AHRQ Dissertation Proposal: Managed Care Contracting and Care for the Uninsured

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RESEARCH PLAN

A. Specific Aims

The objective of this study is to determine the effects of managed care contracting on the viability of community and migrant health centers as safety-net providers for medically under-served populations. The nation’s approximately 700 federally-supported health centers provide primary care services to more than eight million U.S. residents annually, most of whom have few alternative sources of care. This study uses longitudinal observations of these health centers to examine the effects of managed care contracting on three important elements of health center performance: survival; financial performance; and service delivery to the uninsured. Health reform policies implemented by many states during the 1990s allow managed care plans to enroll Medicaid beneficiaries and other under-served populations that traditionally received care from health centers and other safety-net providers. Increasingly, health centers are responding to these policies by seeking participation in managed care provider networks. These developments potentially affect the national health objective of expanding access to primary care in two important ways. First, participation may affect the availability and continuity of health care in medically under-served areas by influencing health center financial performance, closures, and mergers. Depending on their information and bargaining power relative to managed care plans, health centers may accept contracts that are financially disadvantageous, placing them at elevated risk for closure or merger with other centers. Conversely, health centers may be able to manage costs successfully under managed care payment systems and thereby strengthen their financial performance. Second, managed care participation may affect the volume and scope of services delivered by health centers to uninsured populations. Managed care contracts may expand or restrict health center revenues available to cross-subsidize care for these populations. Moreover, contracts may cause managed care enrollees to crowd out uninsured patients in areas where health center demand exceeds supply.

This study evaluates three primary hypotheses that frequently emerge in policy discussions regarding managed care and safety-net providers: (1) managed care contracting has a negative effect on the financial performance of health centers; (2) managed care contracting increases the risk of health center closure and merger; and (3) managed care contracting has a negative effect on the volume of care delivered by health centers to uninsured populations. Despite mounting policy concerns about the viability of safety-net providers under managed care, existing evidence is inadequate for determining the effects of managed care contracting. Measuring these effects is problematic due to the endogenous selection of health centers into managed care networks—a selection process which derives from joint decisions made by health centers and managed care plans. Important unobservable characteristics, such as health center quality and efficiency and managed care plan quality and efficiency, are likely to influence contracting decisions simultaneously with elements of health center performance.

This study uses full-information simultaneous equation methods to estimate the effects of managed care contracting on health center performance, while controlling for the effects of other measured and unmeasured factors defined both at the organization level and market level. The endogenous network selection process is estimated simultaneously with models of health center performance, using discrete distributions to approximate the effects of unobservable organization-level and market-level characteristics. This discrete factor approximation (DFA) method, which is new to the field of health services research, avoids imposing strict distributional assumptions on the error terms in simultaneous equation models, and offers much more precise estimates than standard two-stage instrumental variables (IV) methods (Mroz and Guilkey 1996; Angeles, Guilkey and Mroz 1998).

Results will provide unbiased estimates of the direct and indirect effects of managed care contracting on the national population of health centers and their service to vulnerable and under-served populations, during a period of high managed care growth (1991-1996). These findings will inform both policy and managerial approaches for preserving and expanding access to primary care services in medically under-served communities. Specifically, findings will offer insight into optimal managed care contracting arrangements for supporting health center viability and uncompensated care delivery.
B. Background and Significance

Federally-supported health centers are vital sources of primary health care for millions of U.S. residents who are unable to obtain care from private medical practices due to insurance status or financial, geographic, and cultural barriers to care. These not-for-profit organizations operate in low-income, medically under-served communities and provide a comprehensive array of primary care services. Services are provided to individuals using free and reduced-fee payment systems that are based on an individual’s insurance status and income. In return, health centers receive operating subsidies from one or more of five federal grant-in-aid programs administered by the U.S. Health Resources and Services Administration. Approximately 725 health centers operate within the U.S., providing health services to more than eight million individuals annually through a network of 2,204 clinics located in all 50 states (U.S. Health Resources and Services Administration 1997). Studies conducted over the past three decades have demonstrated the beneficial effects of these health centers in expanding access to primary care services (Blumenthal, Mort and Edwards 1995; Okada and Wan 1980), improving efficiency in health care resource use (Needleman et al 1997; Starfield et al. 1994; Hockheiser, Woodward and Charney 1971; Duggar, Balicki and Zuvekas 1981), enhancing the quality of health services provided to vulnerable and under-served populations (Needleman et al 1997; Starfield et al. 1994), and improving health status in medically under-served communities (Goldman and Grossman 1988; Corman, Joyce and Grossman 1987; Dignan, Hall and Hastings 1979; Depres, Pennel and Libby 1987; Klein et al. 1973).

Managed Care Contracting. The growth of managed care within local health care markets has important implications for health centers and their ability to provide care for vulnerable and under-served population groups. Medicaid managed care programs, which now cover almost half of all Medicaid beneficiaries, threaten to redirect an important source of revenue and patients from health centers to the private managed care plans that contract to serve these beneficiaries (Hawkins and Rosenbaum 1998). Growth in managed care enrollment among individuals with employer-based health insurance and Medicare coverage also affect health center revenue and patients from these sources. Health centers use the revenue generated by serving publicly- and privately-insured beneficiaries to subsidize the free and reduced-fee care they provide to uninsured individuals. By restricting health center revenue from these sources, managed care growth may compromise the ability of health centers to serve the growing numbers of uninsured and under-insured individuals—many of whom face few if any alternative sources of health care (Cunningham and Tu 1997).

Health centers may take a variety of actions in response to the challenges posed by managed care growth in the public and private health insurance markets. An increasingly common response is to seek participation in the provider networks maintained by managed care plans (Henderson and Rossier 1996). Data from year-end 1996 indicate that almost half of all health centers participate in managed care networks—a proportion that has risen dramatically during the 1990s as Medicaid managed care has expanded (U.S. Health Resources and Services Administration 1998; Henderson and Markus 1996). By 1994 approximately 566,000 managed care enrollees were served through health centers—a 30 percent increase since 1993 and a 148 percent increase since 1985 (U.S. Health Resources and Services Administration 1997).

Most health centers participate in managed care arrangements by contracting with existing managed care plans. These contracts typically require health centers to assume some or all of the financial risk associated with health services which are utilized by their enrollees. In 1994, approximately 73 percent of the contracting arrangements between managed care plans and health centers entailed full or partial capitation payment systems (U.S. General Accounting Office 1995). The remaining subcontracts were based upon negotiated fee-for-service payment systems. Capitated payment arrangements create strong financial incentives for health care providers to adopt efficient service delivery practices and effective utilization management systems. These arrangements also entail substantial financial risks for health centers, especially those with limited expertise in projecting costs and managing service utilization. A 1995 study of health centers receiving capitated payments from managed care plans indicates that many centers do not maintain sufficient cash reserves to cover unusually high medical expenses that may be incurred by their enrollees (U.S. General Accounting Office 1995). Federal legislation enacted in 1996
provides some protection to health centers and other managed care contractors by requiring managed care plans serving Medicaid or Medicare beneficiaries to carry stop-loss insurance coverage for their providers.

As an alternative to subcontracting arrangements, some health centers develop their own managed care plans either alone or in combination with other health care organizations (Henderson and Markus 1996). Most of these plans involve the participation of multiple health centers operating within a state or sub-state region, in collaboration with one or more local hospitals. These plans directly contract with state Medicaid agencies on a capitated basis for serving Medicaid beneficiaries. Some plans also secure state licensure as health insurance corporations and market their products to Medicare beneficiaries and privately-insured groups. As of June 1998, a total of 29 health center-based managed care plans were operating with the participation of 120 health centers (U.S. Health Resources and Services Administration 1998). The federal Bureau of Primary Health Care, together with national and state associations of community health centers, actively promote and assist in the development of these health center-based managed care plans (U.S. Health Resources and Services Administration 1995).

**Health Center Financial Performance and Survival:** The effects of managed care contracting on health center performance remain far from clear. Of primary concern is the effect that this contracting may have on health center financial performance and survival. Data from the U.S. Health Resources and Services Administration show that during period from 1991 to 1996, the average end-of-year fund balance among health centers has declined precipitously, while the annual number of health center closures has increased (U.S. Health Resources and Services Administration 1998). Several case study analyses have implicated Medicaid managed care enrollment growth as a primary contributor to diminished financial performance and increased risk of closure among health centers (Bodenheimer 1997; Harrington, Frazer and Aizer 1997; U.S. General Accounting Office 1995; Abrams et al. 1995; Lewin/VHI and MDS Associates 1994). Few studies, however, have empirically examined how managed care contracting mitigates these effects on health center performance. By participating in managed care networks, health centers may be able to retain or even expand the revenues they receive for serving Medicaid and Medicare beneficiaries. In this way, managed care contracting may reduce the risk of health center closure. Several published case studies document such beneficial effects for some health centers (Felt-Lisk, Harrington and Aizer 1997; Harrington, Frazer and Aizer 1997; Abrams et al. 1995; U.S. General Accounting Office 1995). Conversely, health centers that are inexperienced in negotiating payment arrangements or that are unable to accurately anticipate and manage health care costs may incur financial difficulties as a result of participating in managed care networks. In this light, managed care participation may diminish financial performance and increase the risk of health center closure, as has been observed in some cases (Bodenheimer 1997; U.S. General Accounting Office 1995).

Health centers may choose to consolidate with other organizations in order to improve their marketplace competitiveness or to realize operational efficiencies (Finkler 1995). Mergers may benefit health centers in several ways, including: (1) reducing competition from other health centers in their service area; (2) increasing their bargaining power with managed care plans; (3) pooling cash reserves that are needed to accept the financial risks of capitated payment arrangements under managed care; and (4) realizing operational efficiencies through shared staff, supplies, and other resources. In light of these potential benefits, health centers participating in managed care contracts may face greater incentives to merge with other health centers, compared with centers that do not participate. Mergers may, in turn, support the survival of health centers by reducing operating costs through economies of scale, and by enhancing their bargaining power relative to managed care plans. Health center mergers may also entail the disadvantages of reducing geographic access to care in under-served areas by promoting consolidation of delivery sites.

The existing empirical studies of managed care contracting, reviewed above, identify important issues and trends concerning health center financial performance and survival. All of these studies rely on descriptive case study methodologies, and are therefore unable to offer unbiased and generalizable estimates of effect on health center performance. Multivariate methods are needed to untangle the effects
of managed care contracting from other organization-level and market-level factors—some of which may not be fully observable.

**Health Center Service Delivery to the Uninsured:** Managed care participation may also affect the volume and scope of care that health centers provide to insured and uninsured population groups (Hawkins and Rosenbaum 1998). Of particular concern are health centers’ abilities to provide uncompensated care to individuals who lack any form of public or private health insurance coverage for primary care. Health centers participating in managed care networks may be able to maintain or expand their levels of service to the uninsured if they secure enhanced revenue through this participation—such as by successfully managing utilization and costs under capitated payment systems. Alternatively, managed care participation may force health centers to reduce their service to the uninsured if managed care contracts result in diminished health center revenue. These contracts may also require health centers to increase their service to managed care plan members, thereby crowding out services to the uninsured. Additionally, managed care contracts may create incentives for health centers to focus their marketing and outreach activities on Medicaid beneficiaries rather than on the uninsured and under-insured—effectively reducing access to care for these non-Medicaid populations.

The case study analysis conducted by the U.S. General Accounting Office includes several examples of health centers that increased their uncompensated care delivery after developing contracts with managed care plans (U.S. General Accounting Office 1995). Another case study analysis identified several health centers that reported reducing uncompensated care delivery as a result of their managed care contracts (Felt-Lisk, Harrington and Aizer 1997). These existing studies, however, are unable to control for the effects of other important trends such as growth in the demand for uncompensated care due to the rising number of uninsured individuals (Cunningham and Tu 1997). Moreover, these studies do not provide generalizable, quantitative estimates of the effect that managed care contracting has on uncompensated care delivery.

**Improvements to Existing Studies:** To date, no systematic, quantitative study has been undertaken to examine health center performance under managed care contracting, and thereby address some of the inconsistencies and limitations of the existing descriptive and anecdotal information (Schauffler and Wolin 1996). The proposed study will address gaps in current knowledge about managed care contracting by offering the following improvements over earlier studies:

- enhancing the generalizability of findings by analyzing a data set that includes the full U.S. population of federally-supported health centers;
- using multivariate modeling to control for the effects of health center characteristics, managed care plan characteristics, market area characteristics, and state policy characteristics that may confound the effects of managed care contracting;
- using time-series methods to model the dynamic nature of decision-making involving managed care contracting and health center performance;
- using a simultaneous equation estimation strategy that treats the managed care contracting decision as an endogenous variable determined jointly with elements of health center performance; and
- using a DFA modeling approach to control for unobserved characteristics that are likely to effect the endogenous managed care contracting decision as well as elements of health center performance.

These methods will allow examination of the organizational and economic factors which give rise to health center participation in managed care networks. More importantly, these methods will provide unbiased estimates of the direct and indirect effects of managed care contracting on health center performance. Findings from this study promise to inform the decisions faced by policy-makers and health center administrators regarding strategies to assure access to primary health care for medically underserved communities under managed care.
C. Preliminary Studies

**Managed Care Contracting:** Several preliminary studies conducted by Glen Mays and colleagues examine service contracting arrangements and the formation of provider networks in health care. In one study, cross-sectional data are used to analyze contracting arrangements between HMOs and public health agencies (Mays et al. under review). HMO for-profit ownership and national corporate affiliation were found to have significant negative effects on contract development, while the market-level characteristics of HMO market penetration and HMO market concentration emerged as significant positive predictors of contracting. In a similar study examining the formation of networks among hospitals and public health agencies, investigators confirmed the importance of organizational ownership and market structure in influencing contract development (Mays, Halverson and Kaluzny 1998). The strongest positive predictors of contract development included governmental hospital ownership, hospital market share, hospital market concentration, and HMO market penetration. A third study examining contracts between community health centers and public health agencies found HMO market penetration and health center federal funding to have the strongest positive effects on contract development (Halverson, Mays and Kaluzny in press).

Using qualitative methods, Mays and colleagues have explored the effects of managed care contracting on the performance of health centers operated by public health agencies. Based on information collected through in-person interviews with administrators of managed care plans, public health agencies, and health centers in eight diverse health care markets, a typology of contracting mechanisms was developed (Halverson, Mays and Kaluzny 1997; Mays 1998). Using this information, investigators examined the effects of alternative contracting mechanisms on such activities as tuberculosis prevention, treatment and control efforts (Halverson, Mays, and Miller 1997); systems of care for the uninsured (Mays, Halverson and Miller in press); chronic disease management strategies (Halverson and Mays 1998); and public health surveillance efforts (Halverson et al. 1998). Investigators also used this information to examine the effects of recent changes in managed care plan organization and operation on the nature of contracts between plans and public health agencies (Roper and Mays 1998). These efforts offer insight about the causes and consequences of managed care contracting within individual organizations—information that is used to inform the structure of the empirical models to be estimated in the proposed project.

Studies by other research team members offer additional insight for the proposed project. Edward C. Norton is co-investigator of a multi-year evaluation of Massachusetts’s Medicaid managed care carve-out program for mental health services. As part of this effort, investigators examined the formation of psychiatric care provider networks by managed care plans, and confirmed that plans take into account the quality and accessibility of services when forming these networks (Fisher, Lindrooth, Norton and Dickey 1997). Sally C. Stearns, another committee member, examined the responses of primary care physicians to a change from fee-for-service payment to capitated payment under managed care. This study found reductions in hospital admissions but increases in lengths of stay and ambulatory care visits as a result of the payment change (Stearns, Wolfe and Kindig 1992). These studies provide insight about the behavior of managed care plans and health care providers under service contracting arrangements—suggesting that service quality is important to contract development, and that payment mechanisms are important to contract effects.

**Discrete Factor Approximation Methodology:** Another set of studies informs the choice of empirical methods used in the proposed project. Research conducted by David Guilkey and colleagues has focused on developing the DFA methodology for simultaneous equation models, and evaluating the performance of these models in comparison to alternative methodologies. Based on Heckman and Singer’s (1984) approach for modeling unobserved explanatory factors in hazard rate models, the DFA methodology examined by Mroz and Guilkey (1995) approximates the joint distribution of common unobservable factors in a simultaneous equation system with a step function having a discrete number of points of support (or steps). The location and the height of each step are estimated simultaneously with the other parameters in the model using a maximum likelihood approach. Monte Carlo studies conducted by Mroz and Guilkey (1995) and Mroz (1997) demonstrate that this method is often preferable to
alternative methodologies such as two-stage instrumental variables (IV) estimation in models with both continuous and discrete endogenous variables. These studies show that both methods perform well in producing unbiased parameter estimates for the endogenous explanatory variable, but that IV estimators often produce estimates with extremely large variances—suggesting that the IV method may be too inaccurate for use with moderate-sized samples. Consequently, these studies show that the DFA method is preferred to IV estimation when unbiased parameter estimates are needed with reasonable degrees of precision—such as when the primary variable of interest is the endogenous explanatory variable.

Based on this work, several researchers have begun to use the DFA methodology in health services research applications (Goldman 1995; Goldman, Liebowitz and Buchanan 1998; Angeles, Guilkey and Mroz 1998). The DFA method is not yet widely used in the health services research field because standard statistical software packages do not include pre-programmed routines for this methodology. Because the primary variable of interest in the proposed study—managed care contracting—is an endogenous explanatory variable, the DFA methodology will be used to derive parameter estimates with reasonable degrees of precision.

D. Research Design and Methods

Three separate empirical models are used to estimate the effects of managed care contracting on health center performance. The first model estimates the effects of managed care contracting on the risks of health center closure and merger. A second, similar model examines the effects of contracting on a continuous measure of health center financial performance. A final model examines the effects of contracting on the amount of uncompensated care provided by health centers. In all three models, the managed care contracting decision is specified as an endogenous, semi-continuous explanatory variable. The specification of each model is described below, followed by a description of the estimation strategy and the data set.

1. Model Specification

Closure/Merger Model: Health center decisions to close and to merge are modeled as a function of organizational and market factors affecting health center service demand, costs, revenues, and service capacity. A multinomial logit model is used to estimate the effects of covariates on three unordered, discrete choices faced by health centers: closure; merger with another health center; and no action (survival). The general form of the multinomial logit model is:

$$\Pr(Choice = k) = \frac{e^{Z\gamma_k}}{\sum_{j=0}^{J} e^{Z\gamma_j}}$$

where $Pr(Choice=k)$ is the probability that the $k$th alternative is chosen from among $j=0,1,\ldots,J$ alternatives; $Z$ is a matrix of organizational and market covariates; and $\gamma_k$ is a vector of coefficients for each alternative (Maddala 1983). To identify the parameters of this model, the restriction that $\gamma_0=0$ must be imposed. Therefore, the probabilities associated with choosing other alternatives are estimated relative to the reference category $Choice=0$.

I use the multinomial logit model to estimate the effects of covariates on health center choices among two operational strategies—closure ($Choice=1$) and merger ($Choice=2$)—relative to the reference strategy of no action ($Choice=0$). This decision is modeled as a function of: (1) a continuous variable indicating the extent of the health center’s participation in managed care networks ($Participate$); (2) a series of three dummy variables indicating the existence of ownership affiliation arrangements with hospitals, medical schools, and public health agencies ($Affiliate$); and (3) an array of other health center and market characteristics ($X$). For health center $i$ at time $t$, this model can be expressed by the equation:

$$\ln\left(\frac{Pr(Choice_{it} = k)}{Pr(Choice_{it} = 0)}\right) = Participate_{it} \gamma_k + \sum_{m=1}^{3} Affiliate_{it,m} \delta_{k,m} + X_{it} \beta_k$$

for $k=1, 2$. 
This estimation strategy is complicated by the fact that several covariates in the model are potentially endogenous. That is, several covariates are outcomes of health center decisions which are made simultaneously with the choice among closure and merger strategies. The endogenous decisions are those involving participation in managed care networks, and affiliation with other organizations. Common unobserved factors are likely to affect health center decisions regarding managed care participation, interorganizational affiliation, closures, and mergers. A single equation model (such as equation 3.2) can not account for these common unobservable factors, and therefore it is likely to yield biased estimates of the effects that managed care participation and interorganizational affiliation have on health center closures and mergers.

The empirical model used in this analysis expands the single equation specification by allowing for two possible sources of endogeneity. First, unobserved characteristics of individual health centers and the markets in which they operate may contribute to endogeneity. For example, unmeasured dimensions of health center quality may have positive effects on managed care participation and interorganizational affiliation, but they may have negative affects on the risk of health center closure and merger. If these unmeasured dimensions are not accounted for in the empirical model, then parameter estimates may overstate the effects of managed care participation and interorganizational affiliation in preventing closures and mergers. A second source of endogeneity exists at the state level. Unmeasured statewide policies and programs may simultaneously influence health center decisions regarding closure, merger, participation, and affiliation. These policies include Medicaid program attributes, state insurance regulations, and special programs for health centers implemented by state government agencies and state primary care associations. The empirical model assumes that all health centers operating within a given state are subject to the same unobserved state-level effects.

Even in the absence of potentially endogenous explanatory variables, the single-equation model specified in [2] presents problems for hypothesis testing. Specifically, this model can not produce parameter estimates with correct standard errors unless it is modified to account for the error correlation that is introduced by the presence of multiple observations on the same health center (autocorrelation), and multiple health centers in the same state (clustering). Conveniently, the same econometric technique that is used to address the problem of endogenous explanatory variables also corrects for this error correlation problem (Angeles, Guilkey, and Mroz 1998).

To address these estimation problems, I expand the single equation specification into a system of simultaneous equations that explicitly model the endogenous decisions and the error correlation structure. This system includes a main equation for mergers and closures which is similar to equation [2], as well as ancillary equations that model affiliation decisions and managed care participation decisions. Each of these equations includes terms to control for unobserved, time-invariant characteristics at the health center level and at the state level. These terms explicitly model the across-equation error correlation that results from endogeneity, as well as the within-equation error correlation that results from autocorrelation and state-level clustering.

Like the main equation involving closures and mergers, the ancillary equation involving affiliation choices takes the form of a multinomial logit model. The dependent variable reflects discrete, unordered choices among the categories of no affiliation, affiliation with hospital, affiliation with medical school, and affiliation with public health agency. No affiliation serves as the reference category. This equation includes a range of exogenous variables as covariates, several of which are excluded from the main equation involving closures and mergers. As described below, these excluded variables are hypothesized to affect affiliation decisions but not closure and merger decisions. Specification tests are use to evaluate the appropriateness of these exclusion restrictions. Like the main closure/merger equation, the affiliation equation also includes a measure of the extent of managed care participation—a potentially endogenous explanatory variable.

To account for the potential endogeneity of managed care participation in the merger/closure and affiliation equations, the simultaneous equation system includes a model of participation decisions. A continuous measure of managed care participation is used in this model: the number of managed care
member-months served by health centers. This measure appears to follow a bimodal distribution due to the large number of health centers that do not participate in managed care networks and therefore have zero member months served. This result is consistent with the view that two distinct decision processes give rise to the observed levels of managed care participation. The first process involves the discrete choice of whether or not a health center will participate at all in managed care networks, while the second process determines a health center’s level of participation in managed care networks, conditional on having some participation. I use a two-part model approach to estimate these two sequential decisions, which are made jointly by health centers and managed care plans. The first process in this model is specified as a logit model. I use a log-linear equation to model the second process, because the dependent variable (number of managed care member months) is positively skewed in its distribution (Manning 1998). Unlike the typical application of the two-part model, the model used here controls for error correlation between the two parts by including terms that account for common unobserved characteristics at the state level and at the health center/market level.

Managed care participation is specified as a function only of exogenous health center and market characteristics. Both parts of the participation model include market-level variables that are excluded from the main equation. As described below, these variables measure specific characteristics of the managed care market that are expected to affect managed care participation but not health center closures and mergers. Specification tests are use to evaluate the appropriateness of these exclusion restrictions.

The complete set of equations to be estimated simultaneously form the following triangular system:

\[ \ln \left( \frac{\Pr(\text{Choice}_{ijt} = k)}{\Pr(\text{Choice}_{ijt} = 0)} \right) = \sum_{m=1}^{2} \text{Affiliate}_{ijt,m} \delta_{k,m} + \text{Participate}_{ijt} \gamma_k + X_{ijt} \beta_k + p_{1,k} \mu_j + p_{2,k} \lambda_i \quad \text{for } k=1,2 \]

\[ \ln \left( \frac{\Pr(\text{Affiliate}_{ijt} = m)}{\Pr(\text{Affiliate}_{ijt} = 0)} \right) = \text{Participate}_{ijt} \gamma_m + X_{ijt} \beta_m + p_{3,m} \mu_j + p_{4,m} \lambda_i \quad \text{for } m=1,2,3 \]

\[ \ln \left( \frac{\Pr(\text{Participate}_{ijt} > 0)}{\Pr(\text{Participate}_{ijt} = 0)} \right) = X_{ijt} \beta'' + p_5 \mu_j + p_6 \lambda_i \]

\[ \ln(\text{Participate}_{ijt}) = X_{ijt} \beta''' + p_7 \mu_j + p_8 \lambda_i + \epsilon_{ijt}, \text{ if } \text{Participate}_{ijt} > 0 \]

where \( i \) denotes individual health centers; \( j=1,...,50 \) denotes the individual states in which health centers are located; \( t=1,...,T \) denotes time; \( k=1,2 \) denotes the two closure and merger choices faced by health centers; and \( m=1,2,3 \) denotes the three affiliation choices faced by health centers (hospitals, universities, or public health agencies). Participate and Affiliate are vectors containing values of the endogenous explanatory variables, while \( X \) is a matrix of exogenous explanatory variables in each equation. Note that the \( X \) matrix is not identical across equations (\( X \neq X' \neq X'' \neq X''' \)), because both the affiliation equation and the participation equations include exogenous variables which are excluded from the closure/merger equation. These exclusion restrictions are evaluated empirically using the specification tests described below. The terms \( \gamma, \delta, \) and \( \beta \) denote matrices containing unknown coefficients that must be estimated; each equation has its own unique sets of coefficients. The terms \( \mu \) and \( \lambda \) represent components of the error term contributed by common, unobserved characteristics which vary at the state level and at the health center level, respectively. The terms denoted by \( p \) represent each equation’s correlation with each unobserved heterogeneity term. The individual variables included and excluded from each equation are shown in Table 1.

**Financial Performance Model:** This study also examines the effects of managed care participation on a continuous measure of financial performance, rather than the discrete measures of closure and merger. This model is identical to that used in the closure/merger analysis, except that the main equation takes a linear form rather than a multinomial logit form. The dependent variable is a continuous measure of each health center’s year-end fund balance (analogous to profit). The main equation for the financial performance model is specified as follows:
Like the closure/merger model, the financial performance model includes endogenous variables indicating organizational affiliation (Affiliate) and managed care participation (Participate). The ancillary equations for these endogenous variables are specified exactly as they are in the closure/merger model in [4] through [6] above. Organization-level and state-level heterogeneity terms are included in each equation. The explanatory variables included and excluded from each equation are the same as those shown in Table 1, variables 3 through 38.

**Uncompensated Care Model:** Finally, this study uses a model to estimate the effects of managed care participation on the volume of services delivered to uninsured patients. This model assumes that health center decisions regarding uncompensated care delivery are made so as to maximize total output, subject to budget and capacity constraints. These decisions are therefore modeled as functions of variables that affect demand for health center services, health center costs and revenues, and health center capacity. As in the closure/merger model, these explanatory variables include the extent of participation in managed care networks, the existence of ownership affiliations with other organizations, and an array of other health center and market characteristics. The dependent variable in this model is a continuous variable indicating the amount of uncompensated care delivered by health centers to patients who are not covered by public or private health insurance plans. The amount of uncompensated care is measured in dollars rather than in patient visits. Operationally, this measure is constructed as the difference between the patient care costs incurred by health centers in serving patients without insurance coverage for their services, and the out-of-pocket fees (if any) paid by these patients. Therefore, a health center’s uncompensated care costs derive from services provided to uninsured and under-insured patients, as well as to members of managed care plans that seek out-of-network care from the health center.

Like many financial measures, the uncompensated care variable is positively skewed due to a subset of health centers showing exceptionally large volumes of uncompensated care delivery. The natural logarithm of uncompensated care volume is therefore used in the empirical model to reduce the influence of outliers and to give greater weight to proportional changes in the dependent variable rather than to absolute changes (Manning 1998). A small positive constant $c$ is added to the dependent variable so that the logarithmic transformation will be defined for observations having zero uncompensated care costs. This constant will be selected by performing a grid search over small positive numbers to determine the value that causes $\ln(\text{Cost}+c)$ to most closely approximate the Normal distribution based on skewness and kurtosis statistics.

Using a log-linear model, the amount of uncompensated care ($\text{Cost}$) delivered by health center $i$ during time $t$ can be expressed as a function of managed care participation ($\text{Participate}$), ownership affiliation ($\text{Affiliate}$), and other health center and market characteristics ($X$):

$$\ln(\text{Cost}_{it} + c) = \sum_{m=1}^{3} \text{Affiliate}_{it,m} \delta_m + \text{Participate}_{it} \gamma + X_{it} \beta + p_1 \mu_j + p_2 \lambda_t + e_{it}$$

As in the closure/merger model, the affiliation and participation variables are modeled as endogenous explanatory variables using the ancillary equations specified in [4] through [6] above. I allow for two potential sources of endogeneity. First, unobserved characteristics of individual health centers and the markets in which they operate may contribute to endogeneity. For example, unmeasured health risks within the populations served by health centers may increase the demand for uncompensated care, but these same risks may diminish managed care plans’ propensities to offer health centers membership in their provider networks. If the empirical model does not account for these unobserved characteristics, then the results may reflect a negative bias in the relationship between managed care participation and uncompensated care delivery. A second source of endogeneity exists at the state level. Unobserved state policies and programs may simultaneously influence uncompensated care delivery, managed care participation, and interorganizational affiliation. These policies include Medicaid program attributes, statewide uncompensated care programs, state insurance regulations, special health center programs maintained by state health agencies and primary care associations. As in the closure and merger analysis,
the terms $\mu$ and $\lambda$ capture unobserved characteristics that vary at the state level and at the health center level, respectively. The terms denoted by $p$ represent each equation’s correlation with each unobserved heterogeneity term. The explanatory variables included and excluded from each equation are the same as those shown in Table 1, variables 3 through 38.

2. Estimation Methods

*Estimating the Models:* In each of the three empirical models, nonzero correlation in the unobserved heterogeneity terms across equations ($p \neq 0$) insures that single-equation estimation strategies will produce biased coefficient estimates. One common method of accounting for this endogeneity involves a two-stage instrumental variables (IV) estimation strategy. Monte Carlo studies show that these models typically perform well in producing unbiased parameter estimates, but they often perform poorly in producing estimates with reasonable precision when sample sizes are limited (Mroz and Guilkey 1996). Unless extremely large sample sizes are used, IV models produce parameter estimates with large standard errors—that may be too imprecise for practical use in policy and managerial decision-making. Another disadvantage of IV estimation is that it fails to produce consistent parameter estimates in models where a multinomial logit equation depends on a discrete endogenous explanatory variable. Each of the three models examined in this study include at least one such equation (the affiliation equation), and the closure/merger model contains two equations of this type.

Another approach for addressing endogeneity involves full-information maximum likelihood estimation, which requires assumptions to be made about the joint distribution of the error terms that occur in the equations. Rather than making arbitrary distributional assumptions about how unobservable characteristics are related between equations, I use a method of approximating the distribution of unobservable characteristics using a discrete distribution, and estimating how these characteristics relate between equations. This full-information method, which is new to the field of health services research, is referred to as the discrete factor approximation (DFA) method.

To use full information maximum likelihood estimation, it is necessary to construct a likelihood function that includes all of the observed dependent variables that occur in the simultaneous equation system. This likelihood function is conditional on the observed and unobserved characteristics that appear in these equations. Suppressing notation for the explanatory variables, the contribution of health center $i$ from state $j$ in year $t$ to the likelihood function for the closure/merger model, conditional on the unobservable factors, is:
Table 1  Parameters Estimated in the Health Center Merger/Closure Analysis

<table>
<thead>
<tr>
<th>Variables</th>
<th>Source</th>
<th>Equations</th>
</tr>
</thead>
<tbody>
<tr>
<td>I. Endogenous Variables</td>
<td></td>
<td>(1) (2) (3) (4)</td>
</tr>
<tr>
<td>1. Closed at time t+1 (0,1)</td>
<td>BPHC</td>
<td>1</td>
</tr>
<tr>
<td>2. Merged with another health center at time t+1 (0,1)</td>
<td>BPHC</td>
<td>1</td>
</tr>
<tr>
<td>3. Affiliated with hospital (0,1)</td>
<td>BPHC δ1 1</td>
<td></td>
</tr>
<tr>
<td>4. Affiliated with university (0,1)</td>
<td>BPHC δ2 1</td>
<td></td>
</tr>
<tr>
<td>5. Affiliated with public health agency (0,1)</td>
<td>BPHC δ3 1</td>
<td></td>
</tr>
<tr>
<td>6. Participate in managed care networks (0,1)</td>
<td>BPHC γ γ' 1</td>
<td></td>
</tr>
<tr>
<td>7. Log number of managed care member months served</td>
<td></td>
<td></td>
</tr>
<tr>
<td>II. Exogenous Variables</td>
<td></td>
<td></td>
</tr>
<tr>
<td>8. Health center capacity (FTE physicians and nurses)</td>
<td>BPHC β β' β° β''</td>
<td></td>
</tr>
<tr>
<td>9. Scope of health center services (Number of ancillary services provided)</td>
<td>BPHC β β' β° β''</td>
<td></td>
</tr>
<tr>
<td>10. Population size of service area</td>
<td>ARF β β' β° β''</td>
<td></td>
</tr>
<tr>
<td>11. Percent of population below poverty</td>
<td>ARF β β' β° β''</td>
<td></td>
</tr>
<tr>
<td>12. Percent of population below poverty covered by Medicaid</td>
<td>CPS β β' β° β''</td>
<td></td>
</tr>
<tr>
<td>13. Primary care physicians per 100,000 population</td>
<td>ARF β β' β° β''</td>
<td></td>
</tr>
<tr>
<td>14. Number of competing health centers</td>
<td>BPHC β β' β° β''</td>
<td></td>
</tr>
<tr>
<td>15. HCFA hospital wage index</td>
<td>HCFA β β' β° β''</td>
<td></td>
</tr>
<tr>
<td>16. Number of hospitals operating in the market</td>
<td>ARF β'</td>
<td></td>
</tr>
<tr>
<td>17. Percent of hospitals that are government owned</td>
<td>ARF β'</td>
<td></td>
</tr>
<tr>
<td>18. Number of medical schools located in the state</td>
<td>AAMC β'</td>
<td></td>
</tr>
<tr>
<td>19. Number of local health departments operating in the market</td>
<td>NACCHO β'</td>
<td></td>
</tr>
<tr>
<td>20. Percent of population enrolled in HMOs</td>
<td>Interstudy β β' β° β''</td>
<td></td>
</tr>
<tr>
<td>21. Percent of Medicaid beneficiaries enrolled in HMOs</td>
<td>Interstudy β β' β° β''</td>
<td></td>
</tr>
<tr>
<td>22. Mandatory managed care enrollment for Medicaid beneficiaries (0,1)</td>
<td>HCFA β β' β° β''</td>
<td></td>
</tr>
<tr>
<td>23. Enrollment of aged or disabled Medicaid beneficiaries (0,1)</td>
<td>HCFA β β' β° β''</td>
<td></td>
</tr>
<tr>
<td>24. 1115 Medicaid waiver (0,1)</td>
<td>HCFA β β' β° β''</td>
<td></td>
</tr>
<tr>
<td>25. State Medicaid regulation requiring contracts with health centers (0,1)</td>
<td>GWU β β' β° β''</td>
<td></td>
</tr>
<tr>
<td>26. Proportion of Medicaid/Medicare HMOs that are nonprofit</td>
<td>Interstudy β° β''</td>
<td></td>
</tr>
<tr>
<td>27. Proportion of Medicaid/Medicare HMOs that are group or staff model</td>
<td>Interstudy β° β''</td>
<td></td>
</tr>
<tr>
<td>28. Average age of Medicaid/Medicare HMOs</td>
<td>Interstudy β° β''</td>
<td></td>
</tr>
<tr>
<td>29. Average enrollment of Medicaid/Medicare HMOs</td>
<td>Interstudy β° β''</td>
<td></td>
</tr>
<tr>
<td>30. Year dummy variables</td>
<td>β β' β° β''</td>
<td></td>
</tr>
<tr>
<td>31. Health center heterogeneity term</td>
<td>p1 p3 p5 p7</td>
<td></td>
</tr>
<tr>
<td>32. State heterogeneity term</td>
<td>p2 p4 p6 p8</td>
<td></td>
</tr>
<tr>
<td>33. Middle point of support for health center heterogeneity term</td>
<td>Ψμ</td>
<td></td>
</tr>
<tr>
<td>34. Weight #1 for health center heterogeneity term</td>
<td>θμ1</td>
<td></td>
</tr>
<tr>
<td>35. Weight #2 for health center heterogeneity term</td>
<td>θμ2</td>
<td></td>
</tr>
<tr>
<td>36. Middle point of support for state heterogeneity term</td>
<td>Ψλ</td>
<td></td>
</tr>
<tr>
<td>37. Weight #1 for state heterogeneity term</td>
<td>θλ1</td>
<td></td>
</tr>
<tr>
<td>38. Weight #2 for state heterogeneity term</td>
<td>θλ2</td>
<td></td>
</tr>
</tbody>
</table>

(1) = Main equation for predicting closures and mergers
(2) = Affiliation equation
(3) = Equation for any managed care participation
(4) = Equation for log number of managed care member months
ARF = Area Resources File
BPHC = Bureau of Primary Health Care
HCFA = Health Care Financing Administration
GWU = George Washington University (Rosenbaum 1997)
AAMC = Association of American Medical Colleges Data Book
CPS = Current Population Survey March Supplement
Interstudy = Interstudy HMO Census
NACCHO = National Association of County and City Health Officials
where \( F \) indicates values of the cumulative distribution functions corresponding to the multinomial logit model for closures and mergers; \( G \) indicates values of the cumulative distribution functions corresponding to the multinomial logit model for affiliations; \( \Gamma \) indicates values of the cumulative distribution function corresponding to the logit model for any managed care participation; and \( \gamma \) indicates values of the probability density function corresponding to the model of log managed care member months served, conditional on positive member months. The dummy variables \( C, M, H, U, A \) and \( P \) indicate discrete choices regarding closure, merger, affiliation, and any managed care participation. Analogous likelihood functions are specified for the financial performance model and the uncompensated care model. For these models, a probability density function \( f \) is used to model the main equation—rather than the set of three cumulative distribution functions \( F \)—because the main outcome variables are continuous rather than discrete measures.

To obtain the unconditional likelihood, it is necessary to integrate this conditional likelihood with respect to the distribution of the unobservable characteristics. This integration requires assumptions to be made about the distribution of unobservable characteristics. Estimates obtained from the unconditional likelihood function are dependent on the validity of these assumptions. Rather than relying on arbitrary distributional assumptions, I use nonparametric, discrete approximations to the true distribution of unobservable characteristics (Heckman and Singer 1984; Mroz and Guilkey 1996). This method approximates the cumulative distribution of unobserved characteristics with a step function having a finite number of steps. The locations and heights of the steps are parameters estimated simultaneously with the other parameters in the model. This approach can approximate a wide variety of underlying distributions for the unobservable characteristics.

To obtain the unconditional likelihood function, I assume that the unobserved health center/market effect follows a discrete distribution with \( Q \) points of support. This distribution is defined as:

\[
\Pr(\lambda_i = \lambda_q) = \pi_c(q), \quad \text{for } q = 1, 2, \ldots, Q.
\]

Similarly, I assume the unobserved state effect follows a discrete distribution with \( R \) points of support. This distribution is defined as:

\[
\Pr(\mu_j = \mu_r) = \pi_s(r), \quad \text{for } r = 1, 2, \ldots, R.
\]

The contribution to the likelihood function for an individual health center \( i \) during year \( t \), unconditional on unobserved factors at the health center/market level, is given by:

\[
L_{ijt}(\mu_j, \lambda_i) = \sum_{q=1}^{Q} \pi_c(q) \cdot L_{ijt}(\mu_j, \lambda_q).
\]

Using this expression, it is simple to express the contribution to the likelihood function for the \( N_j \) health centers located in state \( j \) as:

\[
L_j(\mu_j) = \prod_{i=1}^{N_j} \prod_{t=1}^{T} L_{ijt}(\mu_j).
\]

This equation can then be transformed to an unconditional expression by integrating over the possible values of the state-level unobserved factors:

\[
L_j = \sum_{r=1}^{R} \pi_s(r) \cdot L_j(\mu_r).
\]
The full likelihood function can then be expressed as the product of the 50 unconditional state-specific likelihoods:

\[ L = \prod_{j=1}^{50} L_j \]

I maximize this likelihood function with respect to the parameters defined in model, along with the additional parameters associated with the discrete distributions that are used to approximate the distributions of unobserved characteristics. These additional parameters are the locations of the points of support (steps) in each distribution, and the probabilities associated with each step. Initially I use three points of support for each of the two discrete distributions \((Q=R=3)\). I use likelihood ratio tests to determine whether more points of support should be included in the model (Mroz 1997).

To make the discrete factor estimation feasible, each distribution is approximated to scale only. Therefore, rather than approximating distributions for the actual unobserved terms \(\mu_j\) and \(\lambda_i\), I approximate distributions of the terms scaled by their standard deviations: \(\frac{\mu_j}{\sigma_\mu}\) and \(\frac{\lambda_i}{\sigma_\lambda}\). For each distribution, one of the points of support is fixed at zero and another is fixed at one:

for \(\mu\): \[ \frac{\mu_{1j}}{\sigma_\mu} = 0, \quad \frac{\mu_{3j}}{\sigma_\mu} = 1; \quad \text{and for } \lambda: \quad \frac{\lambda_{1j}}{\sigma_\lambda} = 0, \quad \frac{\lambda_{3j}}{\sigma_\lambda} = 1. \]

A middle point of support, bounded by zero and one, is estimated from the data. I use a logistic transformation to allow the parameter that determines this middle point of support \(\Psi\) to have an unrestricted range:

for \(\mu\): \[ \frac{\mu_{2j}}{\sigma_\mu} = \frac{e^{\psi_\mu}}{1 + e^{\psi_\mu}}; \quad \text{and for } \lambda: \quad \frac{\lambda_{2i}}{\sigma_\lambda} = \frac{e^{\psi_\lambda}}{1 + e^{\psi_\lambda}}. \]

For each of the three points of support, an associated probability must be determined from the data. Because these probabilities must sum to unity, only two probabilities are estimated. I use logistic transformations to allow the parameters which determine these probabilities \(\theta\) to have unrestricted ranges:

for \(\mu\): \[ \frac{w_{\mu 1}}{1 + e^{\theta_{\mu 1}}} = e^{\theta_{\mu 2}}, \quad \frac{w_{\mu 2}}{1 + e^{\theta_{\mu 2}}} = e^{\theta_{\mu 3}}, \quad w_{\mu 3} = 1 - w_{\mu 1} - w_{\mu 2}; \quad \text{and} \]

for \(\lambda\): \[ \frac{w_{\lambda 1}}{1 + e^{\theta_{\lambda 1}}} = e^{\theta_{\lambda 2}}, \quad \frac{w_{\lambda 2}}{1 + e^{\theta_{\lambda 2}}} = e^{\theta_{\lambda 3}}, \quad w_{\lambda 3} = 1 - w_{\lambda 1} - w_{\lambda 2}. \]

To approximate the distributions of unobserved factors, I estimate a total of six parameters: \(\Psi_\mu\), \(\Psi_\lambda\), \(\theta_{\mu 1}\), \(\theta_{\mu 2}\), \(\theta_{\lambda 1}\), and \(\theta_{\lambda 2}\). In addition to these parameters, I estimate the correlation that each factor has with each endogenous variable in the system of equations. These correlation estimates are designated as \(p_1\) through \(p_8\) in the simultaneous equation models specified above. The pair of correlation estimates appearing in the main equation \((p_1\) and \(p_2)\) are normalized to equal one; therefore, the remaining correlation estimates are computed relative to the main equation.

To maximize the system of equations, single equation models are first estimated to obtain reasonable starting values for the parameters that are not used in approximating the unobserved factors. These starting values are then used in a full information optimization routine that searches over all parameters for the maximum value of the unconditional likelihood function. This search is programmed in FORTRAN using GQOPT optimization subroutines (Quandt 1998). Standard diagnostic tests will be performed on all models, including tests for near multicollinearity, heteroskedasticity, and
autocorrelation. Appropriate variable transformations and changes in model specification will be undertaken to correct any problems that are identified.

**Evaluating Model Specification:** Several specification tests are used to evaluate key assumptions in each of the three models. First, a set of tests are used to evaluate the appropriateness of excluding certain covariates from the main equation that occur in the affiliation equation or the managed care participation equations. These exclusion restrictions help to achieve identification in each of the three models. First, a variant of the Lagrange Multiplier test (the NR$^2$ test) is used to determine whether three variables used in the affiliation equation—the number of hospitals, medical schools, and public health agencies operating in the market—should be excluded from the main equation. To conduct this test, I compute residuals from the main equation. After correcting these residuals for heteroskedasticity and nonlinearity, I use them as the dependent variable in an ordinary least squares regression that includes all the covariates used in the original main equation, as well as the variables excluded from this equation. A test statistic distributed Chi-square with degrees of freedom equal to the number of excluded variables is computed by multiplying the coefficient of determination from this regression with the total number of observations used in the analysis (NR$^2$). This test evaluates the null hypothesis that the three market-level variables should not be included in the merger/closure equation.

The same Lagrange Multiplier test is used to evaluate the appropriateness of excluding four variables from the main equation that appear in the managed care participation equations. These excluded variables indicate the ownership type, organizational structure, age, and enrollment size of Medicaid and Medicare HMOs operating within the local market. These variables and other covariates in the main equation are regressed on the adjusted residuals described above. These regression results are used to construct an NR$^2$ test statistic with four degrees of freedom, in order to evaluate the null hypothesis that the four HMO variables should not be included in the merger/closure equation.

Next, a series of Wald tests are used to evaluate the assumptions of endogeneity in managed care participation and interorganizational affiliation. The endogeneity test for managed care participation evaluates the null hypothesis that the coefficient estimates for the unobserved heterogeneity terms appearing in the two participation equations are all equal to zero (H$_0$: $p_5=p_6=p_7=p_8=0$). If at least one of these estimates is statistically different from zero, then the null hypothesis of exogeneity can be rejected due to correlation between the participation equations and the merger/closure equation. Wald test statistics computed for each individual heterogeneity estimate can be examined to determine the severity of any identified endogeneity problem. Wald tests are also used to separately examine the potential for state-level endogeneity (H$_0$: $p_5=p_6=0$) and for market-level endogeneity (H$_0$: $p_6=p_8=0$). Similar Wald tests are used to evaluate the assumption of endogeneity in the affiliation arrangements maintained by health centers. An overall test evaluates the null hypothesis that the coefficient estimates on the heterogeneity terms appearing in the affiliation equation (Equation 3.3) are all equal to zero (H$_0$: $p_{3,m}=p_{4,m}=0$ for m=1,2,3). The null hypothesis of exogeneity is rejected if one or more of these estimates are statistically different from zero. I also use Wald tests to examine separately the potential for state-level endogeneity and market-level endogeneity.

A modified likelihood ratio test is used to evaluate the appropriateness of modeling health center affiliations with hospitals, universities, and public health agencies separately, rather than collapsing these choices into a simple dichotomous decision model of affiliation. A restricted model will be estimated that collapses these three categories of the dependent variable into a single category, thereby imposing an equality constraint on all three sets of parameter estimates from equation [4]. A correction factor for the restricted log likelihood value will be applied to ensure that constant terms remain unrestricted, as specified by Cramer and Ridder (1991). The likelihood ratio test statistic is then computed in the usual way: twice the difference in the log likelihood values from the unrestricted model and the restricted model. This statistic tests the null hypothesis that the restricted model provides an adequate fit to the data in comparison to the unrestricted model, and is distributed Chi-square with degrees of freedom equal to twice the number of covariates included in the affiliation model (not including constant terms) plus the number of parameters that are restricted in the main equation (two in this case).
Finally, a likelihood ratio test will be used to evaluate the appropriateness of restricting the distribution of each heterogeneity term to three points of support, compared with an unrestricted model using four points of support. Monte Carlo studies suggest that this test performs better than alternative tests based on the coefficient estimates for endogenous explanatory variables (Mroz 1997).

**Testing Hypotheses:** The first hypothesis, concerning the effects of managed care contracting on health center closures and mergers, is evaluated by examining the coefficient estimates and variances for the variable *Participate* in equation [3]. The null hypothesis of no effect on closures is rejected if the coefficient $\gamma_1$ differs from zero with 95% confidence. Similarly, the null hypothesis of no effect on mergers is rejected if $\gamma_2$ differs from zero with 95% confidence. An analogous test based on the estimate of $\gamma$ from equation [7] is used to evaluate the effect of contracting on financial performance (Hypothesis 2). Similarly, a test based on $\gamma$ in equation [8] examines the effect on uncompensated care delivery (Hypothesis 3). These three tests focus exclusively on the direct effects of managed care contracting, but results from the empirical models can also be used to evaluate indirect and total (direct+indirect) effects on these elements of health center performance. The indirect effects of managed care contracting occur through health center affiliations with other organizations, and they may offset or augment the direct effects of contracting. Indirect effects are assessed by testing for non-zero coefficient estimates on *Participate* in the Affiliation equations of each model ($\gamma$ in equation [4]), together with non-zero coefficient estimates on the Affiliation variables that appear in the main equation of each model ($\delta$). Evidence of a significant indirect effect is found if both $\gamma_m' = 0$ and $\delta_{k,m} = 0$ can be rejected at the 95% confidence level for some $k \in (1,2)$ and $m \in (1,2,3)$. Total effects are assessed by computing partial derivatives of each simultaneous equation system with respect to the variable *Participate*.

**Simulations for Policy Analysis:** Results from the empirical models will be used to simulate the effects of key changes in policy, market conditions, and management strategies. One set of analyses will simulate the effects implementing changes in state Medicaid policy, including: implementing requirements for Medicaid managed care plans to contract with health centers; increasing the proportion of Medicaid beneficiaries enrolled in managed care; and implementing mandatory managed care enrollment for disabled and/or aged beneficiary groups. Another set of analyses will simulate the effects of changes in managed care market structure, including: increasing the number of competing HMOs; increasing HMO penetration among commercial, Medicaid, and Medicare enrollees; and increasing the proportion of HMOs that are for-profit and that are part of national corporations. A final set of analyses will simulate the effects of changes in managed care contracting and management strategies, including: increasing physician and nursing staffing within health centers; increasing the scope of services offered through health centers; and increasing the number of clinic sites operated by health centers. These simulations will offer valuable insight about health policy and management decisions that may have important effects on managed care contracting behavior and health center performance.

### 3. Data Sources

**Health Center Data:** This study combines secondary data available from several different sources to construct a unique and rich data set for analysis. All data required for this study have already been acquired by the principal investigator, and all necessary permissions for use have been secured. The data set consists of annual observations on all federally-supported health centers operating in the United States from 1991 through 1996, along with information on community and market characteristics from the service areas in which each center operates—including the characteristics of managed care plans operating in these areas. Information on the structural, financial, and operational characteristics of each health center is obtained from the Bureau of Primary Health Care (BPHC), U.S. Health Resources and Services Administration (1998). All health centers report this annualized information to the Bureau at the end of each calendar year. This data set includes variables that indicate: health center revenues by source; expenditures by cost center; patient encounters by type of service; number of salaried and contracted
personnel by specialty; number of clinic sites; and number of member months covered through managed care contracts.

Information on health center closures, mergers, and financial performance are also derived from the Bureau of Primary Health Care data set. When health centers close, they are dropped from the data set in calendar years following their closure. When health centers merge, the data set notes the merger during the calendar year in which it occurs, and during subsequent years it reports data for the merged health center under the name of the largest health center involved in the merger. Smaller health centers involved in mergers are dropped from the data set in years subsequent to the merger. Following an approach developed to analyze HMO mergers and failures (Feldman, Wholey, and Christianson 1996), I use this information to construct a categorical variable which indicates one of three possible outcomes for each health center: (1) the health center did not close or merge during the year; (2) the health center closed; (3) the health center merged with another health center. The data set also captures information on ownership arrangements between health centers and other types of organizations such as hospitals, health departments, and universities. I construct a separate indicator variable to capture these types of arrangements, which are forms of vertical integration rather than horizontal mergers.

Area Characteristics: Health center observations are matched with annual data describing the demographic and market characteristics of the medically-under-served areas that each center serves. County-level measures of demographic and health resource characteristics are obtained from the Area Resource File, maintained by the Bureau of Health Professions, U.S. Health Resources and Services Administration (1998). These measures are aggregated to geographic units which approximate each health centers’ service area (market). Ideally, a health center’s service area would be defined to encompass the full extent of transactions with patients and with purchasers such as managed care plans (Dranove 1990). I approximate each center’s service area using the group of counties that encompass the federally-designated medically under-served area that each center is authorized to serve. This approximated service area overstates the geographic extent of the federally-designated area in cases where only parts of counties are included in the federal designation. The federally-designated area, however, may under-state the true market for health center services. Case studies of several health centers suggest that they often do not monitor the residency status of their patients (Mays, Miller and Halverson in press). Consequently, centers that officially serve only federally-designated areas may nonetheless experience service demand from patients outside these areas. The approximated service areas used in this study may therefore provide better estimates of the true market for health center services than do the federally-designated areas. However, the approximated service areas may still under-state the true market for health center services, if patients from outside these areas seek care from health centers. Borrowing a technique developed for analyzing hospital markets (Dranove 1992), I use data from counties that are adjacent to the approximated service areas to control for market mis-specification.

Managed Care Data: Health center observations are also matched with annualized data describing the local managed care market. These data are obtained from two sources. Data on licensed health maintenance organizations (HMOs) are obtained from the annual survey of HMOs conducted by Interstudy (1998). For each HMO operating in the United States, this survey collects annual information on enrollment, plan type, ownership, national affiliation, service areas, participation in Medicaid and Medicare, and numbers of affiliated physicians and medical centers. Data on managed care plans that are not licensed as HMOs but that do participate in state Medicaid programs as full-risk plans are obtained from the U.S. Health Care Financing Administration’s annual Medicaid managed care enrollment reports. These plans, which are often sponsored by hospitals, physicians, and other providers, represent 44 percent of all managed care plans serving Medicaid beneficiaries (Felt-Lisk and Yang 1997). The Health Care Financing Administration data set contains annual information on Medicaid enrollment and service areas for each plan. Taken together, the two managed care data sets capture information on all full-risk managed care plans that operated in the commercial, Medicaid, and Medicare managed care markets during the period 1991 through 1996.
Managed care data must be aggregated from the plan level to the market level for this study. Data limitations prevent the identification of individual managed care plans that do and do not extend network membership to individual health centers; therefore, plan-level data can not be used for this analysis. Aggregating data to the market level is accomplished in two stages. Data is aggregated first to the county level, and then to the multi-county level that approximates each health center’s service area. County-level aggregations of managed care data are complicated by the fact that health plan enrollment information is defined at the plan level rather than the county level. I use a method of apportioning plan-level enrollment into county-specific enrollment estimates for each of the counties included in a plan’s service area (Feldman, Wholey and Christianson 1996). Using this method, each county receives a fraction of the total plan enrollment that is equal to the ratio of the county’s population to the total service area population. This method has been found to produce accurate county-specific estimates of enrollment when compared with county-level data collected by several state insurance departments (Christianson, forthcoming). Once plan-level data are apportioned to the county level, these county estimates are aggregated to each health center’s service area.

Other Data Sources: Several additional data sources are used to obtain more information about market characteristics. The U.S. Health Care Financing Administration’s (1997) Medicaid Managed Care Program Summary data set is used to obtain county-level information about state Medicaid managed care programs. This information includes program starting and ending dates, mandatory and voluntary enrollment policies, and types of Medicaid beneficiaries involved. Additionally, the U.S. Department of Commerce’s (1998) Current Population Survey, March Supplement is used to obtain annual, state-level estimates of the uninsured population and of the proportion of individuals below the poverty level who are eligible for Medicaid. The Association of American Medical College’s (1997) AAMC Data Book is used to construct measures of the number of medical schools and teaching hospitals in each market and state. Finally, the National Association of County and City Health Officials’ (1993; 1997) National Profile of Local Health Departments is used to identify the number of health departments in each market.

A total of 4,464 annual health center observations are included in the six-year panel data set. The proportion of health centers that participate in managed care networks increased dramatically during the period under study, from 6 percent in 1991 to 46 percent in 1996. This growth in managed care participation paralleled the growth in managed care enrollment among Medicaid beneficiaries, which increased from 9.5 percent in 1991 to 40.1 percent in 1996. Health center financial performance declined precipitously during this period, while uncompensated care delivery increased somewhat. This rich and timely data set provides a unique opportunity to examine the effects of managed care contracting on health center performance, and to identify implications for the nation’s health care safety net.

4. Timeline

The proposed project is designed to be completed over a 12-month period. During the first quarter, all data will be reviewed, cleaned, and merged, and necessary variable transformations data imputations will be completed. During the second quarter, single-equation models will be estimated for each of the equations specified in the analysis (equations [3] through [8]) to obtain reasonable starting values for the simultaneous equation estimations. The remainder of the second and third quarters will be devoted to estimating the simultaneous equation models with DFA methods, conducting appropriate diagnostic procedures for these models, and completing simulation analyses based on results. The final quarter will be devoted to preparing manuscripts and related papers for publication in peer-reviewed scientific journals. Results will also be presented at a scientific meeting during the fourth quarter of the project. A final copy of all manuscripts will be submitted to the AHCPR by the end of the 12-month period, as will reprints of all published papers.

E. Human Subjects

No individual-level data are used in this study. Data consist of annual program information collected from each federally-funded health center by the U.S. Health Resources and Services
Administration, combined with county-level data on socio-demographic characteristics and health resources that are available from public use sources. Exemption from the School of Public Health human subjects institutional review board (IRB) is documented in the Appendix.

F. **Vertebrate Animals**

None used.

G. **Literature Cited**


Halverson PK, Mays GP, Kaluzny AD. (in press). Interorganizational alliances in public health: implications for the quality of community health services. *Medical Care*.


