Context or Composition: What Explains Variation in SCHIP Disenrollment?

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Objective. To investigate (1) the relative contributions of family and contextual characteristics to observed variation in disenrollment rates from the State Children's Health Insurance Program (SCHIP), and (2) whether context explains observed family-level patterns.

Data Sources. We use secondary data on 24,628 families enrolled in New Jersey's SCHIP program (NJ KidCare), and county-level data from the Area Resource File, the Census, and the NJ FamilyCare provider roster.

Study Design. Information on family characteristics, SCHIP plan, and dates of enrollment and disenrollment are taken from NJ KidCare administrative records, which provided surveillance data from January 1998 through April 2000.

Data Collection/Analysis. We estimate a multilevel discrete-time-hazards model of SCHIP disenrollment.

Findings. Families enrolled in plans involving cost-sharing, blacks, and those with only one enrolled child have higher than average rates of disenrollment. Disenrollment rates for blacks are lower in counties with a high share of black physicians. These characteristics account for part of the intercounty variation in disenrollment rates; remaining intercounty variation is largely explained by physician density or population density.

Policy Implications. It may be worthwhile to pay special attention to black families and counties with high disenrollment rates to address the reasons for their lower retention. Addressing cultural differences between physician and client and the geographic distribution of medical providers might reduce disenrollment.

Key Words. SCHIP, disenrollment, health insurance, demographic factors, multilevel models

Many studies show that medically uninsured children are less likely to have a regular source of care or to have coordinated, comprehensive preventive health services (Eisert and Gabow 2002; McCormick et al. 2000; Newacheck et al. 1998; Szilagyi et al. 2000). It was thus of great concern that, in the mid-1990s, an estimated 11 million children were uninsured—many of them from poor and near-poor families (Szilagyi et al. 2000). To extend health coverage to children in low income families not covered by Medicaid or private health insurance, the State Children's Health Insurance Program (SCHIP) was enacted in 1997 (Ross and Hill 2003). By the close of FFY2001, more than four and a half million children had been enrolled in SCHIP (Ellwood, Merrill, and Conroy 2003) and public health insurance coverage of near-poor children had increased 3.4 percentage points, nearly all attributable to SCHIP (Hoffman and Pohl 2002). As a result, the rate of child uninsurance declined significantly, especially among the near poor (Dubay, Kenney, and Haley 2002; Holahan 2002).

Recently, however, concern has been raised about the relatively high share of SCHIP enrollees who drop out of the program, disrupting their health care and adding to the administrative burden of health care systems. To identify those at elevated risk of disenrolling, several recent studies (reviewed below) have documented variation in disenrollment rates across states, program designs, and demographic characteristics. However, none analyze demographic, programmatic, and geographic factors *simultaneously*, raising important questions about the relative contributions of contextual and family characteristics to observed variation in disenrollment across places and population subgroups.

An understanding of these issues would shed light onto ways to improve program design and outreach to maximize the chances that eligible children retain SCHIP coverage. We use multilevel hazards models to determine whether contextual characteristics and program attributes influence disenrollment from New Jersey's SCHIP program. We address two main questions: First, what explains the geographic variation in disenrollment rates? Is it *composition*—clustering of families with high disenrollment propensities in certain geographic locations, for instance? Or is it *context*—something about the socioeconomic or programmatic setting in those areas—that yields lower

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retention in some areas than others? Second, does context explain observed family-level associations with disenrollment? For example, to what degree are the higher disenrollment rates of black families explained by differences in places where black families live? After discussing previous studies of SCHIP disenrollment, we identify elements of the geographic and social context that may influence those disenrollment patterns.

BACKGROUND

Previous Research on SCHIP Disenrollment

Aggregate Disenrollment Estimates. A major concern with many past studies estimating aggregate disenrollment is the widely varying and often-incorrect methods of calculating disenrollment rates (Hill and Lutzky 2003; Rosenbach et al. 2001). However, several recent studies use hazards methods to adjust estimates of disenrollment for varying time since enrollment. A comparative study of SCHIP in Kansas, Oregon, New York, and Florida found disenrollment rates of roughly 20 percent within a year of enrollment (Dick et al. 2002). Shenkman, Vogel, and colleagues (2002) reported a 31 percent disenrollment rate, more than half of whom subsequently reenrolled. Miller and colleagues (2004) found that 13 percent of children enrolled in the New Jersey non-Medicaid SCHIP plans disenrolled within 9 months, and 34 percent within 18 months. However, these aggregate figures mask some potentially important geographic and sociodemographic patterns (see below).

Geographic Variation in Disenrollment. Although estimates of state-level SCHIP disenrollment can be gleaned from single-state reports or multistate comparisons, these estimates are difficult to compare because programs differ substantially from state to state in terms of eligibility levels, premiums, renewal processes, and other design attributes. Only a few studies examine geographic variation in disenrollment *within* a state—comparing families who face similar program design. Birnbaum and Holahan (2003) found substantially lower disenrollment rates in the five boroughs of New York City than in neighboring counties, although disenrollment rates at renewal varied from 30 percent to 57 percent among the boroughs. Miller et al. (2001) found more than a two-and-a-half-fold difference in rates between the lowest and highest disenrollment counties in New Jersey. However, neither study took into account differences in demographic composition of participating children or county characteristics that might explain geographic variation in disenrollment rates.

Demographic Variation in Disenrollment. Multivariate analyses of demographic patterns of SCHIP disenrollment have been conducted in only a few states. In both Florida (Shenkman et al. 2002) and New Jersey (Miller et al. 2004), families with only one enrolled child and those with children under age five had higher disenrollment rates, although in New Jersey, families with infants had the lowest disenrollment rates. Blacks had higher disenrollment rates in both Texas (Shenkman, Schaffer, and Vargas 2002) and New Jersey (Miller et al. 2004); in New Jersey, the pattern was observed only for families above 150 percent of the Federal Poverty Level (FPL).

THE ROLE OF CONTEXT IN EXPLAINING SCHIP RETENTION

Researchers have long noted variation in health outcomes across places (Blaxter 1990; Duncan, Jones, and Moon 1998). While such geographic variation may be partly attributable to compositional factors (e.g., unhealthy people are clustered in certain areas), environmental characteristics such as socioeconomic disadvantage also may have a direct impact on health. Jencks and Mayer (1990) identified five primary ways in which neighborhood conditions could influence individual outcomes. Most relevant to health research are those related to epidemic or contagion theory, which refers to the power of peer or neighbor influences in promoting behaviors that may or may not be conducive to good health, and 'institutional models,' which assert that a neighborhood's institutions rather than its residents are what matter (see also Duncan and Raudenbush 1999).

A number of different contextual characteristics might be expected to influence SCHIP program retention over and above family characteristics. Some of these factors, such as accessibility and quality of care and availability of alternative forms of health insurance, are related to institutions that may affect disenrollment rates. Others, namely demographic and socioeconomic characteristics, may alter the probability of disenrollment more indirectly, through their influence on both normative climate and individual health status.

In terms of programmatic features, some counties, particularly rural ones, have few SCHIP affiliated health care providers. Thus, SCHIP participants in those areas may have limited access to services and increased costs and travel time. Furthermore, families living in counties with many enrolled children for each physician may experience longer waits and shorter patient–doctor contact time, increasing dissatisfaction with the program, which in turn might increase disenrollment. With regard to provider characteristics, studies show that black physicians are more likely to serve black clients (see Cantor et al. 1996 for a review); hence, areas with higher shares of minority physicians might be more likely to retain minority families in the program.

Children must disenroll from SCHIP if they obtain alternative health insurance through employment; thus, availability of employment-based insurance should increase disenrollment. Since the nonprofessional service and retail sectors and small firms are less likely to offer employer-sponsored health insurance coverage (Cantor et al. 1995), counties with high shares of employment in those categories are expected to have lower disenrollment due to families finding other insurance. Similarly, locally high unemployment rates reduce the availability of employer-sponsored coverage, directly for those out of work and indirectly for employed persons, by reducing labor market pressure on employers to offer coverage.

Finally, socioeconomic and demographic characteristics of counties may influence retention rates. Contagion theory posits that individual behavior is influenced by interactions with others (Crane 1991; Robert 1998), suggesting that living among individuals who do not engage in health-promoting behaviors or carry health insurance might increase a family's propensity to disenroll. For example, if poor families place lower value on insurance and health behavior, local norms might reduce SCHIP retention in counties with high poverty rates. Alternatively, disadvantaged communities may have a poorer infrastructure such as public transportation, increasing time costs of program use and discouraging participation.

Conversely, living in economically disadvantaged communities could increase program retention in several ways. First, such areas may worsen individual health status or perceived health risks through environmental hazards or high levels of stress, either of which would increase the incentive to remain enrolled in SCHIP. Second, economically disadvantaged communities may attach less stigma to participation in government programs, reducing the "costs" associated with such participation and increasing program retention.

Data and Methods

Family-Level Data

We obtain information on demographic characteristics of enrolled families from the NJ KidCare administrative records. These data comprise the 24,628 families (41,271 children) who enrolled in the three non-Medicaid plans of NJ KidCare (Plans B, C, and D)[1] between January 1998 and April 2000 (Birch and Davis 2000). Plan B covered children with family income 133–150 percent of the FPL; Plan C, 150–200 percent of the FPL; and Plan D, 200–350 percent of the FPL; (Department of Human Services 1998). Infants in families up to 185 percent of the FPL are covered by Medicaid—hence the few infants in this sample are in plans C or D. Plans B and C took effect in January 1998, Plan D in July 1999. Plans C and D required cost sharing in the form of monthly premiums per family (Plan C: $15; Plan D: sliding scale from $30–$100) and copayments for some services.

We study disenrollment from NJ KidCare for any reason (finding other insurance, being placed in another government program, non-payment of premium [Plans C and D only], and other reasons). Very few disenrolled due to nonrenewal because the SCHIP program was new during the study period; hence few people had reached the period of eligibility redetermination. See Miller et al. (2004) for a discussion of reasons for disenrollment.

Contextual Data

Data on the percent of the county population that is black, percent Hispanic, child poverty rate, unemployment rate, and population density (persons per square mile) are from the 2001 Area Resource File (Quality Resource Systems 2001). Percent foreign born and percent non-English speakers are from the 2000 U.S. Census (2003a). The Indices of Dissimilarity (a measure of residential segregation) for blacks and Hispanics are from the 2000 Census (Iceland, Weinberg, and Steinmetz 2002) for each of the nine PMSAs that cover parts of New Jersey, assigned to the pertinent counties.

The shares of firms with fewer than 20 employees and from the service and retail sectors are calculated from information in the 2000 City and County Data Book (U.S. Census Bureau 2002). Number of health care providers per enrolled child and providers per square mile are calculated from the NJ FamilyCare provider roster (New Jersey Department of Human Services 2002), excluding physician specialties whose primary focus was adults. Each provider was counted in every county where they had an office. Percentages of physicians in each county who were black and Hispanic are from the 1990 Census (U.S. Census Bureau 2003b).

Methods

To analyze how family and county characteristics affect disenrollment from NJ KidCare, we combine hazards (event history or survival) analysis and multilevel modeling approaches. Hazards models take into account the fact that people enrolled at different dates, that Plan D started later than the other plans, and that censoring took place by the end of the observation period (Allison 1995). We adopt a multilevel approach since the families enrolled in NJ KidCare (level-1 unit of analysis)[2] are nested within counties (level-2 unit of analysis) (Bryk and Raudenbush 1992). The multilevel approach corrects for common-group correlation and nonconstant variance in the error term (Barber et al. 2000).

The family-level equation is defined identically for each county and is of the general form (Bryk and Raudenbush 1992; Wong and Mason 1985):

$$\ln[P_{t(ij)}/(1-P_{t(ij)})] = \beta_{tj} + \beta_{1j}X_{1t(ij)} + \beta_{2j}X_{2t(ij)} + \ldots + \beta_{kj}X_{kt(ij)} \qquad (1)$$

The dependent variable is the logit of the probability of disenrollment in time interval t for family i living in county j, given that the family remained enrolled at the beginning of interval t. β_{tj} is an estimate of the natural log of the baseline hazard of disenrollment for each time interval t. $X_{t(ij)}$ represents the matrix of family-level characteristics for each family i in county j and interval t. One record was created for each month a family was enrolled in NJ KidCare for a total of 172,232 family-month records. We adopt a discrete-time hazards specification, estimated using logistic regression (Allison 1995). This approach provides an estimate of the baseline hazard of disenrollment for each time interval and the relative hazard (or hazard ratio) of disenrollment for each covariate.

Variation in odds of disenrollment across counties is estimated by the level-2 equation:

$$\beta_{kj} = \theta_{k0} + \theta_{k1}Z_{1j} + \theta_{k2}Z_{2j} + \ldots + \theta_{kq}Z_{qj} + \mu_{kj} \qquad (2)$$

The family-level parameters, β, are assumed to vary across counties as a function of county-level characteristics, Z_j, as well as random variation, μ_j. The level-two error terms, μ_j, are random effects that model the correlation between timing of disenrollment for families in the same county.

Substituting equation (2) into equation (1) yields a mixed model. The parameters of the mixed model are estimated using the GLIMMIX macro in *SAS* software (SAS Institute website), which employs a restricted/residual pseudo likelihood (REPL) procedure. *MLwiN* estimates using a second-order approximation are very similar to those obtained using *SAS* (See Miller and Phillips [2002] for more detail).

Analysis

Only a few county-level variables can be included in the models at one time because there are so few counties ($N = 21$) and because some county characteristics are highly correlated (See correlation matrix in Appendix available online at www.blackwell-synergy.com). In exploratory analysis, we considered several parsimonious specifications that included representative indicators of the different theoretical constructs in one model and took into account correlation among the variables. Cross-level interactions were tested to determine whether the effects of family-level characteristics vary by county characteristics. Random-coefficients models were also estimated, but none of the coefficients for the family-level explanatory variables varied across county (j). We present only the best-fitting multilevel model, based on overall goodness-of-fit statistics for the model.

RESULTS

Descriptive Statistics/Sample Characteristics

Table 1 presents the distribution of enrolled families by demographic characteristics and NJ KidCare plan. Non-Hispanic white families comprise the largest single racial-ethnic group (38 percent), followed by Hispanic (28 percent), non-Hispanic black (19 percent), and families of other races (primarily Asian; 10 percent). Nearly half of enrolled families were English speakers while 22 percent spoke Spanish either along with English (20 percent of all families) or exclusively (2 percent); the 24 percent of families for whom language was unknown were retained as a "missing" category.

Contextual attributes vary considerably across the 21 New Jersey counties (Table 2). In terms of sociodemographic characteristics, the percent of the county that is black differs dramatically (0.6 percent to 41.2 percent), while the child poverty rate also shows substantial variation (3.9 percent to 27.9 percent). Proxies for availability of alternative insurance vary considerably, with the share of service and retail firms ranging from 29 percent to 67 percent. Although some counties had as many as 8 to 10 percent of their physicians from each of the minority racial/ethnic groups in 1990, six counties had no black MDs and six had no Hispanic MDs. Finally, programmatic traits differ markedly across counties, with more than a six-fold difference in the number of enrolled children per NJ KidCare provider. Life table estimates of the percentage disenrolled within nine months of enrollment range from 14.2 percent in Warren County to 36.3 percent in Salem County.

Table 1: Distribution of Ever-Enrolled Families[1] and Disenrollment Rates by Family Characteristics, NJ KidCare Plans B, C, and D, January 1998–April 2000

	No. Families	%[2]	No. Family-Months	No. Disenrolled	Average Monthly Disenrollment Rate
All children[3]	24,628	100%	172,232	3,233	1.9%
Race					
Non-Hispanic white	9,455	38%	67,159	1,144	1.7%
Non-Hispanic black	4,707	19%	30,928	803	2.6%
Hispanic	6,921	28%	48,315	837	1.7%
Other	2,344	10%	15,855	265	1.7%
Missing race	1,360	6%	11,077	196	1.8%
Language					
English	11,505	47%	65,913	1,310	2.0%
Spanish, some English	4,855	20%	34,117	564	1.7%
Spanish, no English	550	2%	3,226	56	1.7%
Other language	1,797	7%	12,966	161	1.2%
Missing language	5,951	24%	56,268	1,145	2.0%
Age group					
<1 year	458	2%	3,352	36	1.1%
1–5 years	11,248	46%	77,422	1,545	2.0%
6–12 years	13,554	55%	96,947	1,688	1.7%
13–17 years	7,481	30%	56,940	876	1.5%
No. children on account					
One	12,448	51%	84,136	1,826	2.2%
Two	8,633	35%	61,873	973	1.6%
Three	2,815	11%	20,791	350	1.7%
Four or more	731	3%	5,432	84	1.5%
Gender					
Male	16,095	65%	113,308	2,070	1.8%
Female	15,548	63%	109,835	1,975	1.8%
Plan					
B	4,336	18%	34,765	322	0.9%
C	14,375	58%	108,027	2,342	2.2%
D	5,917	24%	29,490	569	1.9%

[1]Enrolled at any time from January 1998 through April 2000.

[2]Families may have children in more than one age or gender group, hence numbers add up to more than the total.

[3]Includes children age 0 to 17 years at time of enrollment.

Family-Level Discrete-Time-Hazards Models

We begin with a set of preliminary models (1–4) that exclude county-level characteristics (Table 3). Model 1 estimates the baseline hazard and variation between counties in the odds of disenrollment without accounting for family

Table 2: Descriptive Statistics for County-Level Variables, New Jersey ($N = 21$ counties)[4]

Variable	*Mean*	*Standard Deviation*	*Minimum*	*Maximum*
Demographic				
Population density (pop/mile^2)	2,123.0	2,994.0	190.0	12,957.0
Percent black	11.9	9.4	1.0	41.2
Black residential segregation	0.66	0.11	0.41	0.80
Percent Hispanic	10.1	9.6	2.4	39.8
Hispanic residential segregation	0.55	0.08	0.38	0.65
Percent Spanish speakers	10.1	9.1	2.5	38.5
Percent foreign born				
Socioeconomic				
Child poverty rate (%)	13.9	7.2	3.9	27.9
Unemployment and Occupation Composition				
Percent <20 employees	69.3	7.4	57.1	87.8
Percent service/retail	39.5	8.4	29.0	67.1
Unemployment rate	4.9	2.0	2.1	10.1
Physician characteristics (1990)				
Percent of physicians who are black	2.7	2.5	0.0	7.7
Percent of physicians who are Hispanic	4.1	4.0	0.0	15.2
Programmatic				
Program uptake[5]	75.7	4.2	63.2	80.0
Public/total HMO enrollment (%)	29.7	13.8	6.9	57.6
No. enrolled kids/KidCare provider	4.4	1.9	1.0	9.0
No. KidCare providers/sq. mile	2.9	4.6	0.2	19.7

[4]Data are from 1999–2001 unless otherwise noted.

[5]No. enrolled in/no. eligible, expressed as a percentage.

characteristics. Model 2 adds controls for family characteristics, but ignores county clustering. Models 3 and 4 include family characteristics but adopt different approaches to controlling for county of residence: Model 3 includes county dummy variables, thereby accounting for all stable county characteristics, whereas Model 4 allows the intercept to vary randomly across counties.

We display this progression of models to make several points. First, the odds of disenrollment appear to vary nonrandomly across counties even after accounting for family-level characteristics (Model 4). Model 1, which provides an estimate of the baseline hazard with no controls for family characteristics, estimates a between-county variance of 0.16. Put differently, families living in counties that are one standard deviation above the 'average New Jersey county' in terms of all possible characteristics are 13.5 percent ($e^{\sqrt{0.016}}$) more likely to disenroll from SCHIP in any given month. This random county effect is slightly reduced (to 11.6 percent) when we take into account composition of enrolled families in the county (Model 4). The between-county random effect, although small, is significant at $p = .056$, indicating that a correctly specified model should consider variation between counties.

Second, the estimated effects of the family-level characteristics on odds of disenrollment do not change appreciably when county of residence is controlled (comparing Model 2 with Models 3 and 4). Indeed, the coefficients are virtually identical across specifications, suggesting that little of the observed relationship between family-level characteristics and disenrollment is due to county clustering. For example, the strong and persistent effect of black race on disenrollment from Plans C and D in all models cannot be attributed to characteristics of counties where black families are concentrated. These patterns are observed in the multilevel specification and are discussed in detail below.

Two-Level Discrete-Time-Hazards Model

The best-fitting multilevel model is presented as Model 5 in Table 3. As in Models 1–4, months enrolled and months-squared are specified as level-1 covariates to assess the temporal pattern of disenrollment. The effect of time varies by plan, with the monthly disenrollment rate increasing at a decreasing rate with time since enrollment for Plans C and D, but at an increasing rate for Plan B. None of the other covariates exhibited a time-varying effect. The intercept provides an estimate of the natural log of the average monthly hazard of disenrollment in the reference category, controlling for other factors in the model. For example, the average hazard of disenrollment from Plan B in Model 5 is approximately 0.4 percent per month ($.004 = e^{-5.455}$). The estimated coefficients for other covariates measure the ln (hazard ratio) relative to the reference category; exponentiating the coefficient yields the hazard ratio (HR).

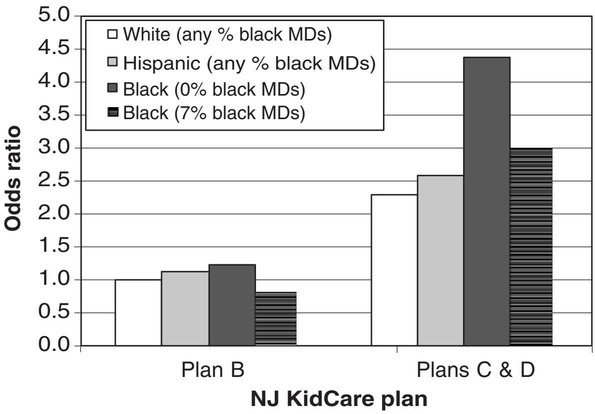
The multilevel model includes county measures of the child poverty rate, number of NJ KidCare providers per square mile (provider density), and the percentage of physicians in the county who are black. In addition, Model 5 reveals a significant cross-level effect between family race (a level-1 variable) and percentage of black physicians (a level-2 variable): Blacks are less likely to disenroll in counties with relatively high shares of black physicians, and the effect of physician racial composition is the same across all NJ KidCare plans.

Table 3: Multilevel Discrete-Time-Hazards Models of Disenrollment from SCHIP for Any Reason, January 1998–April 2000

	Baseline Hazard (1)		*Ignoring County of Residence (2)*		*County Fixed-Effects Model (3)*		*Random-Effects Model Family Factors Only (4)*		*Random Effects Model Family + County Factors (5)*	
Variable	*LRH*	*S.E.*	*LRH*	*S.E.*	*LRH*	*S.E.*	*LRH*	*S.E.*	*LRH*	*S.E.*
Intercept	**−4.327**	**(.049)**	**−5.426**	**(.140)**	**−5.581**	**(.159)**	**−5.421**	**(.142)**	**−5.455**	**(.159)**
Family-level characteristics										
Months enrolled	**0.072**	**(.012)**	0.018	(.034)	0.018	(.034)	0.018	(.034)	0.018	(.034)
Months enrolled-squared	−0.0008	(.0007)	**0.0046**	**(.002)**	**0.0046**	**(.002)**	**0.0046**	**(.002)**	**0.0046**	**(.002)**
Black race			0.016	(.149)	0.047	(.150)	0.038	(.149)	0.198	(.165)
Hispanic race			0.091	(.062)	0.121	(.064)	0.109	(.063)	0.124	(.064)
Plans C and D (ref = Plan B)			**0.819**	**(.142)**	**0.826**	**(.142)**	**0.823**	**(.142)**	**0.825**	**(.142)**
One enrolled child			**0.313**	**(.038)**	**0.317**	**(.038)**	**0.316**	**(.037)**	**0.316**	**(.038)**
Age composition of family										
No. infants			**−0.555**	**(.168)**	**−0.562**	**(.168)**	**−0.555**	**(.168)**	**−0.550**	**(.168)**
No. 1–4 year olds			**0.174**	**(.028)**	**0.165**	**(.028)**	**0.167**	**(.028)**	**0.166**	**(.028)**
Spanish with some English			**−0.152**	**(.068)**	**−0.136**	**(.069)**	**−0.144**	**(.069)**	**−0.139**	**(.069)**
Spanish with no English			0.015	(.146)	0.0092	(.146)	0.0084	(.146)	0.013	(.146)
Interactions										
Black * Plans C/D			**0.461**	**(.154)**	**0.449**	**(.154)**	**0.456**	**(.154)**	**0.451**	**(.154)**
Plans C/D * Months			**0.078**	**(.036)**	**0.078**	**(.036)**	**0.078**	**(.036)**	**0.077**	**(.036)**
Plans C/D * (Months Squared)			**−0.0069**	**(.0019)**	**−0.0069**	**(.0019)**	**−0.0069**	**(.0019)**	**−0.0068**	**(.0019)**
County-level characteristics										
KidCare provider density									**−0.019**	**(.007)**
% Poor									0.0054	(.005)
% Black physicians									0.007	(.012)
Cross-level interaction										
Black * % black physicians									**−0.039**	**(.019)**
Random effects										
Between-county variance	**0.016**	**(.009)**					**0.012**	**(.007)**	**0.005**	**(0.006)**
Scaled Deviance Statistic	**31,432.4**		**30,877.6**		**30,824.5**		**30,948.4**		**30,895.4**	

Note: Bolded coefficients indicate $p < 0.05$.

Figure 1: Odds Ratios of Disenrollment from NJ KidCare by Race of Family and % of Physicians in the County Who Are Black (1990)



Note: All odds ratios are statistically significantly different from the reference category (White, Plan B) except Hispanic Plan B and Black Plan B 0% M.D.s. (Model 5, Table 3).

The percentage of physicians in the county who are black does not affect disenrollment for other racial groups.

The net effects of interactions among family race, NJ KidCare plan, and county physician racial composition are shown in Figure 1. In counties with no black physicians, there is no statistically significant racial difference in disenrollment from Plan B. However, in the county with the highest percentage of black physicians (7.7 percent of physicians in that county), the odds of disenrolling for blacks in Plan B are 9.6 percent *less* than those for whites in the same plan (left cluster in Figure 1).

For all racial groups, disenrollment from Plans C and D is considerably higher than from Plan B. Whites are 2.3 times as likely to disenroll from Plan C or D as from Plan B, while for blacks the difference across plans is 3.7. As a result, there is a substantial racial gap in disenrollment rates in Plans C and D. In counties with no black physicians, blacks are about 90 percent more likely than whites to disenroll (compare the white and solid black bars in the right cluster of Figure 1). However, in counties with the highest percentage of black physicians, the excess risk of disenrolling for blacks compared to whites in Plans C and D is cut to 42 percent—less than half of that in counties with no black physicians (compare the white and striped bars in the right cluster). Note that there is no significant difference between Hispanics and whites in disenrollment patterns within any of the three plans.

With regard to other family-level characteristics, having only one child enrolled in the program is associated with higher disenrollment (HR = 1.37). Families with infants are less likely to disenroll (HR = 0.58), and the odds of disenrollment increase by 18 percent for each child aged 1–4 years, all else equal. Number of children above age 5 does not affect disenrollment. Those who speak Spanish with some English are less likely to disenroll (HR = 0.87) than are those who speak English only, but there is no difference between people who speak only Spanish and those who speak only English.

In terms of county traits, an increase of one NJ KidCare provider per square mile is associated with a 1.9 percent decline in the odds of disenrollment, controlling for level of poverty and the percentage of black physicians in the county. Once provider density is controlled, there is no longer any statistically significant variation between counties in disenrollment rates. Exploratory analyses (not shown) revealed that disenrollment is lower in counties with higher population density, but because physician density and population density are almost perfectly correlated ($r = 0.96$, $p < .01$), they cannot be included in the same model. Percent foreign-born, percent Spanish-speaking, percent Hispanic, and percent of county physicians who are Hispanic are each statistically significant when entered as the only county characteristic, but they too are highly correlated with population or physician density and do not retain statistical significance when either density measure is included. None of the socioeconomic factors, unemployment or occupational composition is significantly related to disenrollment in any of the specifications.

DISCUSSION

This study is one of a handful (Barber et al. 2000; Hedeker, Siddiqui, and Hu 2000; Ma and Willms 1999; Reardon, Brennan, and Buka 2001) to employ multilevel discrete-time-hazards models and one of the first to apply these methods to policy issues. Consistent with prior results, we found that family characteristics and SCHIP plan level have substantial effects on disenrollment from NJ KidCare (Miller et al. 2004). These family characteristics account for some, but not all, of the intercounty variation in disenrollment rates. The remaining intercounty variation is largely explained by geographic density of NJ KidCare physicians. However, because physician density is highly correlated with population density, percent foreign born, percent who speak other languages, and percent of county physicians who are Hispanic, we cannot distinguish whether it is access to care or one of these other factors that explains patterns of disenrollment across counties.

In terms of contextual factors, we found that county attributes do not account for the observed family effects on disenrollment, and that several family-level sociodemographic and plan characteristics remain important predictors of disenrollment. Most notably, the effects of race on disenrollment levels from Plans C and D are virtually unchanged even after controlling for county of residence. This suggests that the estimated race differences are individual rather than compositional in nature. In other words, the effect of race on disenrollment cannot be explained by the fact that blacks may be clustered in certain types of counties that tend to have low retention rates. Indeed, results of the fixed effects model suggest that other stable factors not measured here, such as quality of services in counties with high concentrations of black enrollees, cannot explain the observed racial differences.

One intriguing finding is that blacks are less likely to disenroll in counties where a relatively high share of physicians are black than in counties with no black physicians, pointing to the possible importance of cultural differences between physician and client. Nonetheless, even in counties with the largest relative shares of black physicians, rates of disenrollment remain considerably higher among blacks in the income ranges above 150 percent of the FPL covered by SCHIP plans. One explanation may be that black families have fewer assets than do white families at comparable income levels (Conley 1999; Eller and Fraser 1995), meaning that they have less money to cover premiums in cases of temporary income shortfalls. Alternatively, the disparity might result from differing cultural views about risk and the importance of sustained insurance coverage, which in turn increase program dissatisfaction among minority families. These topics cannot be addressed with the current data.

Study Limitations

There are several limitations of our study. First, although little of the observed relationship between family-level characteristics and disenrollment appears to be attributable to county of residence, this result may be an artifact of the level of aggregation. If data were available for smaller geographic units such as zip code or census tract, context might play a larger role. Moreover, hypotheses concerning normative climate would be better tested using measures that more closely proxy neighborhoods. Finally, due to the small number of counties in New Jersey, we are limited in our ability to estimate county-level effects. Data limitations precluded us from analyzing patterns at a lower level of aggregation.

Second, we have not adjusted for possible endogeneity bias. If unmeasured factors such as health status predict both program enrollment and disenrollment, coefficient estimates may be biased (Duncan and Raudenbush 1999). In addition, if unmeasured factors determine both where a family lives and whether they disenroll, the effect of context may be measured with some error. For example, if a family has some unobserved characteristic that makes them more likely to disenroll *and* more likely to live in a poor county, the effect of poverty would be overstated in our models. There are few satisfactory solutions to these possible biases (Duncan and Raudenbush 1999). In the absence of true or quasi-experimental designs, one must rely on statistical solutions such as instrumental variables or fixed-effects models, each of which has its own limitations (Barber et al. 2002).

Third, the finding of lower disenrollment of black enrollees in counties with higher shares of black physicians should be interpreted with caution because we do not know the race of physicians treating individual NJ KidCare clients. Moreover, the measures of physician racial composition are nearly a decade old, and may not accurately reflect the locations where physicians now practice. Finally, physicians who serve SCHIP clients typically include higher shares of minority physicians than the general roster of physicians. However, the relative levels of minority physicians across counties should be correlated with the figures used here based on the general physician population. Additional research would help clarify whether this result reflects cultural differences between physician and client or is an artifact of ecological data.

Finally, we are constrained by the use of administrative data, which has several weaknesses for this type of analysis. First, administrative records appear to overstate the extent to which eligible persons disenroll from SCHIP. A comparison of survey and administrative data by the National Academy for State Health Policy (NASHP) revealed that many people who were dropped because they did not pay premiums or renew their eligibility were in fact no longer eligible because of changes in family size or income (Pernice et al. 2002). Second, these data do not include measures of program quality or satisfaction. The NASHP report revealed higher levels of satisfaction among currently rather than formerly enrolled persons, suggesting that dissatisfied families were less likely to remain in SCHIP. If satisfaction varies across demographic, plan, or geographic groups, differences in satisfaction could explain observed intergroup and intercounty differences in program retention.

Third, this analysis combined all reasons for disenrolling prior to renewal, including nonpayment of premium, finding other insurance, and placement in other government programs. An alternative strategy would be to examine these reasons separately to investigate whether family and contextual characteristics have different effects on each reason for leaving SCHIP. We examined all reasons combined because this approach is consistent with previous studies of disenrollment (Dick et al. 2002; Miller et al. 2004; Shenkman, Schaffer, and Vargas 2002; Shenkman et al. 2002), and because a recent evaluation of SCHIP administrative data suggests that reason codes may be imprecise (Hill and Lutzky 2003).

POLICY IMPLICATIONS

Our results suggest several ways in which state funds earmarked for retention could be targeted. It may be worthwhile to pay special attention to black families and counties with high disenrollment rates to understand and address the reasons for their lower retention. Efforts to improve the recruitment of blacks into medical school may have a payoff for retaining black children in public coverage programs; however, increasing the supply of black physicians is a long-term proposition at best. In the near term, research that identifies effective intervention strategies by understanding why black children seem to benefit from living in areas with comparatively more black physicians and determines ways to improve physician cultural competence into medical education curricula for physicians working with black children may prove beneficial.

In addition, our results suggest that physician density may be related to disenrollment, although these patterns are also explained by population density. Increasing the number and distribution of physicians in counties with sparse physician density might improve access to care for enrolled children.

Our findings also suggest that charging premiums may increase disenrollment. Dick and colleagues (2002) found similar patterns in New York State. In Kansas, however, families who paid premiums had lower disenrollment rates until renewal time, when nonpayers were dropped from the program. If states are to expand their SCHIP programs to higher-income groups as New Jersey has done, they may need to consider the implications of cost sharing.

However, there are several reasons in addition to a price effect that could explain the higher disenrollment rates observed for the two cost-sharing plans. First, the plans that involve premiums are for families with higher incomes (150 percent to 350 percent of the FPL). National statistics suggest that families in those income ranges have better access to alternative forms of insurance coverage, such as employer-based health insurance. Second, remaining enrolled in the cost-sharing plans requires that families remember to pay the premium each month, which involves making the effort of mailing a monthly check. Third, higher-income families may be willing to risk having to pay occasional health expenses out of pocket because they have more financial resources to fall back on. Additional research is needed to identify the reasons for higher disenrollment in SCHIP plans for moderate-income families, ideally involving experimental assignment of families with similar incomes into different cost-sharing arrangements.

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NOTES

1. Nearly half of all children in NJ KidCare Plan A (Medicaid expansion) enrolled through county social service agencies and these children are believed to differ substantially from those enrolled through the statewide enrollment broker. Data from the social service agencies were not available, hence these analyses exclude Plan A.
2. See Miller and Phillips (2002) for a discussion of family as the unit of analysis.

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