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RESEARCH ARTICLE

Factors Associated with the Income Distribution of Full-Time Physicians: A Quantile Regression Approach

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Objective. Physician income is generally high, but quite variable; hence, physicians have divergent perspectives regarding health policy initiatives and market reforms that could affect their incomes. We investigated factors underlying the distribution of income within the physician population.

Data Sources. Full-time physicians ($N = 10{,}777$) from the restricted version of the 1996–1997 Community Tracking Study Physician Survey (CTS-PS), 1996 Area Resource File, and 1996 health maintenance organization penetration data.

Study Design. We conducted separate analyses for primary care physicians (PCPs) and specialists. We employed least square and quantile regression models to examine factors associated with physician incomes at the mean and at various points of the income distribution, respectively. We accounted for the complex survey design for the CTS-PS data using appropriate weighted procedures and explored endogeneity using an instrumental variables method.

Principal Findings. We detected widespread and subtle effects of many variables on physician incomes at different points (10th, 25th, 75th, and 90th percentiles) in the distribution that were undetected when employing regression estimations focusing on only the means or medians. Our findings show that the effects of managed care penetration are demonstrable at the mean of specialist incomes, but are more pronounced at higher levels. Conversely, a gender gap in earnings occurs at all levels of income of both PCPs and specialists, but is more pronounced at lower income levels.

Conclusions. The quantile regression technique offers an analytical tool to evaluate policy effects beyond the means. A longitudinal application of this approach may enable health policy makers to identify winners and losers among segments of the physician workforce and assess how market dynamics and health policy initiatives affect the overall physician income distribution over various time intervals.

Key Words. Physician workforce, quantile regression, managed care, physician income

Physicians in the United States are generally well compensated, with a median annual income of $175,000 (Kane and Loeblich 2003), nearly seven times the

$25,279 that a typical salaried worker earns (U.S. Census Bureau 2002). Yet, with a $127,000 difference between the 25th and 75th percentiles of income, physicians experience sizeable differences in aggregate earnings and sources of income, with a corresponding variety of economic interests (Kane and Loeblich 2003). Ongoing changes in health care financing, organization, and delivery continue to erode the economic autonomy of the medical profession (Starr 1982; Scott 1993) as purchasers, employers, (McKinlay and Stoeckle 1988; Navarro 1988), and consumers (Haug and Lavin 1983; Haug 1988) exercise countervailing power (Light 1993). This fragmentation of the profession has led to diverse preferences for health care reform, depending on a physician's practice specialty, employment setting, location, and clientele. For example, a survey of 300 primary care physicians (PCPs) in North Carolina revealed that PCPs in family or general practice were less likely to support a single-payer system than pediatricians (Millard et al. 1993). Health policy analysts will thus benefit from a better understanding of the factors underlying physician income distribution.

Previous studies of physicians' incomes have mostly focused on the impact of selected factors on the *average* physician income. Certain variables, however, may not affect physician income "on average," but may have distinct and significant effects at other points of the distribution, such as in the upper or lower percentiles. In this paper, we introduce a conceptual framework and a theoretical foundation to examine factors associated with physician income distribution, and provide hypothesized relationships between income and each selected factor. We then describe our use of both the least squares and quantile regression models (QRMs) in the empirical study to examine the above relationships, using data from the 1996 to 1997 Community Tracking Study Physician Survey (CTS-PS) and the mean, median, 10th, 25th, 75th, and 90th percentiles of physician incomes to capture the range of the distribution. We present our empirical findings and discuss their policy implications, and we also discuss the unique contribution of the quantile regression method to policy makers.

Findings from this study may provide a more comprehensive understanding of correlates of physician income, and also help to identify factors

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contributing to and consequences associated with income inequality among physicians. Physicians' incomes are often important, if indirect, targets of health care policy reforms, while at the same time individual physicians and professional organizations representing different segments of the medical profession are often prominent and vigorous participants in policy debates. The economic and political payoff and fallout associated with any health care policy initiative requires solid information about how relative income gains and losses within the physician sector are likely to be distributed. Hence, information about how income is distributed within this occupational group is critical in crafting proposals for even modest incremental reform.

CONCEPTUAL MODEL

Conceptual Framework

We developed a conceptual framework from the current literature related to physicians' incomes to guide our empirical analysis. Our conceptual model grouped factors likely to be associated with physicians' incomes into three broad categories according to their level of analysis, which might be visualized as three concentric circles. At the inner level is the *individual physician* with associated demographic characteristics such as age and gender, and occupationally relevant attributes, which might be considered human capital factors (e.g., specialty, formal qualifications as indexed by location of training and board certification, and years of experience). The next circle includes factors operative at the *organizational level* of the physician's workplace, including the overall organizational structure, management and governance factors, and the clientele and market strategy. The outer ring represents the environment in which the practice organization is embedded. These *market-level* factors are operative at the local level through resources available to the organization, competition from other providers, and the penetration of managed care organizations (MCOs). The market is also reflected in the regional and urban or rural character of the community.

Model Elements and Hypothesized Relationship with Income

Individual factors such as age, gender, education, training, and hours worked per week have been found to be associated with variations in physician income (Pope and Schneider 1992; Moser 1995; Bernstein 1998; Simon, Dranove, and White 1998). We anticipated finding higher incomes among male physicians, physicians with more years of experiences, who worked more hours per week, and who were board certified or were graduates of U.S. medical schools. In addition, we anticipated finding higher incomes among surgical specialists (Gonzalez 1996; MGMA 1996; Kane and Loeblich 2003).

Organizational factors include ownership status, and type, number and size of practices. We hypothesized a positive relationship between ownership status and physician income (Moser 1995), and expected to find higher incomes among physicians in a large group practice (Gonzalez 1996) and those practicing in multiple locations. As more physicians choose to work as employees of large organizations, the basis of their rewards change from that of productivity (in a smaller, fee-for-service practice) to that of adherence to specific rules or mandates to follow specific practice guidelines (in a managed care environment). Even when physicians own their practices, health insurance plans that pay for their services may use the results of patient satisfaction surveys or practice profiles to inform physicians of their "performance" and to assess their "cost-effectiveness." More aggressive "primary care gatekeeping" mechanisms used by managed care may control patient access to specialists and also aim to contain costs. Physicians' reports of such medical care management techniques have been linked to fees for office visits (Gaynor 1989), physician job satisfaction (Konrad et al. 1999; Williams et al. 1999), and job stress (Williams et al. 2002); however, few studies have related these factors to physician income or its distribution. Considering the association between job stress and poor performance at work (Kahn and Byosiere 1992), which correlates with income, we hypothesized a negative association between income and the existence of stringent controls from upper management.

Factors representing clientele and market strategy include the sources of revenue within the physician's practice and the number of contracts with MCOs. Newer physician payment arrangements, including capitation and performance-based payment, might provide physicians with incentives for cost-containment and quality improvement (Cooper 1994; Simon and Born 1996). Different fee schedules used by various payers provide incentives to treat patients in certain plans, and to encourage PCPs to provide care to patients instead of referring them to specialists. We hypothesized that physicians with a large proportion of revenue from capitated managed care plans would have lower incomes because they would be less likely to recover the higher expenses associated with caring for sicker patients under a capitation system. A study by the Medical Group Management Association (MGMA) found a dip in income with fewer managed care contracts among PCPs, and higher incomes for PCPs with no or a higher number of managed care contracts (MGMA 1996). The same report showed a decline in specialists' incomes as the number of managed care contracts increased. Thus, we hypothesized that PCPs and specialists with no managed care contracts would have higher incomes. In addition, among physicians who had any managed care contracts, we expected to find greater incomes for PCPs with higher numbers of contracts, and lower incomes for their specialist counterparts. Finally, we expected that physicians with a higher percentage of revenue from Medicaid or Medicare would have lower incomes, due to the low payments and administrative complexity associated with such programs (Coombs, Miller, and Leeper 1995; Phillips and Kruse 1995).

Market factors measure managed care penetration, availability of health care workers (including physicians and nonphysician workers), and the geographic and economic characteristics of local markets. The rapid but uneven growth of managed care across the United States has dramatically changed physicians' revenue sources (Simon and Emmons 1997). Simon, Dranove, and White (1998) found a strong positive association between the state-level managed care penetration and increased income for PCPs, but an insignificant association between penetration and growth of nonhospital-based specialists' incomes over time. Hence, we hypothesized that managed care penetration would have a positive association with the incomes of PCPs and a negative association with those of specialists.

Health workforce availability is measured by two ratios at the county level: the number of physicians per 1,000 people, and the number of nurse practitioners and physician assistants (nonphysician providers) per physician. The distribution of nonphysician health care providers varies substantially across geographic regions (Cooper, Laud, and Dietrich 1998; Shih 1999, 2000), but the association between physician income and geographic variations in the supply of physicians and nonphysician health professionals has not been examined. A higher physician/population ratio is likely to have a negative impact on physician income because a surplus of physicians can create competition in the local markets. The relationship between income and the ratio of nonphysician providers per physician depends on whether the services provided by the nonphysician providers are substitutes or complements to physicians' services; physician income will decrease with the ratio if the services of the nonphysician providers are substitutive but will increase with the ratio if the services are complementary. Because services provided by the nonphysician providers are less likely to be substitutes for care provided by a specialist, we anticipated that the association between physician income and the nonphysician provider/physician ratio would be positive for specialists, and negative for PCPs.

Uneven physician distribution across geographic regions has been a key health policy issue for decades (Madison 1980; Hynes and Givner 1983; Frenzen 1991; Rosenblatt and Lishner 1991; Kindig, Schmelzer, and Hong 1992; Kindig and Yan 1993). Despite numerous federal and/or state policies to attract and retain physicians (Eisenberg and Cantwell 1976; Rogstad, Harris, and Fenderson 1981; de Castanos 1984), many rural areas continue to suffer from physician shortages. Based on geographic variations in physician income documented in the literature (MGMA 1996; Kane and Loeblich 2003), we expected to find income variations across census regions, with the highest incomes found among PCPs and specialists practicing in the South. In addition, we hypothesized higher incomes among physicians in metropolitan areas because studies in the mid- to late-1990s cited economic issues as obstacles to recruiting and retaining rural physicians (NRHA 1998).

METHODS

Data

Data used in this study included the restricted version of the CTS-PS, 1996–1997; the 1996 Area Resource File (ARF); and 1996 health maintenance organization (HMO) penetration data. The CTS-PS comprises surveys of physicians in 60 randomly selected sites, plus a supplemental sample to enable generalizability (Center for Studying Health System Change 1999) for all nonfederal physicians providing direct patient care for at least 20 hours per week. Specialists, such as radiologists, anesthesiologists, pathologists, and medical toxicologists, whose primary responsibility did not involve direct patient care were excluded. The CTS-PS contains physicians' sociodemographic characteristics, specialty, ownership, practice size and type, physicians' perceptions of medical care management and patient interactions, source and level of practice revenue, compensation, and income. A total of 12,528 physicians participated in the 1996–1997 CTS-PS. To ensure that incomes reported in the CTS-PS represented physicians' annual earnings, we included in our study physicians who worked full-time (35 hours or more per week) and who had worked 40 weeks or more during the year in which the income was reported. In addition, we selected the combined sample in our analysis because it was the sample recommended in the CTS Users' Guide for physician-level analyses nationwide. The final study sample consisted of 10,777 full-time physicians.

The ARF is a public-use data file that contains county-specific data on the population, economic factors, and health professions, and facilities. We extracted several market-level variables from the ARF, such as the total population, population composition, and numbers of physicians and nonphysician workers at the county level. The 1996 HMO penetration data were provided by Wholey et al. (Wholey et al. 1997; Wholey, Burns, and Lavizzo-Mourey 1998; Center for Studying Health System Change 1999).[1]

Analytical Approach

We used a QRM to examine physician income at different points of the distribution. The QRM extends beyond the notion of ordinary least squares, which estimates the conditional mean of a dependent variable given a set of explanatory variables (Koenker and Bassett 1978). The QRM can be used to characterize the entire conditional distribution of the dependent variable (Buchinsky 1998). The regression coefficient β_θ associated with an explanatory variable is interpreted as the marginal change in the θth conditional quantile of the dependent variable corresponding to the marginal change in the variable. Computationally, β_θ's at the median (i.e., $\theta = 0.50$) are estimated by minimizing the absolute deviations, and β_θ's at other percentiles are obtained by solving a linear programming problem of minimizing asymmetrically weighted absolute residuals (Buchinsky 1998). Comparisons of β_θ across different percentile levels allowed us to infer the effects of a certain variable at different points in the income distribution.

We examined the factors associated with the physician income distribution using both least squares and quantile regressions. We conducted separate sets of analyses for PCPs and specialists because the literature has suggested a large difference in income between these two groups (Moser 1995; Gonzalez 1996; MGMA 1996; Kane and Loeblich 2003) and also that factors such as managed care penetration have had a distinct impact on the income of the two groups (Simon, Dranove, and White 1998). To the extent possible, we used appropriate weighted procedures to account for the complex survey design of the CTS-PS. In data with complex sample survey designs, estimations accounting for only the sampling weights but not the clustering and/or stratification in the sampling plan will still yield unbiased point estimates of the parameters. However, the standard errors tend to be underestimated, thus causing researchers to overstate the significance of certain parameters in hypothesis testing (Korn and Graubard 1999). To our knowledge, current statistical software dealing with survey data (e.g., *SUDAAN* and *STATA*) is not yet capable of handling QRM in survey data with multistage sampling; therefore, we used a bootstrap method with resampling within a cluster (PSU) as a compromised estimating strategy to obtain the standard deviation of the weighted estimates of the regression parameters. The purpose of applying a bootstrap method to the weighted estimates was to preserve the unbiased nature of the point estimates while correcting for some of the downward bias in the estimated standard errors generated from a simple weighting algorithm.[2]

Variable Definitions

Quantile regression requires a continuous dependent variable; in the restricted version of the CTS-PS data we requested, income data were collected at \$1,000 intervals and top-coded at \$400,000.[3] Table 1 provides the definition of each explanatory variable; most variables are self-explanatory, only a few need to be elaborated. A study by Kane and Loeblich (2003) suggested a nonlinear relationship between physicians' ages and incomes, suggesting that income increase with age until mid-career and then decreases. Therefore, we categorized physicians' ages into three categories: ≤ 40, 41–55, and >55 years to capture the above nonlinear association in our multivariate analyses. We classified ownership status of the practice as full, part, and none. We used a list of mutually exclusive binary variables to represent physicians' practice types: solo or small group practice, large group practice, group- or staff-model HMOs, academic setting, hospital-based practice, and all others. We dichotomized physician perceptions toward several management variables by coding the variable as 1 if the physician indicated that the factor had a large or very large effect on the physician's practice.

Endogenous Variables

In recognition of a potentially endogenous managed care penetration variable, we explored endogeneity using the instrumental variables method. Following Simon, Dranove, and White (1998), we used variables representing hospital concentration and employer size as the instrumental variables. Hospital concentration was measured as the county-level Herfindahl index (HHI) using information on the number of hospitals by bed size from the ARF (Dranove, Simon, and White 1998). Simon, Dranove, and White (1998) measured employer size by the percentage of employees in big firms (≥ 500 workers) and in small firms (<20 workers). We constructed similar measures from the 1996 County Business Patterns file by calculating the ratios of small and large firms per employee at the county level. We added median family income as an instrumental variable because it was found to be a determinant of

Table 1: Descriptive Statistics

Variables		*All Physicians*	*Primary Care Physicians*	*Specialists*
Individual level				
Demographic characteristics				
Age	Age of physician (years)	48.91	48.40	49.23
Male*	= 1 if male (%)	84.98	79.93	88.13
Professional characteristics (human capital) (%)				
SPEC*	= 1 if nongeneralist practice specialty	61.59	0	100
Specialty (%)				
Medical*	= 1 if medical specialist	—	—	38.95
Surgical*	= 1 if surgical specialist	—	—	38.18
Psychiatry*	= 1 if specialized in psychiatry	—	—	12.21
ObGyn*	= 1 if specialized in ObGyn	—	—	10.56
IMG*	= 1 if international medical graduate	19.56	21.24	18.51
BCERT*	= 1 if board certified	86.42	79.78	90.56
Extent of labor				
Hours	Hours per week in medically related activities	57.71	56.15	58.69
Organizational level				
Structural variables				
Ownership status (%)				
Fullowner*	= 1 if fullowner	38.19	35.54	39.84
Partowner*	= 1 if partowner	26.35	21.76	29.21
Nonowner*	= 1 if not an owner	35.46	42.70	30.95
Practice type (%)				
SOLOSML*	= 1 if in solo practice or two-physician practice	41.00	38.19	42.76
LRGSPEC*	= 1 if in group practice	28.90	26.01	30.69
GRPHMO*	= 1 if in group-model or staff-model HMOs	4.92	7.29	3.43
ACADGRP*	= 1 if in academic	7.00	4.21	8.73
HOSPBASE*	= 1 if in hospital-based facilities	10.26	13.69	8.12
OTHPRAC*	= 1 if in practice settings not listed above	7.93	10.60	6.26
MULPRAC*	= 1 if provide care in more than one practice	8.96	7.71	9.74

continued

Table 1. *Continued*

Variables		*All Physicians*	*Primary Care Physicians*	*Specialists*
Management and incentive variables (%)				
AUT*	= 1 if physician agrees strongly or somewhat that he/she has the freedom to make clinical decisions	76.81	85.03	71.68
GUIDE*	= 1 if practice guidelines have a large or very large effect on practice	18.00	16.03	19.23
PROFILE*	= 1 if physician profiling has a large or very large effect on practice	9.74	9.27	10.03
PTSATIS*	= 1 if patient satisfaction surveys have a large or very large effect on practice	30.32	29.21	31.01
GATE	Percentage of patients requiring gatekeeping (among PCPs)	14.87	38.71	0.00
PRODUCT*	= 1 if physician's compensation is affected by own productivity	49.89	53.40	47.70
SALARIED*	= 1 if a salaried physician	47.51	52.20	44.58
Clientele and market strategy				
Source of payment (%)				
NOCAPMCO	Percentage revenue from noncapitated MCOs	24.22	21.22	26.10
PCAPMCO	Percentage revenue paid on capitated or other prepaid basis	15.79	22.99	11.31
MCARE	Percentage revenue from Medicare	31.52	29.50	32.78
MCAID	Percentage revenue from Medicaid	14.07	14.98	13.51
Number of MCO contracts in practice (%)				
# MCO: $\leq 3^{\#*}$	= 1 if number of MCO contracts ≤ 3	16.76	19.18	15.26
# MCO: 4–9$^{\#*}$	= 1 if number of MCO contracts >3 and <10	28.05	31.78	25.72
# MCO: ≥ 10*	= 1 if number of MCO contracts ≥ 10	46.63	41.61	49.75
# MCO: 0*	= 1 if number of MCO contracts = 0	8.56	7.44	9.26
Market level				
Local market characteristics (%)				
MDRATIO	Population/MD ratio (county level)	492.80	601.45	425.04
PENET	HMO penetration (county level)	21.68	21.51	21.79
SUBPHYS	Nonphysician providers/MD ratio (county level)	4.55	5.23	4.13
Census region/urbanization (%)				
NORTHE*	= 1 if located in Northeast	23.42	22.98	23.70
MIDWEST*	= 1 if located in Midwest	20.66	21.30	20.27
SOUTH*	= 1 if located in South	34.28	33.05	35.04
WEST*	= 1 if located in West	21.25	22.35	20.56
MSA*	= 1 if located in metropolitan areas	88.48	83.53	91.56

*Binary variable, where 1 is designated and other non-missing cases = 0; MSA, metropolitan statistical area; MCO, managed care organization; HMO, health maintenance organization.

managed care penetration by Dranove, Simon, and White (1998), and was shown not to be associated with PCPs' or specialists' incomes in our analyses.

Several organizational-level variables are also likely to be endogenous. Endogeneity in variables such as ownership status or type of practice is likely to arise from physicians' self-selection, as these job attributes may be correlated with the error term in the regression model through certain unobserved physician characteristics. The percentage of revenue from Medicare or Medicaid can potentially be endogenous. Because these two sources of payment are financially less attractive than commercial third-party payers, it is possible that a higher percentage of clientele from Medicare or Medicaid are more likely to be found among physicians who are less successful financially and thus cannot afford to be selective of their clientele. In addition, hours worked per week could also be endogenous due to self-selection—a classic example is that female physicians may choose not to work extensive hours for family reasons.

For the Medicare and Medicaid variables, we used variables that differ across localities (i.e., counties) such as the proportion of elderly population and the median family income as instrumental variables. We also included HHI as an instrument because areas with a high concentration of elderly are likely to have more hospitals (and thus a lower HHI), whereas areas with a high concentration of low-income households are likely to have fewer hospitals (and thus a higher HHI). The cross-sectional data used in our study severely limited our ability to identify viable instruments for the other variables (ownership status, practice type, and hours worked) that are potentially endogenous. However, excluding these variables from the regression model might have introduced omitted variable biases. We explored this issue empirically by comparing two different model specifications: one with these variables excluded; the other with them included. We then compared the estimates between the two specifications and examined the statistical significance of the variables in the second model specification (Stock and Watson 2002). If the estimated coefficients varied noticeably between the two specifications or if the added variables were statistically significant, we kept the potentially endogenous variables to avoid omitted variable biases. We then explored the possible direction of an endogeneity bias associated with ownership status and practice type by comparing estimates across various quantiles in the QRMs. The rationale behind this strategy was that the unobserved characteristics (e.g., entrepreneurship) correlated with both income and the choice of ownership type were likely to place physicians at various points of the income distribution. This would then allow us to use the variations in the quantile regression estimates at different percentiles to infer the possible effect of ownership, had the unobserved variable been observable. We addressed the possible endogeneity of weekly working hours by comparing two sets of regression models. The first set used physician income as the dependent variable and included hours as an independent variable (the income equation); the second set used hourly wages as the dependent variable and excluded hours from the model (the wage equation). We did not replace the income equation with the wage equation, as was done in many labor economics studies, because the pay structure for physicians is different from that of many other professions. Physicians' incomes do not necessarily depend on the hours worked; therefore, presenting only information from the wage equation for the purpose of avoiding an endogeneity bias may overlook many other important factors associated with physicians' income distribution.

RESULTS

Descriptive Statistics

Physician income distribution by percentile is illustrated in Figure 1 (see Appendix A) for PCPs and specialists, jointly and separately. The income of PCPs was consistently lower than that of specialists across all percentile levels, and the gap between PCPs and specialists widened at the higher percentile of the distribution. The average annual income of physicians was $167,161 (SD = $83,764); median income was $150,000. At the 10th percentile, the specialists' incomes were $16,000 higher than those of PCPs ($96,000 versus $80,000), whereas at the 95th percentile, the difference was $150,000 ($360,000 versus $210,000). The top-coded amount of $400,000 appeared to affect only a very small proportion of PCPs (those close to the 99th percentile of the income distribution) and specialists whose incomes were at the 92nd percentile or higher. Also included in Appendix A is a simple example demonstrating how to interpret findings from quantile regressions, as this method is relatively new to health services researchers. Summary statistics of the independent variables can be found in Table 1.

Regression Analyses of Physician Income

The dependent variable in our analysis of physician income was log(income) because of the skewed income variable. Tables 2 and 3 summarize the results of the least square and quantile regressions at selected percentile levels (i.e., 10th, 25th, median, 75th, and 90th) for the PCPs and specialists, respectively.

Table 2: Regression Analyses of Primary Care Physicians' Incomes (in %)

Variable	*Mean*	*10th*	*25th*	*Median*	*75th*	*90th*
Individual level	$F=107.3$**	$F=57.0$**	$F=63.0$**	$F=63.8$**	$F=106.6$**	$F=32.9$**
Demographic characteristics (%)						
Age $\leq 40^{\dagger}$	0.26	7.76	0.28	– 3.15	– 5.30	– 3.09
Age: 41–55†	7.99**	13.75**	7.76**	5.42**	3.22	6.10*
Male	22.45**	25.88**	19.84**	21.90**	19.00**	18.78**
Professional characteristics (human capital) (%)						
IMG	1.56	– 0.05	0.92	0.43	0.04	1.94
BCERT	5.75**	9.28**	11.18**	7.07**	3.57	0.77
Extent of labor (%)						
Hours	0.46**	0.34**	0.43**	0.46**	0.55**	0.57**
Organization level	$F=33.2$**	$F=21.2$**	$F=16.2$**	$F=7.5$**	$F=23.1$**	$F=21.5$**
Structural variables						
Ownership status (%)						
Partowner†	1.16	9.31	3.84	3.75	– 2.42	– 8.90*
Nonowner†	– 11.46**	– 1.75	– 5.69	– 7.66	– 18.68**	– 22.52**
Practice type (%)						
LRGSPEC†	9.56**	17.81**	13.72**	9.65**	4.95	2.50
GRPHMO†	10.93**	23.77**	17.06**	12.14**	5.36	– 0.31
ACADGRP†	1.42	17.40**	6.65	– 0.09	– 3.95	– 3.67
HOSPBASE†	13.15**	19.15**	18.22**	13.24**	12.16**	5.93
OTHPRAC†	5.81**	16.59**	9.83**	7.04*	4.12	– 4.91
MULPRAC	1.12	– 3.05	– 3.69	1.11	5.06	1.19
Management and incentive variables (%)						
AUT	4.33	7.77**	5.12*	3.14	3.04	– 1.00
GUIDE	– 2.85	– 4.56	– 2.15	– 1.72	– 2.91	– 1.91
PROFILE	– 0.28	0.15	– 0.30	– 0.87	2.62	0.35
PTSATIS	1.88	– 2.09	0.19	1.48	1.46	4.14
GATE	– 0.01	– 0.03	– 0.04	– 0.02	– 0.03	– 0.05
PRODUCT	3.62*	4.78	3.19	1.97	3.63*	4.44
SALARIED	– 1.09	2.65	– 1.73	– 4.16	– 2.93	– 3.00
Clientele and market strategy						
Source of payment (%)						
NOCAPMCO	0.03	0.06	0.06	0.06*	0.07*	0.04
PCAPMCO	0.05	0.13	0.11*	0.05	0.06	0.07
MCARE	– 0.001	0.08	0.01	– 0.02	– 0.01	– 0.02
MCAID	– 0.18**	– 0.13*	– 0.14**	– 0.13**	– 0.19**	– 0.28**
Number of MCO contracts in practice (%)						
# MCO $\leq 3^{\dagger}$	– 4.56**	0.22	– 1.59	– 2.78*	– 3.55	– 6.37*
# MCO: 4–9†	– 4.18**	– 3.79	– 4.27*	– 2.12	– 4.20*	– 5.46*
# MCO: 0†	– 8.78*	– 7.86	– 6.21*	– 7.59*	– 5.02	– 5.43
Market level	$F=2.19$	$F=7.0$**	$F=9.8$**	$F=3.9$**	$F=10.5$**	$F=6.8$**
Local market characteristics (%)						
MRATIO‡	0.004*	0.01	0.004	0.003	0.002	0.005
PENET	– 0.07	0.06	– 0.01	– 0.10	– 0.21*	– 0.32*
SUBPHYS	– 0.19	– 0.50	– 0.38	– 0.26	– 0.17	– 0.36

continued

Table 2. *Continued*

Variable	*Mean*	*10th*	*25th*	*Median*	*75th*	*90th*
Census region/urbanization (%)						
NORTHE†	4.09	4.78	3.53	4.72	4.66	5.81
MIDWEST†	3.40	4.61	6.03	4.93	3.03	2.15
SOUTH†	9.30*	11.45**	10.05*	7.46	7.09	7.74
MSA	5.19	4.36	5.68	4.63	5.64	7.70

†Reference groups (RG) for dummy variables are: Age, RG > 55; Practice Form, RG = solo or two physician practice; Ownership, RG = full owner; Managed Care, RG = many ($\geq$ 10) MCO contracts; Geographic region, RG = West.

‡Physician-to-population ratios are transformed using the natural logarithm.

MSA metropolitan statistical area; MCO, managed care organization.

*Indicates statistically significant at $p< = .05$; and

**indicates statistically significant at $p< = .01$ level.

We converted the regression coefficients into relative effects (as percentage changes) for ease of interpretation.[4]

Individual Level. Both gender and hours worked per week showed the expected relationship with income across the board, with the largest discrepancies observed between male and female specialists. Results from quantile regression at the 10th percentile in Table 2 showed that the income of male PCPs at the 10th percentile of their income distribution was 25.88 percent higher than female PCPs' income at their 10th percentile, whereas results from the quantile regression at the 90th percentile indicated that male PCPs at the 90th percentile of their income distribution earned approximately 18.78 percent more than females at the same percentile of the income distribution of female PCPs. That is, the income discrepancy between male and female PCPs was more apparent among lower-pay male and female PCPs and decreased among high-pay PCPs. The hypothesized nonlinear association between age and income was supported at most levels, except for the 75th percentile of the PCPs' income. Board certification status in general had a positive effect on income, except for PCPs at the higher income levels (75th and 90th percentiles). Compared with medical specialists, those with specialties in surgery or obstetrics and gynecology (ObGyn) had higher incomes throughout the entire distribution. With the exception of the 10th and 25th percentiles, psychiatrists had lower incomes than medical specialists, and the income discrepancy was more pronounced at the higher tail of the distribution. Contrary to our hypothesis, we found no difference between the incomes of PCPs trained within or outside of the United States.

Table 3: Regression Analyses of Specialists' Income (in %)

Variable	*Mean*	*10th*	*25th*	*Median*	*75th*	*90th*
Individual level	$F = 72.3$**	$F = 43.6$**	$F = 80.4$**	$F = 100.5$**	$F = 54.2$**	$F = 127.3$**
Demographic characteristics (%)						
Age ≤ 40†	5.17*	1.78	2.95	6.50*	4.87	1.25
Age: 41–55†	14.27**	16.76**	15.51**	15.93**	12.02**	8.11**
Male	28.86**	44.95**	33.28**	26.11**	15.99**	18.27**
Professional characteristics (human capital) (%)						
Surgical†	20.24**	18.74**	24.54**	24.10**	21.01**	11.78**
Psychiatry†	− 13.73**	− 0.86	− 4.58	− 16.84**	− 23.33**	− 28.72**
ObGyn†	17.08**	22.00**	20.38**	16.83**	13.59**	9.60*
IMG	− 0.76	− 9.16*	− 2.87	1.83	0.84	4.91*
BCERT	11.57**	12.67**	13.31**	13.44**	11.03**	10.77**
Extent of labor (%)						
Hours	0.41**	0.35**	0.39**	0.52**	0.46**	0.34**
Organization level	$F = 77.1$**	$F = 12.0$**	$F = 22.3$**	$F = 27.2$**	$F = 19.8$**	$F = 38.1$**
Structural variables						
Ownership status (%)						
Partowner†	1.25	12.47*	6.74	− 1.54	− 4.69	− 4.36
Nonowner†	− 13.05**	− 2.39	− 6.19	− 13.03**	− 19.77**	− 18.80**
Practice type (%)						
LRGSPEC†	20.07**	22.73**	24.99**	23.56**	15.94**	7.53**
GRPHMO†	30.81**	30.30**	39.83**	34.95**	23.71**	12.40
ACADGRP†	0.67	5.29	1.59	− 1.33	− 6.78	− 6.35
HOSPBASE†	17.22**	27.62**	20.95**	19.61**	9.97*	1.44
OTHPRAC†	11.89**	13.12	16.12**	14.13**	9.55*	− 4.02
MULPRAC	− 4.91*	− 5.18	− 4.86	− 4.35	− 3.59	− 4.52
Management and incentive variables (%)						
AUT	4.47**	6.16*	5.71**	4.85*	3.34	0.59
GUIDE	− 6.60**	− 10.50**	− 8.60**	− 5.74*	− 5.70	− 3.34
PROFILE	− 2.36	− 0.06	− 0.97	− 1.20	− 1.67	3.38
PTSATIS	1.84	5.61	2.19	2.68	1.14	− 0.38
PRODUCT	4.54*	6.95	5.12*	2.76	3.20	4.69*
SALARIED	− 4.58**	− 6.71	− 4.57	− 4.93*	− 3.72	− 2.82
Clientele and market strategy						
Source of payment (%)						
NOCAPMCO	− 0.004	− 0.08	− 0.04	− 0.002	0.06	0.02
PCAPMCO	− 0.07*	− 0.01	− 0.08	− 0.12**	− 0.09	− 0.12**
MCARE	0.02	− 0.02	− 0.01	0.01	0.07	− 0.03
MCAID	− 0.15*	− 0.06	− 0.12	− 0.09	− 0.13*	− 0.17*
Number of MCO contracts in practice (%)						
# MCO ≤ 3†	− 4.21	− 2.24	− 3.38	− 3.37	− 5.75	− 4.75
# MCO: 4–9†	1.36	5.12	0.23	0.46	− 0.31	− 2.61
# MCO: 0†	− 2.30	− 6.09	− 6.03	− 0.73	− 2.73	− 3.08
Market level	$F = 21.1$**	$F = 10.1$**	$F = 14.3$**	$F = 17.3$**	$F = 10.4$**	$F = 44.5$**
Local market characteristics (%)						
MRATIO‡	0.0004	0.005	0.003	0.001	− 0.004	− 0.005
PENET	− 0.19*	0.01	− 0.14	− 0.25*	− 0.21	− 0.23*

continued

Table 3. *Continued*

Variable	*Mean*	*10th*	*25th*	*Median*	*75th*	*90th*
SUBPHYS	0.06	− 0.10	− 0.12	0.12	0.32	0.29
Census region/urbanization (%)						
NORTHE†	8.01	8.96	8.42	5.87	6.70	6.67
MIDWEST†	9.31*	12.73**	8.57	6.29	8.97*	4.36
SOUTH†	10.78**	18.01**	13.39**	6.66	8.61	3.72
MSA	16.85**	14.03	21.13**	25.48**	14.92	9.55

†Reference groups (RG) for dummy variables are: Age, RG > 55; Specialty, RG = medical specialists; Practice Form, RG = solo or two physician practice; Ownership, RG = full owner; Managed Care, RG = many ($\geq$ 10) MCO contracts; Geographic region, RG = West.

‡Physician-to-population ratios are transformed using the natural logarithm.

MSA metropolitan statistical area; MCO, managed care organization.

*Indicates statistically significant at $p \leq .05$; and

**indicates statistically significant at $p \leq .01$ level.

The only significant differences, we observed in the same comparison among specialists were lower incomes for international medical school graduates (IMGs) at the 10th percentile and higher incomes for IMGs at the 90th percentile.

Organizational Level. After controlling for factors at the individual and market levels, the majority of the organizational-level variables only showed the hypothesized pattern at selected points of the income distribution. The strongest effect of ownership status was observed at the upper tail of the distribution, especially for income differences between physicians who were full and nonowners. Compared with specialists in solo or two-physician practices (a small practice), those in large group practices earned significantly more at all levels, as we had hypothesized; however, a similar association among PCPs was apparent only at the lower half of the income distribution. Using PCPs in small practices as the reference group, PCPs practicing in hospital-based facilities were found to have significantly higher incomes up to the 75th percentile, whereas a higher income was found among PCPs practicing in group- or staff-model HMOs at the low- to middle-percentile levels. Similar comparisons among specialists showed a positive association with hospital-based facilities and group- or staff-model HMOs for up to the 75th percentile for both cases. For specialists, providing care at more than one practice was found to have a significantly negative association with incomes only at the mean.

Most management and incentive variables were found not to have a significant association with the incomes of PCPs; the only exceptions were a positive association with autonomy at the 10th and 25th percentiles, and a positive association with productivity at the mean and the 75th percentile. Among specialists, a positive association between income and autonomy was found at the mean and the lower half of the distributions, and lower incomes were reported by specialists who thought practice guidelines had a strong effect on practice at the mean and the lower half of the distributions. The hypothesized negative impact of Medicare coverage on income was not accepted. The hypothesized negative association between an increasing proportion of revenue from Medicaid and income was found among PCPs at every point of evaluation and was supported at the mean, 75th and 90th percentiles of the income distribution of specialists. In addition, we did not find an association between the number of managed care contracts and the income distribution of the specialists. However, the hypothesized "dip" in PCPs' incomes was supported at the mean, median, and 90th percentiles among PCPs with three or fewer managed care contracts, and at the mean, 25th, 75th, and 90th percentiles among PCPs with a moderate number (four–nine) of managed care contracts.

Market Level. After controlling for individual- and organizational-level variables, we found that variables representing market-level characteristics had minimal impact on PCPs' incomes, as was evident from a much smaller F-statistic in testing the joint significance of all variables at the market level. Among PCPs, the hypothesized relationship between income and market-level variables was only found between PCPs in the South and the West (census regions) at the mean, and at the 10th and 25th percentiles. Market-level variables had a slightly stronger association with the incomes of specialists. A significantly negative association between specialists' incomes and managed care penetration was reported at the mean, median, and the 90th percentile. As hypothesized, significant income variations across census regions were reported at the mean, 10th and 75th percentiles between specialists in the Midwest and West, and at the mean, 10th, and 25th percentiles between specialists in the South and West. Unlike the lack of association between a metropolitan statistical area (MSA) and the incomes of PCPs, specialists practicing in MSAs were found to have significantly higher incomes at the mean, median, and the 25th percentile of the income distribution, with the largest income differences at the median.

Endogeneity of Managed Care Penetration and Factors at Organizational Level. Results from the two-stage least squares estimates showed that the four instrumental variables we used (HHI, median family income, and percentage of employees in big firms and small firms) were jointly significant in explaining the variation in managed care penetration, and that they satisfied the overidentifying restriction condition (Stock and Watson 2002). However, we found no evidence of endogeneity of managed care penetration for the sample of PCPs or specialists using the endogeneity test proposed by Davidson and MacKinnon (Wooldridge 2000). We explored the endogeneity of the percent revenue from Medicare and Medicaid variables using HHI, median family income, and percentage of population aged 65 and above at count levels as instrumental variables. Although the two-stage least squares models indicated that these instruments satisfied the instrument relevance and exogeneity conditions for both the PCP and specialist samples, Medicare and Medicaid variables were not found to be endogenous according to endogeneity tests. In addition, the two model specifications used to explore omitted variable bias concluded against excluding these potentially endogenous variables from our regression models.

Regression Analyses of Physician Wages

We then examined whether the observed differences in income distribution could be explained by a difference in work effort (number of hours worked per week). We compared hours across various characteristics (e.g., gender) and found that even among full-time physicians, there were wide variations in hours worked in several subgroups (see Appendix B).

Tables 4 and 5 present the regression results for PCPs and specialist, respectively, using log(wage) as the dependent variable. Comparisons of regression coefficients between Tables 2 and 4 allowed us to infer whether the observed difference among various factors in the income distribution of PCPs could be attributed to variations in work efforts (working hours). Similar comparisons between Tables 3 and 5 provided information on the income distribution of specialists. We found significant wage differences between younger and older PCPs at almost all levels, but insignificant differences between the wages of middle-aged and older PCPs. Among specialists, the wage regressions showed that the difference between younger and older specialists remained insignificant, while that between middle-aged and older specialists decreased; but wages of middle-aged specialists were still significantly higher than those of older specialists. The magnitude of differences between male and

Table 4: Regression Analyses of Primary Care Physicians' Wages (in %)

Variable	*Mean*	*10th*	*25th*	*Median*	*75th*	*90th*
Individual level	F = 18.2**	F = 26.8**	F = 33.0**	F = 32.7**	F = 28.8**	F = 6.4**
Demographic characteristics (%)						
Age ≤ 40†	− 5.93**	− 3.63	− 7.84**	− 8.82**	− 7.45**	− 8.80**
Age: 41–55†	1.96	5.71	− 1.72	− 0.39	1.70	− 0.44
Male	13.74**	21.31**	16.11**	12.73**	9.78**	6.29*
Professional characteristics (human capital) (%)						
IMG	2.46	− 2.98	0.59	4.04	4.63*	4.49
BCERT	3.52*	7.18*	11.06**	5.37**	1.96	− 3.91
Organization level	F = 35.7**	F = 24.3**	F = 22.5**	F = 15.8**	F = 20.3**	F = 8.7**
Structural variables						
Ownership status (%)						
Partowner†	5.31*	7.26	8.41*	8.40**	− 0.48	− 11.07**
Nonowner†	− 2.16	5.07	3.46	2.09	− 9.43**	− 22.01**
Practice type (%)						
LRGSPEC†	10.74**	19.37**	16.10**	9.34**	5.83*	7.33
GRPHMO†	13.20**	19.29**	18.14**	11.85**	6.47	11.02
ACADGRP†	0.50	9.49	7.94*	− 2.69	− 8.12*	− 1.23
HOSPBASE†	12.26**	23.76**	20.57**	9.96**	5.93	9.14
OTHPRAC†	6.97**	15.81*	13.95**	5.21	1.52	0.40
MULPRAC	− 4.96	− 4.32	− 9.43**	− 6.95**	− 4.93	− 7.29
Management and incentive variables (%)						
AUT	7.41**	7.93*	6.56*	5.86**	5.19	6.74*
GUIDE	− 2.67	− 4.47	− 3.73	− 4.72	− 1.95	− 0.83
PROFILE	− 2.29	1.18	− 0.90	− 0.77	− 2.84	− 0.92
PTSATIS	0.73	− 2.00	− 0.58	− 0.93	1.23	3.19
GATE	0.003	− 0.03	0.02	− 0.002	− 0.03	0.03
PRODUCT	0.55	2.32	− 1.47	− 0.89	2.35	1.71
SALARIED	− 0.50	5.76	− 1.43	− 2.79	− 1.10	2.83
Clientele and market strategy						
Source of payment (%)						
NOCAPMCO	0.07	0.12	0.08*	0.08*	0.10*	0.01
PCAPMco	0.10**	0.24**	0.14**	0.08*	0.12**	0.00
MCARE	− 0.08**	− 0.01	− 0.07	− 0.09**	− 0.10**	− 0.09
MCAID	− 0.18**	− 0.14*	− 0.09*	− 0.15**	− 0.20**	− 0.32**
Number of MCO contracts in practice (%)						
# MCO ≤ 3†	− 1.39	3.50	1.09	2.01	− 3.87*	− 3.91
# MCO: 4–9†	− 2.12	0.62	− 0.75	− 0.86	− 4.16	− 2.30
# MCO: 0†	− 5.96	− 0.75	− 2.87	− 5.86	− 5.56	− 5.68
Market level	F = 2.6**	F = 6.9**	F = 6.1**	F = 9.0**	F = 10.7**	F = 2.2*
Local market characteristics (%)						
MRATIO‡	0.002	0.003	0.001	0.030	0.002	0.01
PENET	− 0.08	0.01	− 0.04	− 0.10	− 0.15	− 0.22
SUBPHYS	0.005	0.26	0.21	− 0.27	0.02	− 0.61
Census region/urbanization (%)						
NORTHE†	3.20	− 0.91	1.00	3.86	6.54	4.04
MIDWEST†	2.58	− 0.18	1.30	3.07	4.12	1.95

continued

Table 4. *Continued*

Variable	*Mean*	*10th*	*25th*	*Median*	*75th*	*90th*
SOUTH†	6.49	6.57	5.54	5.95	6.26	5.55
MSA	7.09**	10.54	9.39	7.94	5.35	9.88

†Reference groups (RG) for dummy variables are: Age, RG > 55; Practice Form, RG = solo or two physician practice; Ownership, RG = full owner; Managed Care, RG = many ($\geq$ 10) MCO contracts; Geographic region, RG = West.

‡Physician-to-population ratios are transformed using the natural logarithm

MSA metropolitan statistical area; MCO, managed care organization.

*Indicates statistically significant at $p \leq .05$; and

**indicates statistically significant at $p \leq .01$ level.

female physicians, including both PCPs and specialists, was smaller in wages than in incomes. Across various types of ownership status, the difference between PCPs who were fullowners and those who were partowners intensified when economic returns were measured in wages. Specifically, wages of partowners were significantly higher at most lower percentiles (as compared with no difference in incomes at these levels) but were much lower at the highest percentile ($-$ 11.1 percent in wages versus $-$ 8.9 percent in incomes). Differences in wages between PCPs who were fullowners and nonowners were lessened at the higher percentiles as compared with the differences in incomes. A similar pattern was found among fullowner and nonowner specialists.

DISCUSSION

This study analyzes factors associated with physician income distribution using quantile regression analyses, and to our knowledge, is one of few such studies (Kugler and Sauer 2005). This method allowed us to examine issues beyond the "mean" or "typical" level of inquiry normally associated with physician income studies. As we anticipated, quantile regression analysis permits the identification of variables that affect physician income on a different scale at various levels of the income distribution.

In some instances, variables exhibiting statistically insignificant differences at the mean were found to be significant at other levels. For example, the income of academic PCPs was found to be compatible with, and higher than that of nonacademic physicians at the mean, and the lower tail, respectively. This finding suggested that academic PCPs may receive more favorable

Table 5: Regression Analyses of Specialists' Wages (in %)

Variable	*Mean*	*10th*	*25th*	*Median*	*75th*	*90th*
Individual level	$F = 25.1^{**}$	$F = 20.6^{**}$	$F = 54.1^{**}$	$F = 39.5^{**}$	$F = 21.4^{**}$	$F = 39.9^{**}$
Demographic characteristics (%)						
Age $\leq 40^{\dagger}$	– 3.70	– 6.53	– 3.41	– 1.58	– 1.71	– 4.11
Age: 41–55†	6.84**	7.79	9.18**	7.95**	7.18**	4.72
Male	21.85**	27.74**	27.92**	16.69**	14.74**	16.19**
Professional characteristics (human capital) (%)						
Surgical†	19.29**	19.41**	21.57**	21.39**	19.31**	15.03**
Psychiatry†	– 8.03**	6.37	– 0.06	– 9.35**	– 16.53**	– 20.82**
ObGyn†	14.10**	17.30*	17.52**	14.00**	10.78*	9.21*
IMG	– 0.25	– 3.87	– 1.14	0.58	1.97	3.59
BCERT	9.47**	14.58**	11.25**	12.31**	8.71**	10.61**
Organization level	$F = 44.3^{**}$	$F = 12.3^{**}$	$F = 23.8^{**}$	$F = 22.6^{**}$	$F = 10.8^{**}$	$F = 19.8^{**}$
Structural variables						
Ownership status (%)						
Partowner†	4.17	11.24	6.57	1.84	0.21	– 3.82
Nonowner†	– 7.30*	– 0.40	– 4.30	– 8.56*	– 7.86*	– 17.50**
Practice type (%)						
LRGSPEC†	20.10**	31.10**	22.06**	24.49**	13.28**	11.29**
GRPHMO†	34.53**	50.63**	44.16**	41.46**	19.31	21.61
ACADGRP†	– 6.24	6.08	– 6.58	– 5.45	– 16.76**	– 11.43
HOSPBASE†	17.65**	37.10**	24.02**	15.87**	4.83	9.04
OTHPRAC†	13.38**	27.83**	16.92**	15.56**	0.34	0.99
MULPRAC	– 7.88**	– 7.15	– 8.66*	– 5.19	– 5.99*	– 9.76*
Management and incentive variables (%)						
AUT	6.68**	8.35	6.88**	8.34**	4.10*	2.77
GUIDE	– 6.46**	– 9.31*	– 8.24**	– 4.15	– 5.46	– 2.77
PROFILE	– 3.17	0.41	2.12	– 1.09	– 2.22	– 0.11
PTSATIS	0.57	1.98	2.83	0.67	1.36	0.38
PRODUCT	3.22	4.53	3.64	0.37	3.56	5.98
SALARIED	– 3.73*	– 7.60	– 3.31	– 3.77	– 3.50	– 5.76
Clientele and market strategy						
Source of payment (%)						
NOCAPMCO	0.01	– 0.002	– 0.03	– 0.02	0.09	0.02
PCAPMCO	– 0.07	– 0.03	– 0.10	– 0.14**	– 0.07	– 0.03
MCARE	– 0.05	– 0.14*	– 0.10*	– 0.03	0.04	– 0.05
MCAID	– 0.20**	– 0.19	– 0.15	– 0.18**	– 0.11	– 0.15*
Number of MCO contracts in practice (%)						
# MCO $\leq 3^{\dagger}$	– 0.16	– 1.50	1.18	– 1.67	– 0.70	– 0.22
# MCO: 4–9†	2.84	6.43	1.83	1.54	– 0.01	– 0.18
# MCO: 0†	0.41	0.11	– 5.08	0.58	– 2.24	3.53
Market level	$F = 21.8^{**}$	$F = 7.0^{**}$	$F = 6.7^{**}$	$F = 11.5^{**}$	$F = 6.4^{**}$	$F = 13.5^{**}$
Local market characteristics (%)						
MRATIO‡	0.001	0.001	0.003	– 0.0002	– 0.002	– 0.003
PENET	– 0.17*	– 0.05	– 0.05	– 0.20*	– 0.16	– 0.14
SUBPHYS	0.05	– 0.02	– 0.08	0.25	0.25	0.24

continued

Table 5. *Continued*

Variable	*Mean*	*10th*	*25th*	*Median*	*75th*	*90th*
Census region/urbanization (%)						
NORTHE†	6.89	1.66	7.82	5.81	5.01	6.81
MIDWEST†	8.39*	12.46*	10.62*	3.36	7.20	7.95
SOUTH†	7.93*	13.54**	12.84**	6.63	4.28	2.15
MSA	14.68**	3.53	11.46	24.09	11.73	11.05

†Reference groups (RG) for dummy variables are: Age, RG > 55; Specialty, RG = medical specialists; Practice Form, RG = solo or two-physician practice; Ownership, RG = full owner; Managed Care, RG = many ($\geq$ 10) MCO contracts; Geographic region RG = West.

‡Physician-to-population ratios are transformed using the natural logarithm.

MSA, metropolitan statistical area; MCO, managed care organization.

*Indicates statistically significant at $p \leq .05$; and

**indicates statistically significant at $p \leq .01$ level.

income at entry level, but that their income may grow at a much slower rate than the nonacademic physicians; consequently, their income advantages diminished at the higher income levels. Findings like this not only provide more information to help researchers disentangle the intricacy of factors associated with physicians' income distribution, they represent the situations where policy recommendations based on the conventional method may fail to recognize some effective policy parameters, thus, missing real opportunities to "make a difference" in decision making. A good example from our data is whether policy makers should target IMG specialists to recruit to ease the shortage of specialists in under-served communities. Our results showed that the incomes of IMG specialists were not statistically different from those of non-IMGs at the mean; but at the 10th percentile, IMG specialists earned significantly less than non-IMGs. This finding suggests that programs providing financial incentives for physicians to relocate to underserved areas are likely to be attractive to a group of lower-income IMG specialists. Using only information from the least squares model, policy makers would not know that a group of IMG specialists may be responsive to such programs.

In other instances, variables found to be significant at the mean were not found to be significant at some other levels. For example, autonomy was significantly positively associated with incomes at the mean for specialists, but not at the higher levels of the distribution; a finding suggested that specialists who valued autonomy highly may exhibit certain personality traits that were more important to one's financial success at the early stage of one's career but less so at the late stage. In these cases, policy makers may design policies around certain parameters based on the information from the mean estimated from the conventional method, anticipate seeing an impact but find the policy to be ineffective. The variable of MSA in the analysis of specialists can be used to illustrate our point. At the mean level, a significant difference was found between urban and rural specialists. Some policy makers may decide that the shortage of rural specialists is due to the lower income of specialists in those regions and decide to provide financial subsidies or bonuses to increase specialists' income in rural area as a way to retain specialists in rural communities. However, our study suggested that at the 10th percentile level, there was no difference in incomes between MSA and non-MSA specialists, but the incomes of these two groups were significantly different at the middle range (the 25th percentile and median) of the distribution. Therefore, unless the amount of subsides or bonuses offered is large enough to be financially attractive to rural physicians at the middle range of their income distribution, these policies are unlikely to succeed.

Our findings have produced data that will assist health workforce policy makers to project the impact of proposed policy initiatives, whether regulatory or market-based, on the physician labor market. Information on the local variations across health care markets that may affect physicians' income distribution may, in turn, assist policy analysts to assess the political reaction of physicians' professional organizations in support of or opposition to policy initiatives that are intended to encourage a more rational allocation of health care resources. Most importantly, these analyses can help identify appropriate parameters for workforce policies targeted at reducing income disparities between segments of the physician workforce while simultaneously improving the geographic distribution of physicians and influencing the relative proportion of specialists and generalists in the physician workforce. One concrete example that builds on our findings is a better design of incentive-based recruitment policies for physician relocation. Recall that our analyses reported a higher income among specialists in MSAs at the middle range of the income distribution and a lower income of IMGs at the 10th percentile of specialists' incomes. This finding suggests that policies providing financial incentives to IMGs at lower income levels are likely to be effective and relatively less costly relocation strategies to alleviate the shortage of specialists in rural communities. In fact, that may be what successful state and federal loan repayment programs have been doing by offering to pay off the education debts of relatively young, lower-income physicians in return for a period of service in rural or underserved practice settings (Pathman et al. 2000).

Findings from our study contribute baseline observations for longitudinal analyses to examine how changes in health policies impact physician income distribution. These findings are pertinent for the community of health workforce policy makers attempting to respond with meaningful policy initiatives to the systematic changes produced by the trend of managed care. We found that at all levels of income, the effects of managed care penetration are demonstrable but are more pronounced at the higher levels of physician income. This is consistent with a major objective of managed care plans in the 1990s—to reduce utilization of higher priced medical services, presumably by targeting those with higher fees or procedure volumes. However, within markets driven by managed care, the individual physician's participation in more managed care plans is associated with higher income. This is consistent with the notion that physicians can resist economic pressures where actual competition occurs between health plans for purchase of medical services rather than in near-monopsony arrangements, which erode their bargaining power. Consequently, managed care is related to income level, but in a relatively complex manner, and the modeling approach we have taken to examine these relationships enables a more subtle and informed interpretation of how various segments of the physician workforce are affected.

A study based on the 2001 AMA Patient Care Physician Survey reported unadjusted median income differences by various physician characteristics employment type, specialty, census division, board certification status, gender, age, and country of medical school graduation (Kane and Loeblich 2003). Our study, after adjusting for many possible confounding factors, found similar associations with the majority of the above variables but on a much smaller scale. A disturbing trend found in the AMA study was a widening gender gap of earnings among physicians in the late 1990s, and continuing into the current millennium. Our analyses showed that even after accounting for differences in working hours, ownership status, and specialty, the female/male income disparity persisted but was more pronounced at lower levels of the income distribution. Male physicians on average worked more hours than female physicians, thus, when we explored the gender difference in hourly wages, the gender differentials in median wages of PCPs and specialists were reduced but remained statistically significant. This finding indicated that part, but not all, of the observed gender differences in physician income can be attributed to male physicians working more hours per week. Future studies should apply the quantile regression method to disentangle the factors contributing to this apparently increasing income disparity by gender.

The nonlinear relationship between age and income observed in the univariate analyses by Kane and Loeblich (2003) was supported at most levels in our multivariate analyses. A similar pattern persisted when examining the relationship between age and wages among specialists, although the magnitude of differences between middle-aged and older specialists decreased, suggesting that the lower working hours observed in older specialists attributed to part, but not all, of the differences in income distribution across various age categories. Among PCPs, a nonlinear relationship was not found between age and wages. Although a significant lower wage was found in younger PCPs when compared with older PCPs at most levels, there was no difference in wages between middle-aged and older PCPs, indicating that the observed nonlinear relationship between age and income was possibly due to older PCPs practicing fewer hours.

Our study encountered several methodological challenges. The first challenge involved incorporating complex survey designs in the estimation of quantile regressions; we addressed this issue by obtaining weighted estimates with standard errors generated from bootstrapping with resampling within PSUs (see footnote 2). The second methodological issue concerned the top coding of income variables. In the restricted CTS-PS data, physician income was top coded at $400,000, which was close to the 99th and the 92nd percentile of the income distributions of PCPs and specialists, respectively. Therefore, the truncation in income caused by top coding should be less problematic for analyses of PCPs, especially at the lower percentiles. At the 75th percentile and higher of the income distribution of specialists, approximately 34 percent of the conditional quantiles were above the censoring point ($400,000) and the proportion increased to 86 percent for the 90th percentile and higher of the distribution. Therefore, estimates of specialists' incomes at the higher percentiles were likely to be biased due to top coding. One solution is to use a censored quantile regression (Buchinsky 1998); however, methods to apply these algorithms to complex survey data have not yet been developed.

A third methodological problem concerned potential endogeneity. The endogeneity of hours worked per week could be addressed using instruments such as marital status or number of kids in the family; however, none of these variables were collected in the CTS-PS. Therefore, we isolated the effect of hours by comparing the results between regression models using income versus wage as the dependent variable. Unobserved characteristics may motivate physicians to self-select into certain practice types or ownership status, and these characteristics are likely to place physicians at different points of the income distribution. One advantage of quantile regression is that it allows us to estimate income at various points of the distribution, which may reflect the distribution of these unobserved characteristics (Arias, Hallock, and

Sosa-Escudero 2001). Therefore, by examining the impact of these potentially endogenous variables at various percentiles throughout the income distribution, we would be able to infer the direction of biases at the mean. If we believed that "entrepreneurship" was the unobserved variable that correlated with physicians' decisions to become full- or partowners, then we could infer the effect of ownership on physicians' incomes by exploring the relationship between "entrepreneurship" and income. The increasing difference in incomes from lower to higher percentiles between PCPs who were fullowners and those who were nonowners may be due to the fact that business risk tended to have stronger financial impact on the more entrepreneurial physicians, making a more dramatic effect on their losses and gains. If entrepreneurship could be measured, then the difference between fullowner and nonowner PCPs would likely decrease once entrepreneurship was added to the least square regression model. Although some of the biases caused by endogeneity may be mitigated or conjectured through the use of quantile regression, a more recognized approach is to utilize a panel data set to remove the unobserved individual-specific effects by differencing between two periods (Kyriazidou 1997; Askildsen, Baltagi, and Holmas 2003). The more recent rounds of the CTS-PS (Round Two for 1998–1999 and Round Three for 2000–2001) contain a subset of physicians who were interviewed at each round of the survey; future research can utilize the panel data formed by this subset to address the endogeneity bias caused by self-selection.

This study provides a successful demonstration of the feasibility of an analytical framework using the quantile regression method to study physician income distribution. While one-time cross-sectional studies can be useful, more and better information can be obtained with repeated cross-sectional or true longitudinal designs. Such approaches can isolate winners and losers and assess how market dynamics and health policy initiatives affect the overall physician income distribution over various time intervals.

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NOTES

1. The authors initially planned to use county-level HMO market information such as number of HMOs, total HMO enrollment, HMO penetration and competition index from the County Surveyor data. However, further investigation of the County Surveyor data indicated it did not provide reliable estimates for 1996. The staff at InterStudy recommended the HMO penetration data constructed by Dr. Wholey and his colleagues (Wholey et al. 1997; Wholey, Burns, and Lavizzo-Mourey 1998).
2. Because an appropriate weighting algorithm for complex survey data is available in several statistical software packages, such as *STATA*, we ran an experiment in *STATA* with the least square regression model to test whether our bootstrap strategy indeed produced standard errors closer to those generated from proper weighting procedures. Four estimation strategies were compared in our experiments: (a) svyreg, which accounts for sampling weights, PSUs and STRATAs in LS regression; (b) a weighted LS (WLS) model with the "weight" option specified for sampling weights; (c) a bootstrap method for the WLS model; and (d) a bootstrap method with resampling within clusters (PSUs) for the WLS model. The standard errors obtained from strategy (a) are considered the "gold standard" in our comparisons. Results showed that all four methods produced the same point estimates; however, standard errors estimated from strategy (d) were closer to the "gold standard," followed by strategies (c) and (b) (comparison table available upon request). Based on our experiment, we employed strategy (d) to estimate the standard errors for the quantile regression parameters.
3. The possible effect of the top-coded income variable on the results of our analyses was addressed in the Discussion.
4. For continuous variables, the conversion was done by simply multiplying the coefficient by 100. For a binary variable, if the estimated regression coefficient was β, then the relative effect would be $100 \times (\exp(\beta) - 1)$ (Halvorsen and Palmquist 1980).

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Supplementary Material

The following supplementary material for this article is available online:

Appendix A. Income Distribution of Full-Time Physicians and Interpretations of Findings from Quantile Regressions.

Appendix B. Comparison of Working Hours.

This material is available as part of the online article from: http://www.blackwell-synergy.com/doi/abs/10.1111/j.1475-6773.2006.00690.x (this link will take you to the article abstract).

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