Assessing the Impact of an Integrated Care System on the Healthcare Expenditures of Children With Special Healthcare Needs

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ABSTRACT

Objectives: The Children's Medical Services Network, a carved-out fee-for-service healthcare system for Florida's children with special healthcare needs (CSHCN), chose to develop an integrated care system (ICS) for its enrollees. The goals of this study were to analyze the effects of a managed care program on the Medicaid expenditures of CSHCN and to evaluate the performance of econometric models used to analyze healthcare expenditures.

Study Design: We used administrative data from 3947 CSHCN enrolled in Florida's Medicaid program between 2006 and 2008 for 2 treatment and 2 control counties. The 2 treatment counties were subject to the new managed care ICS.

Methods: To account for the unique nature of healthcare expenditures data, 5 econometric models were constructed. Using a difference-in-differences approach, these models were used to estimate differences in healthcare expenditures between CSHCN in the reform and control counties.

Results: The ICS program decreased outpatient, inpatient, pharmacy, and total costs. These effects were statistically significant for 1 of the reform counties. Emergency department costs increased slightly, though not significantly. Among the econometric models, the generalized linear models outperformed the ordinary least squares regressions.

Conclusions: This analysis provides evidence that managed care programs such as Florida's ICS have the potential to reduce healthcare expenditures.

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Children with special healthcare needs (CSHCN) are defined as those who have, or are at increased risk of having, a variety of conditions that require a higher degree of health services than those generally required by children.[1] Approximately 11.2 million (15.1%) children aged between 0 and 17 years in the United States are identified to have special healthcare needs.[2] It has been shown that healthcare costs for CSHCN are about 3 times that of children without special needs; further, CSHCN account for more than 40% of total medical care costs for children.[3]

Considerable pressure has been placed on organizations to reduce costs while providing high-quality care.[4] The growing number of CSHCN places additional pressure on these organizations to contain costs of providing care to this high-cost group. In an attempt to contain expenditures and improve outcomes, a number of state Medicaid programs have adopted managed care models for CSHCN.[5] Several studies have analyzed the impact of managed care models targeted at CSHCN on the quality of and access to care[5,6]; however, little work has been dedicated to determining the impact of managed care on healthcare expenditures for CSHCN.

Moving to a managed care program is expected to lead to cost savings through improvements in the coordination of care and incentives for cost reductions within the managed care organizations. A growing literature illustrates such cost savings when considering the entire Medicaid population, and, in particular, these studies found that the cost savings are highest for the aged, blind, and disabled.[7] One study, that analyzed Florida's managed care reform for the entire Medicaid population, attributed the observed cost savings to reductions in the number of nonemergency visits and in average cost per hospital visit.[8] Two studies investigated the effect of managed care on healthcare expenditures for CSHCN.[9,10] The first took on an observational (non–quasi-experimental) approach to analyze the performance of Ohio's "Access to Better Care" program.[9] Alternatively, the second study used a quasi-experimental approach relying on California's medical managed care expansion in the 1990s.[10] These studies found no statistically significant change in expenditures.

In Florida, CSHCN enrolled in public insurance programs are primarily served by the Children's Medical Services Network (CMSN), which serves more than 135,000 CSHCN enrolled in Medicaid in the state.[11] Florida uses the Maternal Child Health Bureau's definition of CSHCN, as "those who have or are at increased risk for a chronic physical, developmental, behavioral, or emotional condition and who also require health and related services of a type or amount beyond that required by children generally."[1] Historically, the network's services were purchased on a fee-for-service basis.

In 2005, CMS approved Florida's waiver to implement several reforms to its Medicaid program. In 2006, these changes began in 2 pilot counties: Broward and Duval. The CMSN chose to participate in the Medicaid reform and developed an integrated care system (ICS) in Broward and Duval counties for its enrollees. Under the ICS, there were 3 important ways the pilot counties differed from the non-reform counties. First, the ICS closed the network of providers that was available to CMSN enrollees; therefore, enrollees were only able to receive care from providers enrolled in the ICS network. Second, a third-party administrator (TPA) was established to oversee claims prior to transferring them to the state Medicaid agency. Before the existence of the ICS, CMSN providers submitted claims directly to the state Medicaid agency. Although the plan was engaging in utilization review prior to the implementation, the TPA made it easier to get more timely and detailed reports, and it should result in better medical management of its enrollees. Third, the ICS imposed additional prior authorization procedures on the providers.

Research on the impact of Florida's ICS on CSHCN is limited. Two studies found that the ICS pilot program did not reduce satisfaction and quality of care for CSHCN, as perceived by the children's parents,[6] and the utilization of inpatient and outpatient services decreased for CSHCN.[12] These studies suggest that the ICS program may reduce costs without altering the CSHCN patient's experience.

Our study makes novel contributions to the literature on managed care, modeling healthcare expenditures, and CSHCN. We used a quasi-experimental design to estimate the impact of a managed care program on healthcare expenditures for CSHCN. Further, unlike prior literature, we used an array of statistical models to account for the unique nature of healthcare expenditures. A growing array of literature is providing alternative methods to account for the unique properties of expenditures data.[13-16] Our study contributes to the methodological debate over the appropriate model when dealing with skewed expenditures data.

Take-Away Points

Using a quasi-experimental difference-in-differences design, we analyzed the impact that a managed care program implemented in Florida, aimed at children with special healthcare needs, has on healthcare expenditures. Further, we used various econometric models to account for the unique nature of expenditures data. We found that the program decreased outpatient, inpatient, pharmacy, and total costs. These effects are systematically statistically significant for 1 of the 2 reform counties.

- The literature on the impact of managed care programs on healthcare expenditures is limited.
- We provide evidence that a managed care integrated care system reduced the healthcare expenditures of a high-cost group of children.

METHODS

Sample and Design

All children in the study were enrolled in Florida's Medicaid program and the CMSN during the 2-year study period. All children in the health plan have had a special healthcare need (SHCN) identified by their primary care physician. Individual-level data were extracted from the Medicaid encounter, pharmacy, and enrollment files for the CMSN ICS enrollees. In total, 3947 CSHCN, ranging in age from 1 to 21 years, were included in the analysis.

The ICS pilot program was implemented in 2 counties: Broward and Duval[17]; for each treatment county, we chose a control county (Palm Beach and Orange, respectively) that closely reflected the reform county in its health and sociodemographic characteristics prior to the treatment. In particular, we chose as a control the closest county on a metric constructed from the 2005 values of all the healthcare and sociodemographic county-level numeric variables in the Area Resource File published by the Health Research and Services Administration.[18] The metric was constructed by weighing all the variables with the inverse of their variance, which is akin to standardizing the variables by translating them onto a common scale.

Start dates for Broward and Duval were staggered. The pre-period for Broward and its control (Palm Beach) was January to December 2006, and the post period was January to December 2007. For Duval and its control (Orange), the pre-period was May 2006 to April 2007, and the post period was May 2007 to April 2008. Only children enrolled for at least 6 months in Medicaid and CMSN, both before and after the implementation of the ICS were included. Children may have gaps in enrollment due to a loss of coverage, so these children were not dropped from the analysis.

Statistical Analysis

We used a difference-in-differences (DID) methodology to estimate the impact of the implementation of the ICS on healthcare expenditures for CSHCN. To implement this DID approach, we considered an array of 2-part econometric models. For each of the reform counties, we compared the difference in costs before and after the implementation of the ICS with the difference in costs before and after the start date of the ICS in the control county.

Explanatory Variables

To implement the DID methodology, we included in all our models an indicator variable for the county (1 for the ICS county and 0 for the control county), an indicator of time (1 for post-ICS implementation and 0 for pre-), as well as an ICS indicator variable that equals 1 for CMSN children in reform counties after the implementation of the ICS, and 0 otherwise. The latter captures the impact of the ICS on the dependent variables of interest.[19]

Several factors were used to control for observable differences of the children, including race/ethnicity (ie, white, black, Hispanic, and other), age, gender, an indicator of Supplemental Security Income disability, and a measure of the child's health status. We included the number of months of CMSN enrollment pre- and post reform as an exposure variable to control for the fact that children were likely to have more expenditures.

To assess the children's health status, the Clinical Risk Groups (CRGs) were used.[20] The CRGs use over 2000 diagnoses and procedure codes from all healthcare encounters to assign children to 1 of 5 health status categories: a) nonsignificant, nonacute; b) significant acute conditions; c) minor chronic conditions; d) moderate chronic conditions; and e) major chronic conditions.

Healthcare Expenditures

Healthcare expenditures were based on the annual costs of CSHCN in Broward, Duval, and the control counties for 5 categories of health services: inpatient, outpatient, emergency department (ED), pharmacy, and total expenditures. Two characteristics of healthcare cost data make their estimation difficult: a significant fraction of individuals have zero healthcare costs and the health cost data are skewed to the right. Although all children in CMSN have a special healthcare need, there are several reasons for which they might have zero costs: a) perceived adequate receipt of healthcare prior to joining the plan, b) poor case management, c) parental perception of good health, or d) missed appointments.

Economists have dealt with the issue of zero health costs by estimating 2-part models. These models exploit the decomposition of expected health costs into the probability of nonzero costs multiplied by the expected costs conditional on them not being zero:

$$E(y_{it} \mid Z_{it}) = \Pr(y_{it}>0 \mid Z_{it}) \times E(y_{it} \mid y_{it}>0, Z_{it}) \tag{1}$$

For the first part, we used logit models to estimate the probability of nonzero healthcare costs ($\Pr(y_{it}>0 \mid Z_{it})$) as a function of the ICS, county, and time dummy variables while controlling for potential confounders. For the second part, to estimate $E(y_{it} \mid y_{it}>0, Z_{it})$, several alternative ways of dealing with the skewedness of nonzero health costs were proposed.[15] In particular, there were 5 potential models that could be used: 3 were ordinary least squares (OLS) models of log costs that differ only in the way the retransformation to the original unit of US dollars is made, and the other 2 were generalized linear models (GLMs). For each type of cost category, we used the model with the lowest root mean square error (RMSE).

OLS Models

The method most frequently used to mitigate the impact of observations with very high healthcare cost is OLS regression on the logarithm of nonzero costs:

$$\ln(y_{it}) = Z'_{it}\beta + \varepsilon_{it} = X'_{it}\gamma + \alpha \times County_i + \delta \times Time_t + \theta \times County_t \times Time_t + \varepsilon_{it}. \tag{2}$$

The explanatory variables contain confounding factors. The impact of the ICS implementation is captured in the interaction term "county × time," which equals 1 for children in a treatment county after the implementation of the ICS, and 0 otherwise.

Our interest was in the impact of policy and explanatory variables on dollar costs, rather than on the log scale. This created the necessity for retransforming the results onto the dollar scale:

$$E(y_{it}) = e^{Z'_{it}\beta} E\left(e^{\varepsilon_{it}} \mid Z_{it}\right) \tag{3}$$

We estimated 3 log OLS models that differed in the way the log results were retransformed:

Normal Distribution. Assuming that the disturbances from the log OLS regression are normally distributed with mean 0 and variance σ^2, we have:

$$E(y_{it} \mid Z_{it}) = e^{Z'_{it}\beta + 0.5\sigma^2} \tag{4}$$

Duan's Smear. If the errors ε_{it} are homoscedastic, the last term in equation (3) is consistently estimated by the smearing factor proposed by Duan even if the errors are not normally distributed[21]:

$$E(y_{it} \mid Z_{it}) = e^{Z'_{it}\beta} s \text{, where } \hat{s} = \frac{1}{N} \sum e^{(\ln y_{it} - Z'_{it}\beta)} \tag{5}$$

Ai-Norton. Ai and Norton proposed an alternative, semi-parametric method for retransforming the results on the scale of interest when the errors are heteroscedastic.[16] Their method is based on modeling the expectation of the exponentiated residuals from the log regression using a polynomial approximation and the predicted values from this regression:

$$E\left(e^{\varepsilon_{it}} \mid Z_{it}\right) = W_{it}'\delta + u_{it} \qquad (6)$$

$$E(y_{it} \mid Z_{it}) = e^{Z_{it}'\beta}E\left(e^{\varepsilon_{it}} \mid Z_{it}\right) = e^{Z_{it}'\beta}W_{it}'\hat{\delta} \qquad (7)$$

We used a polynomial approximation W_{it} in which we included the same variables as in Z_{it}, as well as higher-order terms of age, together with an interaction between these terms and gender.

Generalized Linear Models

GLMs specify a function between the index $Z_{it}'\beta$ and the expected value of the cost variable of interest, and a distribution that reflects the mean-variance relationship in the data.

GLM with gamma distribution. We used the generalized gamma distribution, which subsumes the normal, exponential, and Weibull distributions as particular cases. We used the log link function:

$$\ln(E(y_{it} \mid Z_{it})) = Z_{it}'\beta \qquad (8)$$

The GLM approach performs better than the log transform when the data are severely skewed and log costs are not symmetrically distributed.[14]

Extended generalized linear model (EGLM). Alternative link functions can be used instead of the log link. Box-Cox estimated parameters are close to 0, but statistically significant for all our cost variables of interest, indicating that, although the log link is appropriate, more efficient power transformations may exist. An alternative EGLM framework to simultaneously estimate the parameter λ of a Box-Cox transformation with those of a GLM model was used[14]:

$$\frac{E(y_{it} \mid Z_{it})^{\lambda} - 1}{\lambda} = Z_{it}'\beta \qquad (9)$$

where the variance is assumed to be:

$$V(y_{it} \mid Z_{it}) = \theta_2 E(y_{it} \mid Z_{it})^{\theta_2}, \quad \text{with } \theta_2 = 2 . \qquad (10)$$

Impact of ICS

For each of the 2-part models and the cost categories of interest, we estimated the impact of the ICS on each cost category by the average treatment effect on the treated (ATET). This reflects the overall impact of the ICS program in a given reform county. Using the ATET allowed us to compare the treatment effect of the ICS program across the various econometric models considered.

RESULTS

Table 1 presents the characteristics of children who resided in Broward, Duval, and the corresponding control counties in our sample. Table 1 reveals that various characteristics of the children in the treatment group and corresponding control group are not statistically different, pre-treatment, for both counties. However, the treatment counties have a higher proportion of black non-Hispanics, a lower proportion of Hispanics, a lower average age, and more children categorized as disabled. These important characteristics are included in the re-

Table 1. Characteristics of CMSN Children[a]

	Broward n (%)	Broward Control n (%)	P[b]	Duval n (%)	Duval Control n (%)	P[b]
Race						
White, non-Hispanic	162 (13.5)	171 (17.3)	.014	165 (24.1)	186 (17.3)	<.01
Black, non-Hispanic	634 (52.8)	469 (47.4)	.012	387 (56.6)	365 (34.0)	<.01
Hispanic	200 (16.7)	229 (23.2)	<.01	34 (5.0)	309 (28.8)	<.01
Other	205 (17.1)	120 (12.1)	<.01	98 (14.3)	213 (19.9)	<.01
Gender						
Male	686 (57.1)	561 (56.7)		397 (58.0)	630 (58.7)	
Female	515 (42.9)	428 (43.3)	.853	287 (42.0)	443 (41.3)	.781
Clinical risk groups						
Nonacute	190 (15.8)	133 (13.4)	.109	173 (25.3)	222 (20.7)	.024
Significant acute	52 (4.3)	34 (3.4)	.085	42 (6.1)	57 (5.3)	.463
Chronic minor	61 (5.1)	75 (7.6)	.016	9 (11.5	87 (8.1)	.02
Chronic moderate	437 (36.4)	364 (36.8)	.839	205 (30.0)	323 (30.1)	.953
Chronic major	461 (38.4)	383 (38.7)	.871	185 (27.0)	384 (35.8)	<.01
Disability status						
Disabled (SSI)	877 (73.0)	594 (60.1)	<.01	469 (68.6)	810 (75.5)	<.01

	Broward Mean	Broward SD	Broward Control Mean	Broward Control SD	P[b]	Duval Mean	Duval SD	Duval Control Mean	Duval Control SD	P[b]
Age in years	8.50	5.35	9.29	5.42	<.01	7.90	5.27	10.23	5.11	<.01
Months enrolled	11.15	1.68	11.13	1.71	.721	10.55	2.00	11.27	1.57	<.01
Total number of children	1201		989			684		1073		

CMSN indicates Children's Medical Services Network; SSI, Supplemental Security Income.
[a]Data represent the pre-period, and are for children enrolled in CMS and Medicaid at least 6 months both before and after the implementation of the integrated care system.
[b]The P values represent a test to see if the pre-treatment characteristics differ across the treatment and control counties.

■ **Table 2.** Average Monthly Costs ($) Before and After the Implementation of the ICS[a]

	Broward (Pre-)	Broward (Post)	Control (Pre-)	Control (Post)	Overall				
	Mean	Mean	Mean	Mean	Mean	SD	Skewness	% >0	Max
Inpatient	487.81	385.20	304.80	297.90	375.32	1603.86	9.18	23.7	35,668.33
Outpatient	1365.76	1159.51	1124.96	1080.43	1190.23	3022.38	4.32	98.1	26,303.41
ED	34.53	34.60	29.75	26.01	31.54	60.56	3.66	44.5	733.57
Pharmacy	553.82	401.02	424.63	410.56	450.04	1978.79	18.22	94.0	67,321.95
Total	2409.51	1958.14	1873.84	1815.57	2030.36	4409.02	4.54	98.8	67,351.20

	Duval (Pre-)	Duval (Post)	Control (Pre-)	Control (Post)	Overall				
	Mean	Mean	Mean	Mean	Mean	SD	Skewness	% >0	Max
Inpatient	323.30	184.89	381.86	331.45	316.79	1850.78	13.83	19.4	45,122.35
Outpatient	589.73	461.87	1223.19	1205.81	946.78	2534.16	4.55	97.0	21,352.25
ED	44.32	40.44	30.75	28.07	34.45	71.85	5.22	43.9	1396.60
Pharmacy	374.92	348.97	501.60	531.64	457.53	2721.06	17.38	94.5	67,361.88
Total	1306.61	1009.30	2119.03	2077.21	1731.99	4308.57	6.25	98.4	67,800.90

ED indicates emergency department; ICS, integrated care system; max, maximum.
[a]Data are for children enrolled in CMS and Medicaid at least 6 months both before and after the implementation of the ICS.

gression analyses as covariates to control for these statistically significant differences.

The average monthly costs in each county and period are presented in Table 2. The average monthly costs in each category were higher in Broward than in its control county both before and after the implementation of the ICS, whereas they were lower in Duval than in its corresponding control county. The average monthly costs in each category were lower after the beginning of the implementation of the ICS in each county, with the exception of pharmacy costs in the Duval control. As in most healthcare cost studies, all the cost variables were skewed to the right.

eAppendix Table 1 (eAppendices available at **www.ajmc.com**) shows that the EGLM method proposed systematically had the lowest RMSE among the models we estimated for each of the cost categories.[14] The log OLS model with the retransformation proposed by Ai and Norton performed best among the outpatient models we estimated for Broward and its control county.[16] The log OLS with normal retransformation had the highest in-sample accuracy among the total costs models estimated for Duval and its control county.

Table 3 presents the estimation results of the most accurate (lowest in-sample RMSE) 2-part models for each cost category of interest for Broward and its control, and Table 4 presents the models with the lowest in-sample RMSE for Duval and its control county. Focusing on the ICS variable in the second part of the 2-part models for Duval and its control, the ICS coefficients are negative and statistically significant for the total, inpatient, outpatient, and pharmacy costs. This suggests that the ICS program reduced costs in these categories in Duval County. Alternatively, using Table 3, outpatient, inpatient, pharmacy, and total costs were also lower in Broward County after the implementation of the ICS, but the estimated cost decreases were not statistically significant.

We estimated the ATET, which represents the sample average of the estimated dollar effect of the ICS on the healthcare costs of children in each of the ICS counties (eAppendix Table 2). The implementation of the ICS in Duval County appears to have led to economically and statistically significant outpatient cost savings ($84 and $1008 per CMSN enrollee per month and per year, respectively) and total cost savings ($195 and $2340 per CMSN enrollee per month and per year, respectively).

The lowest RMSE model indicates an average monthly total cost reduction of about $188 per CMSN enrollee per month ($2256 per year) in Broward due to the implementation of the ICS. All ATET estimates for Broward and its control are negative except the ones for average monthly ED costs. However, none of the dollar estimates for Broward is statistically significant at the 5% level.

DISCUSSION

The literature on the effect of enrollment in managed care models on healthcare expenditures of CSHCN is limited. Our study aimed to address this gap by using a recent policy change to describe the effects of an ICS on the healthcare expenditures of CSHCN in Florida. Our study is unique, in that Florida did not carve out specific services for CSHCN, but chose to carve out the entire system of healthcare. Additionally, the ICS ushered in a level of managed care that was not previously experienced.

We found that the average annual outpatient costs and total costs have decreased as a result of the implementation of the ICS in Duval County by approximately $1008 and $2340 per CMSN enrollee, respectively. Outpatient, inpatient, pharmacy, and total costs were also lower in Broward County after the implementation of the ICS, but the cost decreases were not statistically significant. ED costs increased slightly, though not significantly. The findings of our analysis suggest that managed care programs such as

Table 3. Two-Part Models of Average Monthly Costs With Lowest In-Sample RMSE: Broward Versus Broward Control

	Average Monthly Total Cost		Average Monthly Inpatient Cost		Average Monthly Outpatient Cost			Average Monthly ED Cost		Average Monthly Pharmacy Cost	
	1st Part[a] LOGIT	2nd Part EGLM	1st Part[a] LOGIT	2nd Part EGLM	1st Part[a] LOGIT	2nd Part LN OLS	2nd Part Ai-Norton	1st Part[a] LOGIT	2nd Part EGLM	1st Part[a] LOGIT	2nd Part EGLM
Broward	–0.645	0.225*	0.015	0.256	–0.743	–0.083	0.149	–0.064	0.094	–0.529*	0.316
	(0.605)	(0.101)	(0.104)	(0.138)	(0.495)	(0.063)	(0.251)	(0.090)	(0.055)	(0.223)	(0.196)
Time	–1.023	0.050	–0.065	0.097	–1.187*	–0.060	0.403	–0.175	0.042	–0.365	0.000
	(0.587)	(0.059)	(0.111)	(0.148)	(0.471)	(0.065)	(0.296)	(0.094)	(0.056)	(0.232)	(0.045)
ICS	–0.011	–0.088	–0.191	–0.102	0.147	–0.035	0.038	0.091	0.051	–0.134	–0.211
	(0.701)	(0.089)	(0.148)	(0.174)	(0.564)	(0.090)	(0.420)	(0.126)	(0.066)	(0.286)	(0.171)
Disability status	0.280	0.536***	1.004***	0.457*	0.495*	0.443***	0.570*	0.525***	0.033	0.295*	0.255*
	(0.296)	(0.085)	(0.091)	(0.194)	(0.230)	(0.049)	(0.221)	(0.071)	(0.051)	(0.142)	(0.115)
Age	–0.024	–0.245***	–0.316***	–0.099	–0.123	–0.271***	0.103**	–0.259***	–0.038	–0.240***	–0.125
	(0.138)	(0.045)	(0.036)	(0.054)	(0.119)	(0.024)	(0.033)	(0.032)	(0.020)	(0.070)	(0.099)
Age 2[b]	–0.004	0.012***	0.013***	0.005	0.000	0.009***		0.010***	0.002	0.008*	0.010*
	(0.006)	(0.002)	(0.002)	(0.003)	(0.005)	(0.001)		(0.002)	(0.001)	(0.003)	(0.005)
Female* age	–0.272	–0.013	0.178***	–0.043	–0.276	–0.015	–0.110**	0.066	–0.039	0.167	–0.011
	(0.281)	(0.057)	(0.053)	(0.070)	(0.251)	(0.035)	(0.041)	(0.048)	(0.028)	(0.105)	(0.106)
Female* age 2[b]	0.018	–0.001	–0.008**	0.002	0.015	0.002		–0.002	0.002	–0.004	–0.003
	(0.013)	(0.003)	(0.003)	(0.004)	(0.011)	(0.002)		(0.002)	(0.001)	(0.005)	(0.006)
Female* white	–0.931	0.098	0.276	–0.400	–0.519	0.221		0.256	0.052	0.661	–0.032
	(1.290)	(0.249)	(0.226)	(0.311)	(0.910)	(0.133)		(0.188)	(0.110)	(0.454)	(0.410)
Female* Hispanic	–1.341	0.132	0.025	–0.079	–0.363	0.128		–0.026	0.046	–0.102	–0.023
	(1.064)	(0.172)	(0.192)	(0.352)	(1.258)	(0.113)		(0.169)	(0.106)	(0.424)	(0.245)
Female* other race	0.185	0.182	0.497*	–0.287	–0.069	0.043		0.190	–0.188	–0.288	0.399
	(1.202)	(0.203)	(0.222)	(0.243)	(0.901)	(0.145)		(0.189)	(0.149)	(0.359)	(0.339)
White	1.740*	0.313	–0.160	–0.240	1.531**	0.502***	–0.494	–0.426***	–0.034	0.073	0.370
	(0.747)	(0.210)	(0.150)	(0.220)	(0.539)	(0.087)	(0.290)	(0.122)	(0.077)	(0.241)	(0.366)
Hispanic	1.739*	–0.122	0.181	–0.367	2.210**	0.216**	–0.948***	–0.175	0.037	0.671*	–0.072
	(0.726)	(0.137)	(0.128)	(0.267)	(0.726)	(0.073)	(0.230)	(0.111)	(0.070)	(0.282)	(0.211)
Other race	0.735	0.122	–0.255	0.179	1.182*	0.493***	–0.207	–0.251*	0.083	0.017	–0.218
	(0.525)	(0.166)	(0.158)	(0.147)	(0.495)	(0.099)	(0.334)	(0.127)	(0.095)	(0.241)	(0.310)
Female	1.390	0.027	–0.605**	0.247	1.563	–0.017	0.676	–0.368	0.110	–1.097*	0.025
	(1.315)	(0.206)	(0.233)	(0.243)	(1.248)	(0.158)	(0.391)	(0.216)	(0.100)	(0.484)	(0.286)
Healthy		–2.953***		–4.044**		–3.120***	–0.759**		–0.884***		–1.625***
		(0.282)		(1.252)		(0.065)	(0.275)		(0.184)		(0.135)
Significant acute		–1.740***		–5.517**		–2.005***	0.129		–0.194		–0.790**
		(0.179)		(1.840)		(0.120)	(0.670)		(0.106)		(0.261)
Chronic minor		–1.910***		–2.413***		–1.636***	–0.284		–0.523***		–1.473***
		(0.159)		(0.604)		(0.088)	(0.615)		(0.141)		(0.143)
Chronic moderate		–1.225***		–1.067***		–1.307***	–0.001		–0.285***		–0.838***
		(0.081)		(0.156)		(0.055)	(0.241)		(0.050)		(0.147)
Constant	5.350***	0.937***	–0.501**	–0.002	5.390***	7.431***	2.019***	0.938***	0.165	4.324***	0.288
	(0.890)	(0.202)	(0.176)	(0.303)	(0.734)	(0.121)	(0.402)	(0.161)	(0.099)	(0.408)	(0.358)
Lambda[c]		0.006		–0.667**					–1.864**		0.266*
		(0.076)		(0.255)					(0.682)		(0.122)
Theta 1[d]		4.531***		2.391***					0.871***		15.096*
		(1.071)		(0.257)					(0.038)		(7.338)
Theta 2[d]		2.000		2.000					2.000		2.000
N	4362	4310	4356	1032	4356	4273	4273	4356	1938	4112	3865

CRG indicates clinical risk groups; ED, emergency department; EGLM, extended generalized linear model; GLM, generalized linear model; ICS, integrated care system; LOGIT, logistic regression; LN OLS, log-linear ordinary least squares; RMSE, root mean square error.
Asterisks indicate: "*" = P <.05, "**" = P <.01, and "***" = P <.001.
[a]The CRGs drop out of the first part models because they perfectly predict all zero outcomes.
[b]Age 2 reflects the quadratic of age.
[c]Lambda represents the estimated link parameter.
[d]Theta 1 and Theta 2 are estimated variance parameters.
Referent groups are black, non-Hispanic, male, and CRG with chronic major condition.

Table 4. Two-Part Models of Average Monthly Health Costs with Lowest In-Sample RMSE: Duval Versus Duval Control

	Average Monthly Total Cost		Average Monthly Inpatient Cost		Average Monthly Outpatient Cost		Average Monthly ED Cost		Average Monthly Pharmacy Cost	
	1st Part[a] LOGIT	2nd Part LN OLS	1st Part[a] LOGIT	2nd Part EGLM	1st Part[a] LOGIT	2nd Part GLM	1st Part[a] LOGIT	2nd Part EGLM	1st Part[a] LOGIT	2nd Part EGLM
Duval	–0.665 (0.493)	–0.173** (0.063)	–0.224 (0.133)	0.019 (0.207)	–0.630 (0.338)	–0.538*** (0.100)	–0.117 (0.107)	0.238*** (0.071)	–0.549* (0.239)	–0.020 (0.053)
Time	–0.710 (0.431)	0.066 (0.058)	–0.311** (0.114)	0.121 (0.184)	–0.520 (0.308)	0.089 (0.090)	–0.147 (0.090)	0.030 (0.058)	–0.421 (0.219)	0.087* (0.039)
ICS	0.090 (0.585)	–0.162* (0.077)	0.234 (0.182)	–0.562* (0.245)	–0.142 (0.422)	–0.160** (0.037)	0.274 (0.146)	–0.049 (0.083)	0.320 (0.313)	–0.105* (0.054)
Disability status	0.776** (0.283)	0.276*** (0.049)	1.193*** (0.129)	0.841*** (0.190)	0.467* (0.209)	0.561*** (0.085)	0.627*** (0.085)	–0.011 (0.061)	0.234 (0.170)	0.054 (0.048)
Age	–0.008 (0.139)	–0.135*** (0.022)	–0.267*** (0.040)	–0.214** (0.066)	–0.109 (0.099)	–0.208*** (0.031)	–0.246*** (0.035)	–0.080*** (0.022)	–0.012 (0.071)	–0.117* (0.049)
Age 2[b]	–0.003 (0.007)	0.006*** (0.001)	0.011*** (0.002)	0.011*** (0.003)	0.002 (0.005)	0.009*** (0.001)	0.009*** (0.002)	0.003** (0.001)	0.000 (0.003)	0.011** (0.004)
Female,* age	0.058 (0.215)	–0.078* (0.034)	0.020 (0.064)	0.073 (0.088)	0.051 (0.162)	–0.033 (0.047)	–0.096 (0.056)	–0.041 (0.038)	0.014 (0.116)	0.059 (0.056)
Female,* age 2[b]	–0.001 (0.011)	0.004* (0.002)	0.000 (0.003)	–0.002 (0.004)	–0.002 (0.008)	0.002 (0.002)	0.005 (0.003)	0.003 (0.002)	0.001 (0.006)	–0.008* (0.004)
Female,* white	–0.887 (0.775)	–0.116 (0.115)	–0.089 (0.246)	–0.274 (0.374)	–0.246 (0.549)	0.062 (0.187)	–0.255 (0.198)	–0.044 (0.151)	–0.352 (0.428)	–0.137 (0.213)
Female,* Hispanic	–0.061 (0.810)	–0.048 (0.120)	–0.239 (0.255)	–0.610 (0.484)	0.034 (0.615)	0.217 (0.177)	–0.033 (0.196)	0.029 (0.175)	–0.024 (0.450)	–0.768 (0.469)
Female,* other Race	–0.425 (0.835)	0.179 (0.132)	–0.078 (0.252)	–0.503 (0.397)	0.671 (0.711)	0.238 (0.213)	–0.179 (0.205)	–0.051 (0.146)	–0.750 (0.482)	–0.598 (0.575)
White, non-Hispanic	0.939 (0.556)	0.409*** (0.074)	0.191 (0.154)	–0.181 (0.255)	0.452 (0.340)	0.254* (0.114)	–0.034 (0.124)	–0.168 (0.089)	0.582* (0.269)	0.408* (0.207)
Hispanic	0.281 (0.532)	0.113 (0.083)	–0.146 (0.168)	–0.218 (0.362)	0.335 (0.391)	–0.176 (0.127)	–0.195 (0.134)	–0.223* (0.101)	0.311 (0.285)	0.854 (0.466)
Other race	0.502 (0.548)	0.142 (0.089)	0.079 (0.161)	–0.389 (0.235)	0.224 (0.359)	0.171 (0.148)	–0.088 (0.132)	–0.146 (0.098)	0.807* (0.337)	0.866 (0.581)
Female	–0.197 (0.966)	0.242 (0.154)	–0.087 (0.276)	–0.083 (0.326)	0.004 (0.749)	–0.036 (0.200)	0.498 (0.259)	0.072 (0.150)	0.020 (0.510)	0.023 (0.201)
Healthy		–3.233*** (0.067)		–2.443** (0.802)		–3.331*** (0.104)		–0.888*** (0.117)		–1.006*** (0.138)
Significant acute		–1.890*** (0.080)		–2.405*** (0.483)		–2.254*** (0.142)		–0.373*** (0.085)		–0.724*** (0.133)
Chronic minor		–1.699*** (0.071)		–0.812 (0.609)		–1.741*** (0.109)		–0.588*** (0.088)		–0.837*** (0.119)
Chronic moderate		–1.259*** (0.055)		–1.201*** (0.179)		–1.172*** (0.088)		–0.206*** (0.055)		–0.581*** (0.133)
Constant	4.484*** (0.862)	7.772*** (0.120)	–1.005*** (0.222)	0.065 (0.333)	4.389*** (0.594)	8.174*** (0.186)	0.641*** (0.189)	0.505*** (0.118)	2.841*** (0.407)	0.022 (0.187)
Lambda[c]				–0.323 (0.172)				–0.584 (0.397)		0.685*** (0.154)
Theta 1[d]				2.553*** (0.343)				0.916*** (0.076)		12.604*** (2.564)
Theta 2[d]	3482	3428	3478	2.000 674	3478	3374	3478	2.000 1528	3246	2.000 3066

CRG indicates clinical risk groups; ED, emergency department; EGLM, extended generalized linear model; GLM, generalized linear model; ICS, integrated care system; LOGIT, logistic regression; LN OLS, log-linear ordinary least squares; RMSE, root mean square error.
Asterisks indicate: "*" = $P<.05$, "**" = $P<.01$, and "***" = $P<.001$.
[a]The CRGs drop out of the first part models because they perfectly predict all zero outcomes.
[b]Age 2 reflects the quadratic of age.
[c]Lambda represents the estimated link parameter.
[d]Theta 1 and Theta 2 are estimated variance parameters.
Referent groups are black, non-Hispanic, male, with chronic major condition.

the ICS have the potential to reduce healthcare costs for this high-risk group of CSHCN.

These findings are complemented by previous findings that the ICS pilot program did not reduce the satisfaction and quality of care for CSHCN, as perceived by the children's parents.[6] Further, there is evidence that the utilization of inpatient and outpatient services decreased for CSHSN.[12] These findings suggest that the ICS pilot program has the potential to reduce healthcare costs without changing the patient's experience. Although we cannot definitively comment on why the cost reductions occurred, we speculate that this could be due to: a) a reduction in the utilization of services, and b) that processing a large volume of claims in a more efficient manner makes it easier to identify billing- and procedural-based inconsistencies.

By estimating alternative models of healthcare costs, this study also contributes to the literature evaluating the performance of different classes of models used to estimate expenditures data.[15,22] We found that the GLMs performed the best in our sample of CSHCN; this likely arises because CSHCN are a population with high healthcare costs, which increases the importance of modeling the variance in a flexible way. This supports prior findings that the GLMs outperform other methods when analyzing skewed cost data.[22] In addition, because the GLMs are not biased by heteroskedasticity, like other methods, we provide further evidence that the GLM estimators are the best-performing methodology when faced with skewed cost data.

Finally, this study adds to the growing literature on Florida's 2006 Medicaid reform.[8,23-29] In particular, 2 studies examine the impact of Florida's Medicaid reform on healthcare expenditures of the entire Medicaid population. One study found that Florida's Medicaid reforms did not result in a statistically significant reduction in costs.[29] However, the authors do note that cost reductions may have been achieved for subpopulations with higher healthcare needs— precisely what our study suggests. Another study uses a quasi-experimental design similar to the one used in the current study, and the authors find statistically significant cost reductions that can be attributed to a reduction in the number of non-emergency visits and in average cost per hospital visit.[8]

A key assumption in any DID analysis is that the trends in healthcare costs pre-treatment across the treatment and control counties are similar. Due to data limitations, we are unable to directly test this for our subsample of Medicaid enrollees. However, a related study, which analyzed the same treatment and control counties during our period of study, illustrates that the common trends assumption is satisfied when analyzing the healthcare costs of all Medicaid enrollees in Florida.[8] This finding, coupled with the findings in Table 1 that a wide array of pre-treatment characteristics of the CSHCN are not statistically different across our treatment and control counties, helps defend the common trends assumption in our analysis.

Limitations

Several limitations to this study merit attention. First, we used the CRGs to control for the children's health status in our models. About one-fifth of the CSHCN were unassigned, meaning that there were not enough claims data to assign them to a health status category, mostly due to gaps in enrollment. Second, we lack information on several explanatory variables of interest, such as household income and parents' education, which could be linked to the healthcare costs of CSHCN. Third, we are unable to provide any information regarding the impact of the ICS program on access to healthcare service for CSHCN or on outcomes. Although we can state that outpatient costs decreased, for example, we do not know if that decrease results in better, worse, or the same outcomes for the patient. Fourth, the full impact of a managed care program on CSHCN may take several years to be realized. Our study considers a relatively short time horizon.

Despite these limitations, our study is among a limited amount of literature that describes the effects of a managed care program on the healthcare costs of CSHCN. In addition, our study findings contribute to several areas of the CSHCN literature, including Medicaid managed care, carved-out healthcare systems, and Medicaid reform. The findings in this study are timely, as Florida has adopted a statewide managed care system in 2014.[30] Many other states are now moving toward a higher degree of managed care penetration, and they can look to Florida as an example of what might be possible for this high-cost group.

CONCLUSIONS

We used a quasi-experimental DID research design to assess the impact that a managed care program aimed at CSHCN has on healthcare expenditures. We found that the program decreased outpatient, inpatient, pharmacy, and total costs for this high-cost group of children. This paper contributes to the limited research that analyzes the impact of managed care programs on healthcare expenditures. These findings suggest that managed care programs such as the ICS have the potential to reduce healthcare expenditures for CSHCNs. Future research should determine the long-term impacts of ICS implementation on healthcare costs, quality, and access to care, and if these impacts are sustainable. This information is crucial to determining if other states should consider adopting this model of care for CSHCN.

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eAppendix

Table 1. The Root Mean Square Error of Average Monthly Cost Models

	Log OLS with Retransformation			**Generalized Linear Models**	
Cost/Model	**Normal**	**Duan's Smear**	**Ai & Norton**	**GLM**	**EGLM**
Broward vs Broward Control					
Inpatient	1549.28	1546.00	1547.07	1544.53	**1537.57**
Outpatient	2784.63	2787.07	**2736.08**	2737.69	2763.39
Emergency Department	58.41	58.47	58.07	58.05	**57.89**
Pharmacy	1990.14	1987.54	2037.23	1996.48	**1966.08**
Total	4006.91	4017.32	4024.52	3975.87	**3974.77**
Duval vs Duval Control					
Inpatient	1741.62	1769.74	1784.01	1764.46	**1732.42**
Outpatient	2333.95	2332.75	2284.59	**2282.96**	2309.00
Emergency Department	67.66	67.81	67.42	67.33	**67.00**
Pharmacy	2726.35	2730.53	2744.26	2714.75	**2704.14**
Total	**3971.87**	4014.48	4198.45	4022.34	3987.20

EGLM indicates extended generalized linear model; GLM, generalized linear model; OLS, ordinary least squares.

Bolding indicates the lowest root mean square prediction error for each type of cost.

Table 2. Estimated Dollar Effect of ICS on Average Healthcare Costs

	Log OLS With Retransformation			**Generalized Linear Models**	
Cost / Model	**Normal**	**Duan's Smear**	**Ai & Norton**	**GLM**	**EGLM**
Broward vs Broward Control ATET					
Inpatient	–155.85	–84.83	–78.19	–82.66	**–76.99**
Outpatient	–31.03	–31.64	**–22.80**	–1.97	–10.88
ED	3.53	3.34	3.46	3.48	**3.44**
Pharmacy	–7.40	–7.20	–110.91	–118.22[a]	**–95.52**
Total	–251.80	–257.93	–221.47	–189.88	**–188.32**
Duval vs Duval Control ATET					
Inpatient	68.58	38.29	–22.19	–35.92	**–63.82**
Outpatient	–101.28[a]	–106.10[a]	–79.94	**–83.66**[a]	–65.98
ED	1.75	1.63	2.15	2.55	**2.92**
Pharmacy	–66.72[a]	–71.56[a]	69.11	–32.68	**–30.35**
Total	**–194.63**[a]	–231.81[a]	652.59	83.18	30.78

ATET indicates average treatment effect on the treated (children in counties where the ICS was implemented); ED, emergency department; EGLM, extended generalized linear model; GLM, generalized linear model; ICS, integrated care system.

[a]Significant at 5% level.

Bolding indicates the models with the lowest root mean square error on each row.