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Effects of an Integrated Care System on Children with Special Health Care Needs' Medicaid Expenditures

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Abstract

Objective. The Children's Medical Services Network, a carved-out fee-for-service health care delivery system for Florida's Children with Special Health Care Needs (CSHCN), chose to developed an Integrated Care System (ICS) for its enrollees. The goal of this study is to analyze the effects of the ICS managed care program on the Medicaid expenditures of CSHCN.

Data Sources. Administrative data from 3,947 CSHCN enrolled in Florida's Medicaid program between 2006 and 2008 for two treatment and control counties were included in the analyses.

Methods. To account for the unique nature of health care expenditures data, five econometric models were constructed. These models were used to estimate differences in health care expenditures between CSHCN in the reform and control counties before and after the implementation of the ICS controlling for demographic and individual health status.

Principal Findings. The ICS program decreased outpatient, inpatient, pharmacy, and total costs. These effects were statistically significant for one of the reform counties. Emergency room costs increased slightly, though not significantly. Among the econometric models, the Generalized Linear Models outperforms the Ordinary Least Squared regressions.

Conclusions. This analysis provides evidence that Managed Care programs such as Florida's ICS have the potential to reduce health care expenditures.

Key Words. Children, Medicaid, Managed Care, Health Care Cost, Health Econometrics

JEL Codes. I10, C20, I18

INTRODUCTION

Children with Special Health Care 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 (Mcpherson et al. 1998). Approximately 11.2 million (15.1%) children between ages 0-17 in the United States are identified to have special health care needs (CDC 2012). It has been shown that health care expenditures for CSHCN are about three times that of children without special needs (Newacheck and Kim 2005). Further, CSHCN account for over 40% of total medical care costs for children (Newacheck and Kim 2005). An increase in the access to care, awareness, improved screening, and an escalating number of children with chronic conditions have led to an increase in the number of children classified as CSHCN (CDC 2012).

Controlling health care expenditures has been a longstanding policy goal. There has been considerable pressure placed on private and public health care organizations to reduce costs while providing high quality care (IHI 2012). 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 health care expenditures and improve health care outcomes, several State Medicaid Programs have adopted managed care models for CSHCN (Huffman et al. 2010). Managed care models strive to improve access and coordination of care in order to improve quality and reduce health care expenditures. There have been several studies that analyze the impact of managed care models targeted at CSHCN on the quality of and access to care (Huffman et al. 2010, Knapp et al. 2012). However, little work has been dedicated to determining the impact of managed care models on health care expenditures for CSHCN.

Grossman et al. (1999) and Inkelas (2005) investigate the effect of managed care on health care expenditures for CSHCN. Grossman et al. (1999) undertake an observational (non-quasi-experimental) approach to analyze the performance of Ohio's "Access to Better Care Program". Alternatively, Inkelas (2005) uses a quasi-experimental approach relying on California's medical managed care expansion in the 1990's. Both of these studies find that there is no statistically significant increase in overall health care expenditures.

In Florida, CSHCN enrolled in public insurance programs are served by a managed care model established by the Children's Medical Services Network (CMSN). CMSN provides

carved-out health care services for CSHCN. CMSN has a distinct network of primary and specialty care providers, has 20 area offices throughout the State, and serves more than 50,000 CSHCN enrolled in Medicaid (Sloyer et al. 2000). Florida uses the Maternal Child Health Bureau's (MCHB) definition of special health care needs 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 than required by children generally" (CDC 2012, pg. 5). Children are deemed eligible for the CMSN if their clinician confirms that the child has a special health care need as defined by the MCHB. The network's services are purchased on a fee-for-service basis using Florida's Medicaid rates.

In 2005, the Center for Medicare and Medicaid Services (CMS) approved Florida's waiver requesting to implement several substantial changes to its Medicaid program. In 2006, these changes began in two 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, providers were still paid using fee-for-service. However, there were three important differences 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 ICS, CMSN providers submitted claims directly to the State Medicaid agency. It is believed that the TPA allowed the CMSN to have better medical management of its enrollees. Third, the ICS imposed additional prior authorization procedures on the providers. The ICS reflected a significant change in the system used to deliver care to CSHCN.

A central aim for managed care programs such as Florida's ICS is to improve the coordination of health services, increase the use of preventative health services, and provide better medical home services. The expected improvements in care coordination and medical home services are expected to lead to a reduction in unnecessary hospitalizations, procedures, and referrals to specialists, thus reducing health care expenditures (Grossman et al. 1999, Huffman et al. 2010). Twenty-two states have established Managed care programs for CSHCN (Huffman et al. 2010). For example, California's managed care program through Medi-Cal provides a similar program with a set of closed network providers. However, unlike Florida's

ICS program, Medi-Cal's managed care program is paid through capitated payments for each enrollee (Smith et al. 2009).

Our study makes novel contributions to the literature on managed care, modeling healthcare expenditures, and CSHCN. We use a policy change to identify the impact of a managed care program on healthcare expenditures for CSHCN. Further, unlike prior literature, we use an array of statistical models to account for the unique nature of healthcare expenditures. A growing array of literature has developed alternative methods to account for the unique properties of expenditures data (Manning and Mullahy 2001, Basu and Rathouz 2005, Manning et al. 2005, Ai and Norton 2008). We contribute to the methodological debate over the appropriate model specification when dealing with skewed healthcare expenditures data.

METHODS

A. Study Design and Sample

All children in the study were enrolled in Florida's Medicaid program and the CMSN during the two-year study period. Individual level data was extracted from the Medicaid encounter, pharmacy, and enrollment files for the CMSN ICS enrollees. Enrollment files contain demographic information about each child, and the corresponding medical, facility, and pharmacy claims data contain Physician's Current Procedural Terminology (CPT) codes, revenue codes, place of service codes, International Classification of Diseases, 9th Revision (ICD 9-CM) codes, National Drug Codes (NDC) and paid amounts for services rendered and prescriptions ordered. Paid claims accounted for adjustments and denials. In total, 3,947 CSHCN ranging from one to twenty-one years old were included in the analysis.

The ICS pilot program was only implemented in two treatment counties: Broward and Duval. These two counties were chosen by the state because they represent two distinct diverse populations with well-defined health infrastructure (FAHCA 2005). This provides an ideal environment to test how the ICS pilot program performs as market characteristics vary. For each of the treatment counties, we choose a control county that closely reflected the reform county in its health and socio-demographic characteristics prior to the treatment. In particular, we chose as control the closest Florida county on a metric constructed from the 2005 values of *all* the health care and socio-demographic county-level numeric variables in the Area Resource File published by the Health Research and Services Administration (HRSA 2012). 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. The control county for Broward was Palm Beach and the control county for Duval was Orange.

Start dates for ICS in Broward and Duval were staggered. As a result, the pre period for Broward and its control was January to December 2006 and the post period was January to December 2007. For Duval and its control, the pre period was May 2006 to April 2007 and the post period was May 2007 to April 2008. Children who moved from one county to another during the study period were not included in the study sample. 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 periodic gaps in enrollment during the period of the study; these children were not dropped from the analysis.[1] The University of Florida's Institutional Review Board approved this study.

B. Statistical Analysis

We use a difference-in-difference methodology to estimate the impact of the implementation of the ICS on healthcare expenditures for CSHCN in the treatment counties. For each of these counties, we compare 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 a control (non-reform) county. The control county represents the counterfactual, meaning what would have happened in Broward and Duval in the absence of the implementation of CMSN's ICS.

C. Explanatory Variables

To implement the difference-in-difference method, we include in all our models an indicator variable for the county in which the CMSN child resided (equal to one for the ICS county and zero for the control county), an indicator of time (0 for pre and 1 for post ICS implementation), as well as an ICS indicator variable that equals one for CMS children in reform counties after the implementation of the ICS, and zero otherwise. The latter captures the impact of the ICS on the cost dependent variables of interest (Puhani 2012).

Several confounding factors were used to control for observable differences, including: race/ethnicity (White non-Hispanic, Black non-Hispanic, Hispanic, and other race), age, gender, an indicator of SSI disability, and a measure of the child's health status (Table 1). Also included were age squared and interactions between gender and the race and age variables. We include the

number of months of CMS enrollment pre and post reform as an exposure variable in the count data models to control for the fact that children who were enrolled more months are likely to have had more doctor visits.

To assess the children's health status, the Clinical Risk Groups (CRGs) were used (Neff et al. 2004).[2] The CRGs use over 2,000 diagnoses and procedure codes from all health care encounters to assign children to one of five health status categories. The five health status categories are: 1) Non significant, non-acute including children whose underlying chronic condition were not recorded in the claims data but were seen for routine care or whose primary expenditures were pharmacy services, 2) Significant acute conditions including children with acute illnesses that could be precursors to or place the child at risk for developing a chronic disease, 3) Minor chronic conditions including children with illnesses that can usually be managed effectively with few complications, 4) Moderate chronic conditions including children with illnesses that are variable in their severity and progression, can be complicated, and require extensive care, and 5) Major chronic conditions including children with illnesses that are serious, and often result in progressive deterioration, debility, or death.

D. Health Care Expenditures

Health Care Expenditure measures were constructed based on the annual costs of CSHCN in Broward, Duval, and the control counties (pre and post ICS implementation) for five dimensions of health services: inpatient, outpatient, emergency department, pharmacy, and the total expenditures.[3] Two characteristics of health care cost data make their estimation difficult. Usually, a significant fraction of individuals have zero health care costs in a given period of time, while at the same time others have very high costs (the health cost data is skewed to the right).

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

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

For the first part, we use logit models to estimate the probability of non-zero health care costs as a function of the ICS, county, and time dummy variables while controlling for potential confounders. For the second part, several alternative ways of dealing with the skewness of non-zero health costs have been proposed. However, the appropriate model depends on the characteristics of the data at hand (Manning et al. 2005).

We estimate five alternative models for each of our cost dependent variables of interest for the second part of our two-part models. Three are OLS models of log costs that differ only in the way the retransformation to the original US Dollar (USD) scale is made, while the other two are generalized linear models (GLM). These models are briefly described below. For each type of cost dependent variable (inpatient, outpatient emergency department, pharmacy, and total average monthly cost) we use the model with the lowest root mean square prediction error (RMSE) to assess the impact of the ICS on CSHCN's health expenditures.

1. Log OLS Models with Retransformation

The method most frequently used to mitigate the impact of observations with very high health care cost is OLS regression on the logarithm of non-zero costs:

$$\ln(y_{it}) = Z_{it}'\beta + \varepsilon_{it} = X_{it}'\gamma + \alpha \times County + \delta \times Time + \theta \times County \times Time + \varepsilon_{it}. \quad (2)$$

The explanatory variables X_{it}' contains confounding factors, the Greek letters represent true parameters that need to be estimated, and the impact of the ICS implementation is captured in the interaction term ICS=County x Time, which equals 1 for children in Broward County after the implementation of the ICS, and zero otherwise. The OLS on log costs performs well when the data are not too skewed and the log-transformed variable is relatively symmetrically distributed.

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

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

We estimate three log OLS models that differ only in the way the log results are retransformed onto the original USD scale.

a. Normal Distribution Retransformation

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

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

b. 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 (1983) even if the errors are not normally distributed:

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

The homoscedasticity assumption is not innocuous, consistent estimation of the parameters of the log model does not ensure that the estimates on the raw scale will be consistent. Heteroskedasticity in the estimated residuals of the log model can lead to biased estimates of the effect of explanatory variables on costs on the raw scale if it is not correctly taken into account. Duan (1983) also proposed using different smearing factors by group if the errors are heteroscedastic, but the method is inefficient and difficult to apply if the errors are heteroskedastic in several variables, especially if some of the covariates are continuous.

c. Ai-Norton Retransformation

Recently, Ai and Norton (2008) have proposed an alternative, semi-parametric method for retransforming the results on the scale of interest when the errors are heteroscedastic. Their method is based on modeling the expectation of the exponentiated residuals from the log regression using polynomial approximation or splines, and using the predicted values from this regression to do the retransformation:

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

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

We use a polynomial approximation W_{it} in which we include the same variables as in Z_{it}, as well as higher order terms of our only continuous variable, age, together with an interaction between these higher order terms and child gender. We limit the approximation to be of at most 6^{th} order, and choose through cross-validation the polynomial approximation with the lowest out-of-sample mean square prediction error.

2. Generalized Linear Models (GLM)

GLM models specify a link function between the linear 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. A flexible-enough distribution needs to be used.

a. GLM with Gamma Distribution

We use the generalized gamma distribution which subsumes the normal, exponential, and Weibull distributions as particular cases and is the most commonly used distribution and assume a linear link function (Basu and Rathouz 2005):

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

GLM family tests (modified Park tests) revealed that the variance $V(y_{it} \mid Z_{it})$ is approximately proportional to the squared mean $[E(y_{it} \mid Z_{it})]^2$.The GLM approach performs better than the log transform when the data is severely skewed and log costs are not symmetrically distributed, albeit at the cost of stronger distributional assumptions. The GLM predictions can be retransformed by simple exponentiation because the GLM is estimating the $\ln(E(y_{it} \mid Z_{it}))$, not the $E(\ln y_{it} \mid Z_{it})$ as least squares on log costs does.

b. Extended Generalized Linear Model (EGLM)

Alternative link functions can be used instead of the log link. Box-Cox estimated parameters are close to zero but statistically significant for all our cost variables of interest, indicating that, although the log link is appropriate, more efficient power transformations may exist. Basu and Rathouz (2005) have proposed an extended GLM framework to simultaneously estimate the parameter λ of a Box-Cox transformation with those of a GLM model:

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

where the variance is assumed to be:

$$V(y_{it} \mid Z_{it}) = \theta_1 E(y_{it} \mid Z_{it})^{\theta_2}, \text{ with } \theta_2 = 2. \tag{10}$$

E. Dollar Estimates of the Impact of ICS on Health Care Costs

For each of the cost variables of interest (inpatient, outpatient, emergency department, pharmacy, and total average monthly cost) we estimate the five alternative models presented above and chose the model with the lowest root mean square prediction error (RMSE).

We estimate the impact of the ICS on each type of cost by the average treatment effect on the treated (ATET), the sample average of the overall impact of the ICS indicator in each two-part model for the CMSN children in a given reform county (Broward or Duval):

$$\begin{aligned} ATET = {} & \Pr(y_{it} > 0 \mid ICS = 1, County = 1) \times E(y_{it} \mid y_{it} > 0, ICS = 1, County = 1) - \\ & \Pr(y_{it} > 0 \mid ICS = 0, County = 1) \times E(y_{it} \mid y_{it} > 0, ICS = 0, County = 1) \end{aligned} \tag{11}$$

RESULTS

A. Descriptive Statistics

Table 1 presents the characteristics of children who resided in Broward, Duval and the corresponding control counties and were enrolled in CMS and Medicaid for at least six months both before and after the implementation of the ICS. Most children enrolled in CMS in each

county are male. There are more White non-Hispanic and fewer Hispanic children enrolled in CMS in Duval county than in Broward county. There are fewer Hispanic and more Black non-Hispanic children in Broward and Duval than in their corresponding control counties. Most children have chronic moderate or major conditions.[4] More children were categorized as disabled and received Social Security Income in Broward than in the corresponding control county. As smaller percentage of children were categorized as disabled and received Social Security Income in Duval than in the corresponding control county. Children in the control counties are on average slightly older than those in Broward and Duval.

B. Health Care Costs

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 took place, while 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 county. As in the case of most health care cost studies, all our cost variables are skewed to the right.

Table 3 shows that the EGLM method proposed by Basu and Rathouz (2005) had the lowest root mean square error (RMSE) among the models we estimated for each of the cost variables (the models with the best in-sample performance are in bold font). The log-OLS model with the retransformation proposed by Ai and Norton (2008) performed best among the outpatient cost models we estimated for Broward and its control county. The efficiency of the semi-parametric polynomial retransformation method proposed by Ai and Norton (2008) is somewhat limited in our data by the fact that the only continuous explanatory variable at our disposition is the children's age. The log OLS with Normal retransformation had the highest in-sample accuracy among the total costs models estimated for Duval and its control county. The GLM results are fairly similar to the EGLM results.

Table 4 presents the estimation results of the most accurate two-part models for each cost variable of interest for Broward and its control, while Table 5 presents the models with the lowest in-sample RMSE for Duval and its control county. None of the estimated ICS coefficients is statistically significant at 5%, with the exception of the 2nd part coefficients in the inpatient and pharmacy cost estimations for Duval county and its control. However, our interest is in the

overall dollar impact of the ICS on health expenditures, the retransformed, cumulative effect of the ICS from both parts of each model.

C. Estimates of the Dollar Impact of ICS on Health Care Costs

Table 6 presents the estimated average treatment effect on the treated (ATET), the sample average of the estimated dollar effect of the ICS on the health care costs of CMSN children in each of the ICS counties (the ATETs of the lowest RMSE models are in bold font). The implementation of the ICS in Duval county appears to have led to significant outpatient and total cost savings of about $84 and $195 per CMSN enrollee per month, respectively.

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

D. Sensitivity Analysis

The standard errors of the dollar estimates of the impact of ICS on health care costs were obtained by performing 300 bootstrap replications. The median bootstrap ATET estimates and confidence intervals are presented in Table 7.

We also estimated the same health care costs models for the subsample of children that were enrolled in CMSN and Medicaid the entire 12 months both before and after the implementation of the ICS. This allows us to determine if the effect of the ICS program differed for children who were consistently in the program from those who were more likely to bounce in and out of the program. While the estimates differed somewhat in magnitude, the signs and implications of the estimates were similar to those from the analysis for children enrolled a minimum of 6 months.

DISCUSSION

The literature on the effect of enrollment in managed care models on health care expenditures of CSHCN is limited. Our study aimed to address this gap by using a recent policy change to describing the effects of an ICS on the health care expenditures of CSHCN in Florida. Our study is unique in that Florida did not carve-out one type of service for CSHCN, such as mental health or specialty care, but chose to carve out the entire system of health care. Additionally, the ICS ushered in a level of managed care that was not previously utilized.

We find that the average monthly outpatient costs have decreased by about $84 and average monthly total costs have decreased by approximately $195 per CMSN enrollee per month as a result of the implementation of the ICS in Duval county. Outpatient, inpatient, pharmacy, and total costs have also been lower in Broward county after the implementation of the ICS, but the estimated cost decreases are not statistically significant. Emergency room costs have increased slightly, though not significantly. Admittedly, our study only addresses the effects of Medicaid reform on a small percentage of the total enrollees, yet this is a particularly vulnerable group which has greater than average financial and medical needs.

By estimating alternative models of health care costs, this study also contributes to the literature evaluating the performance of different classes of models used to estimate health care costs (Buntin and Zaslavsky 2004). GLM models perform better than methods based on OLS regression of log costs in our sample of CSHCN. This likely arises because by definition CSHCN are a population with high health care costs, which increases the importance of modeling the variance in the data in a flexible way.

Finally, this study adds to the growing literature on Florida's 2006 Medicaid reform program. Several studies, technical reports, and issue briefs related to Florida's Medicaid reform have been produced by academic, non-profit, and government institutions (Alker et al. 2008, Artiga 2008, Coughlin et al. 2008, Hoadley and Alker 2007, Lemak and Yarbrough 2008, OPPAGA 2008, Landry et al. 2011). Most of these documents are focused on the initial development and implementation of Medicaid reform, as well as enrollee experiences with selecting a health plan. One study used a quasi-experimental approach similar to our study to estimate the overall effect that Florida's Medicaid Reform had on per member per month Medicaid health care expenditures. Overall, the study found that Florida's Medicaid reforms did not result in a statistically significant reduction in expenditures when examining the entire Medicaid population (Harman et al. 2011). However, they do note that expenditure reductions may have been achieved for subpopulations with higher health care needs.

There are several limitations to this study that merit attention. First, we used the CRGs to control for the children's health status in our expenditure 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 CSHCN's health care costs. However, all children in our study are enrolled in Medicaid and thus come from relatively low-income families. Third, while we control for socio-demographic characteristics and health status, the population of children enrolled in CMSN in the control counties may differ from that in the counties where the ICS was implemented on other, unobserved dimensions.

Despite these limitations, our study is among a limited area of the literature that describes the effects of an ICS managed care program on the health care costs of CSHCN. In addition, our study findings contribute to several areas of the CSHCN literature including Medicaid managed care, carved-out health care systems, and Medicaid reform. While our estimates of the impact of ICS on health costs are encouraging, we stop short of concluding that the ICS has been successful because the ICS is a novel program with limited experience. Future research should determine the long term impact of ICS implementation on health care costs, and if these cost savings found in the short term, coupled with constant or even increases in satisfaction and access to care, are sustainable. This information is crucial to determining if other states should consider adopting this model of care for CSHCN.

Table 1. Characteristics of CMSN Children

	Broward		Broward Control		P-Value	Duval		Duval Control		P-Value
Children's Race	%	n	%	n		%	n	%	n	
White, non-Hispanic	13.5%	162	17.3%	171	0.014	24.1%	165	17.3%	186	< 1%
Black, non-Hispanic	52.8%	634	47.4%	469	0.012	56.6%	387	34.0%	365	< 1%
Hispanic	16.7%	200	23.2%	229	< 1%	5.0%	34	28.8%	309	< 1%
Other race	17.1%	205	12.1%	120	< 1%	14.3%	98	19.9%	213	< 1%
Children's Gender										
Male	57.1%	686	56.7%	561		58.0%	397	58.7%	630	
Female	42.9%	515	43.3%	428	0.853	42.0%	287	41.3%	443	0.781
Children's Clinical Risk Groups										
Non Acute	15.8%	190	13.4%	133	0.109	25.3%	173	20.7%	222	0.024
Significant Acute	4.3%	52	3.4%	34	0.085	6.1%	42	5.3%	57	0.463
Chronic Minor	5.1%	61	7.6%	75	0.016	11.5%	9	8.1%	87	0.02
Chronic Moderate	36.4%	437	36.8%	364	0.839	30.0%	205	30.1%	323	0.953
Chronic Major	38.4%	461	38.7%	383	0.871	27.0%	185	35.8%	384	< 1%
Disability Status										
Disabled (SSI)	73.0%	877	60.1%	594	< 1%	68.6%	469	75.5%	810	< 1%
	Mean	SD	Mean	SD		Mean	SD	Mean	SD	
Children's Age	8.50	5.35	9.29	5.42	< 1%	7.90	5.27	10.23	5.11	< 1%
Months Enrolled	11.15	1.68	11.13	1.71	0.721	10.55	2.00	11.27	1.57	< 1%
Number of Children	1201		989			684		1073		

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 ICS.

Table 2. Average Monthly Costs Before and After the Implementation of the ICS

	Broward Pre	Broward Post	Control Pre	Control Post	Overall				
	Mean	Mean	Mean	Mean	Mean	Std. Dev.	Skewness	% > 0	Max
Inpatient	487.81	385.20	304.80	297.90	375.32	1603.86	9.18	23.7%	35668.33
Outpatient	1365.76	1159.51	1124.96	1080.43	1190.23	3022.38	4.32	98.1%	26303.41
Emergency Department	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%	67321.95
Total	2409.51	1958.14	1873.84	1815.57	2030.36	4409.02	4.54	98.8%	67351.20

	Duval Pre	Duval Post	Control Pre	Control Post	Overall				
	Mean	Mean	Mean	Mean	Mean	Std. Dev.	Skewness	% > 0	Max
Inpatient	323.30	184.89	381.86	331.45	316.79	1850.78	13.83	19.4%	45122.35
Outpatient	589.73	461.87	1223.19	1205.81	946.78	2534.16	4.55	97.0%	21352.25
Emergency Department	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%	67361.88
Total	1306.61	1009.30	2119.03	2077.21	1731.99	4308.57	6.25	98.4%	67800.90

Data are for children enrolled in CMS and Medicaid at least 6 months both before and after the implementation of the ICS.

Table 3. 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	**2736.087**	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	**1732.424**
Outpatient	2333.95	2332.75	2284.592	**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

The lowest RMSE for each type of cost is in bold font.

Table 4. Two-Part Models of Average Monthly Costs with Lowest In-Sample RMSE - Broward vs. Broward Control

	Average Monthly Total Cost		Average Monthly Inpatient Cost		Average Monthly Outpatient Cost			Average Monthly Emergency Department Cost		Average Monthly Pharmacy Cost	
	1st Part	2nd Part	1st Part	2nd Part	1st Part	2nd Part		1st Part	2nd Part	1st Part	2nd Part
	LOGIT	EGLM	LOGIT	EGLM	LOGIT	LN OLS	Ai-Norton	LOGIT	EGLM	LOGIT	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)
Age2	-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*Age2	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		0.006		-0.667**					-1.864**		0.266*
		(0.076)		(0.255)					(0.682)		(0.122)
theta1		4.531***		2.391***					0.871***		15.096*
		(1.071)		(0.257)					(0.038)		(7.338)
theta2		2.000		2.000					2.000		2.000
N	4362	4310	4356	1032	4356.000	4273	4273	4356	1938	4112	3865

* p<0.05, ** p<0.01, *** p<0.001. Note: Referent groups are: Black, non-Hispanic, Male, with Chronic Major condition. The CRGs drop out of the first part logit models because they would perfectly predicts all zero outcomes.

Table 5. Two-Part Models of Average Monthly Health Costs with Lowest In-Sample RMSE – Duval vs. Duval Control

	Average Monthly Total Cost		Average Monthly Inpatient Cost		Average Monthly Outpatient Cost		Average Monthly Emergency Department Cost		Average Monthly Pharmacy Cost	
	1st Part LOGIT	2nd Part LN OLS	1st Part LOGIT	2nd Part EGLM	1st Part LOGIT	2nd Part GLM	1st Part LOGIT	2nd Part EGLM	1st Part LOGIT	2nd Part EGLM
Duval	-0.665	-0.173**	-0.224	0.019	-0.630	-0.538***	-0.117	0.238***	-0.549*	-0.020
	(0.493)	(0.063)	(0.133)	(0.207)	(0.338)	(0.100)	(0.107)	(0.071)	(0.239)	(0.053)
Time	-0.710	0.066	-0.311**	0.121	-0.520	0.089	-0.147	0.030	-0.421	0.087*
	(0.431)	(0.058)	(0.114)	(0.184)	(0.308)	(0.090)	(0.090)	(0.058)	(0.219)	(0.039)
ICS	0.090	-0.162	0.234	-0.562*	-0.142	-0.160	0.274	-0.049	0.320	-0.105*
	(0.585)	(0.087)	(0.182)	(0.245)	(0.422)	(0.137)	(0.146)	(0.083)	(0.313)	(0.054)
Disability Status	0.776**	0.276***	1.193***	0.841***	0.467*	0.561***	0.627***	-0.011	0.234	0.054
	(0.283)	(0.049)	(0.129)	(0.190)	(0.209)	(0.085)	(0.085)	(0.061)	(0.170)	(0.048)
Age	-0.008	-0.135***	-0.267***	-0.214**	-0.109	-0.208***	-0.246***	-0.080***	-0.012	-0.117*
	(0.139)	(0.022)	(0.040)	(0.066)	(0.099)	(0.031)	(0.035)	(0.022)	(0.071)	(0.049)
Age2	-0.003	0.006***	0.011***	0.011***	0.002	0.009***	0.009***	0.003**	0.000	0.011**
	(0.007)	(0.001)	(0.002)	(0.003)	(0.005)	(0.001)	(0.002)	(0.001)	(0.003)	(0.004)
Female * Age	0.058	-0.078*	0.020	0.073	0.051	-0.033	-0.096	-0.041	0.014	0.059
	(0.215)	(0.034)	(0.064)	(0.088)	(0.162)	(0.047)	(0.056)	(0.038)	(0.116)	(0.056)
Female * Age2	-0.001	0.004*	0.000	-0.002	-0.002	0.002	0.005	0.003	0.001	-0.008*
	(0.011)	(0.002)	(0.003)	(0.004)	(0.008)	(0.002)	(0.003)	(0.002)	(0.006)	(0.004)
Female * White	-0.887	-0.116	-0.089	-0.274	-0.246	0.062	-0.255	-0.044	-0.352	-0.137
	(0.775)	(0.115)	(0.246)	(0.374)	(0.549)	(0.187)	(0.198)	(0.151)	(0.428)	(0.213)
Female * Hispanic	-0.061	-0.048	-0.239	-0.610	0.034	0.217	-0.033	0.029	-0.024	-0.768
	(0.810)	(0.120)	(0.255)	(0.484)	(0.615)	(0.177)	(0.196)	(0.175)	(0.450)	(0.469)
Female * Other Race	-0.425	0.179	-0.078	-0.503	0.671	0.238	-0.179	-0.051	-0.750	-0.598
	(0.835)	(0.132)	(0.252)	(0.397)	(0.711)	(0.213)	(0.205)	(0.146)	(0.482)	(0.575)
White, non-Hispanic	0.939	0.409***	0.191	-0.181	0.452	0.254*	-0.034	-0.168	0.582*	0.408*
	(0.556)	(0.074)	(0.154)	(0.255)	(0.340)	(0.114)	(0.124)	(0.089)	(0.269)	(0.207)
Hispanic	0.281	0.113	-0.146	-0.218	0.335	-0.176	-0.195	-0.223*	0.311	0.854
	(0.532)	(0.083)	(0.168)	(0.362)	(0.391)	(0.127)	(0.134)	(0.101)	(0.285)	(0.466)
Other race	0.502	0.142	0.079	-0.389	0.224	0.171	-0.088	-0.146	0.807*	0.866
	(0.548)	(0.089)	(0.161)	(0.235)	(0.359)	(0.148)	(0.132)	(0.098)	(0.337)	(0.581)
Female	-0.197	0.242	-0.087	-0.083	0.004	-0.036	0.498	0.072	0.020	0.023
	(0.966)	(0.154)	(0.276)	(0.326)	(0.749)	(0.200)	(0.259)	(0.150)	(0.510)	(0.201)
Healthy		-3.233***		-2.443**		-3.331***		-0.888***		-1.006***
		(0.067)		(0.802)		(0.104)		(0.117)		(0.138)
Significant Acute		-1.890***		-2.405***		-2.254***		-0.373***		-0.724***
		(0.080)		(0.483)		(0.142)		(0.085)		(0.133)
Chronic Minor		-1.699***		-0.812		-1.741***		-0.588***		-0.837***
		(0.071)		(0.609)		(0.109)		(0.088)		(0.119)
Chronic Moderate		-1.259***		-1.201***		-1.172***		-0.206***		-0.581***
		(0.055)		(0.179)		(0.088)		(0.055)		(0.133)
Constant	4.484***	7.772***	-1.005***	0.065	4.389***	8.174***	0.641***	0.505***	2.841***	0.022
	(0.862)	(0.120)	(0.222)	(0.333)	(0.594)	(0.186)	(0.189)	(0.118)	(0.407)	(0.187)
lambda				-0.323				-0.584		0.685***
				(0.172)				(0.397)		(0.154)
theta1				2.553***				0.916***		12.604***
				(0.343)				(0.076)		(2.564)
theta2				2.000				2.000		2.000
	3482	3428	3478	674	3478	3374	3478	1528	3246	3066

* p<0.05, ** p<0.01, *** p<0.001. Note: Referent groups are: Black, non-Hispanic, Male, with Chronic Major condition. The CRGs drop out of the first part logit models because they would perfectly predicts all zero outcomes.

Table 6. Estimated Dollar Effect of ICS on Average Health Care 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
Emergency Department	3.53	3.34	3.46	3.48	**3.44**
Pharmacy	-7.40	-7.20	-110.91	-118.22*	**-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*	-106.10*	-79.94	**-83.66***	-65.98
Emergency Department	1.75	1.63	2.15	2.55	**2.92**
Pharmacy	-66.72*	-71.56*	69.11	-32.68	**-30.35**
Total	**-194.63***	-231.81*	652.59	83.18	30.78

* Significant at 5% level. The models with the lowest RMSE on each row are in bold font. ATET stands for Average Treatment Effect on the Treated (children in counties where the ICS was implemented).

Table 7. Median Bootstrap Estimated Dollar Effect of ICS on Average Monthly Health Care Costs

Cost	Lowest RMSE Model	ATET Estimate	Median Bootstrap ATET Estimate	Lower Bound	Upper Bound
Broward and Broward Control					
Inpatient	EGLM	-76.99	-80.13	-414.12	43.90
Outpatient	Ai&Norton	-22.80	-21.53	-194.96	216.72
Emergency Department	EGLM	3.44	3.20	-3.06	8.31
Dental, Visual, Hearing	GLM	-4.74	-4.04	-8.86	-0.53
Pharmacy	EGLM	-95.52	-109.18	-239.05	0.19
Total	EGLM	-188.32	-201.50	-547.77	1631.45
Duval and Duval Control					
Inpatient	EGLM	-63.82	-48.07	-389.94	49.75
Outpatient	GLM	-83.66	-90.91	-185.31	-11.73
Emergency Department	EGLM	2.92	2.81	-8.46	9.50
Dental, Visual, Hearing	GLM	-4.35	-3.90	-9.59	-0.50
Pharmacy	EGLM	-30.35	-33.26	-116.99	20.15
Total	Normal	-194.63	-196.80	-352.33	-49.74

Results based on 300 bootstrap replications.

NOTES

1. To control for differences in enrollment rates, we included months enrolled as a control in the analysis. Further, we are focusing on average monthly costs, which will alleviate some of the problems associated with gaps. Lastly, enrollment gaps will artificially lead to a higher incidence of zero health expenditures. The two-part models that we use account for children with zero health expenditures and hence, assist in controlling for these types of idiosyncrasies.

2. It is important to note that we do not identify children for inclusion in our sample based upon their CRG. Rather, our sample considers children who are classified as having special health care needs. In addition, the CSHCN are also assigned to a CRG. We use pre-treatment CRG data to control for the children's health status.

3. In the analysis, the annual costs were scaled to represent the average monthly costs.

4. About one-fifth of the CSHCN were unassigned to a CRG. If a child is unassigned to a CRG it is likely there were not enough claims data to assign them to a health status category because of gaps in enrollment (Shenkman et al. 2007).

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