses. Hazard ratios in brackets. Models also include an intercept. The nonparametric baseline models include 12 baseline parameters. The 5% χ^2[11] critical value is 19.68.

Table 4 : Estimates From CICU Adoption Models

	All Hospitals (1)	All Hospitals (2)	NICU Sample (3)	NICU Sample (4)
HMO market share /10	0.095	—	-0.006	—
	(0.036)		(0.052)	
	[1.100]		[0.994]	
Medium market share	—	0.078	—	0.179
		(0090)		(0.121)
		[1.081]		[1.196]
High market share	—	0.161	—	-0.041
		(0.104)		(0.136)
		[1.175]		[0.960]
N	5523	5523	3607	3607
LL	-2543.271	-2545.825	-1541.655	-1538.582

Note: Robust standard errors in parentheses. Hazard ratios in brackets. All equations include controls for hospital characteristics, area urbanization, and area demographics.

Table 5: Estimates from Hospital Adoption Hazard Models, Separately for Hospitals that Do and Do Not Merge or Close During 1985-1996

	Mid-Level NICU (1)	High-Level NICU (2)	Mid-Level NICU (3)	High-Level NICU (4)
A. Hospitals that Do not Merge or Close				
HMO market share /10	-0.145 (0.067) [0.865]	-0.028 (0.164) [0.972]	—	—
Market share10-20%	—	—	-0.006 (0.153) [0.994]	-0.219 (0.451) [0.803]
Market share >20%	—	—	-0.352 (0.185) [0.703]	0.244 (0.449) [1.276]
N	3104		3104	
Log Likelihood	-2617.893		-2615.493	
B. Hospitals that Do Merge or Close				
HMO market share /10	-0.351 (0.303) [0.704]	-0.065 (0.657) [0.937]	—	—
Market share10-20%	—	—	-0.328 (0.481) [0.720]	0.288 (0.538) [1.334]
Market share >20%	—	—	-1.460 (0.599) [0.232]	-0.274 (1.155) [0.760]
N	503		503	
Log Likelihood	-261.855		-258.733	

Note: Robust standard errors in parentheses. Hazard ratios in brackets. All equations include controls for hospital characteristics, area urbanization, area demographics, and births per 1000 and percent low birth weight, except that models for closing/merging hospitals exclude the control for children's hospitals due to collinearity. All models use Weibull baseline specifications.

Table 6 : HMO Market Share Coefficients from Specification Tests for Hospital Adoption Hazard Models

Specification test	Mid-Level (1)	High-Level (2)	Log Likelihood (3)	N (4)
Add controls for health system characteristics	-0.196 (0.070) [0.822]	0.068 (0.161) [1.070]	-2884.06	3607
Add quadratic urbanization controls	-0.192 (0.067) [0.825]	-0.061 (0.155) [0.941]	-2896.00	3607
Add CON law controls	-0.146 (0.068) [0.864]	0.016 (0.163) [1.016]	-2899.78	3607
Include Hospitals that did not have active delivery service in 1984	-0.124 (0.062) [0.883]	0.058 (0.133) [1.060]	-3416.92	4790
Include only hospitals in MSAs; measure market share at the MSA level	-0.217 (0.064) [0.805]	-0.189 (0.162) [0.828]	-2173.88	1612
Include only hospitals in MSAs; measure market share using 1996 Interstudy MSA-level market share estimates	-0.140 (0.043) [0.869]	-0.177 (0.119) [0.838]	-2138.13	1582
Include only hospitals in MSAs; measure market share using 1996 data from CTS household survey	-0.351 (0.125) [0.704]	-0.105 (0.288) [0.900]	-966.09	678

Note: Robust standard errors in parentheses. Relative hazards in brackets. All models use Weibull baselines. Areas are defined as HCSAs unless otherwise noted. All equations include controls for hospital characteristics, area urbanization, area demographics, and births.

Table 7: Distribution of sample births and Mortality Rates by level of NICU care

	All	NICU Level in Birth Hospital			
		Level I	Level II	Level II+	Level III
N	29,430	2,599	3,689	13,441	9,701
%	100%	8.8%	12.5%	45.7%	33.0%
N Deaths	5,618	643	729	2,393	1,853
28-day Mortality Rate	19.1%	24.7%	19.8%	17.8%	19.1%

Table 8: Complete Results from Mortality models, VLBW sample

	No Area Dummies (1)	Area Dummies (2)
Level II NICU	-0.399	-0.336
	(0.080)	(0.104)
	[0.671]	[0.715]
Level II+ NICU	-0.568	-0.460
	(0.066)	(0.090)
	[0.567]	[0.631]
Level III NICU	-0.595	-0.444
	(0.068)	(0.101)
	[0.552]	[0.641]
HFPA dummies	No	Yes
N	29430	29430
Pseudo R^2	0.337	0.345
Log Likelihood	-9508.27	-9400.91

Note: Results are from logistic regression. Robust standard errors in parentheses. Odds ratios in brackets. Models also control for sex, birthweight, comorbidities, mothers education, prenatal care use, expected source of payment, and include year dummies.

Table 9: Variation across HFPAs in NICU availability

	Mean	Standard Deviation	10th Pctl	25th Pctl	50th Pctl	75th Pctl	90th Pctl
Level I Units / 1000 births	0.214	0.372	0	0.066	0.162	0.243	0.383
Level II Units /1000 births	0.094	0.132	0	0	0.060	0.141	0.252
Level II+ Units / 1000 births	0.135	0.118	0	0.049	0.099	0.199	0.292
Level III Units / 1000 births	0.068	0.075	0	0	0.061	0.121	0.180

Note: Results are weighted by number of VLBW births.

Table 10: Probability Derivatives Associated with Changes in Area Availability of NICUs

	Derivative of the probability of receiving care in unit of level:			
Area Availability of...	Level I (1)	Level II (2)	Level II+ (3)	Level III (4)
For Areas with No Level III NICU				
Level I Units	0.350	-0.041	-0.328	0.020
Level II Units	-0.018	1.113	-0.603	-0.491
Level II+ Units	-0.318	-0.888	1.854	-0.065
For Areas with a Level III NICU				
Level I Units	0.031	-0.040	-0.752	1.121
Level II Units	-2.142	1.596	0.692	-0.147
Level II+ Units	-2.195	-0.534	3.292	-0.562