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Differential Impact of a Plan-Led Standardized Complex Care Management Intervention on Subgroups of High-Cost High-Need Medicaid Patients

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Abstract

Interventions to better coordinate care for high-need high-cost (HNHC) Medicaid patients frequently fail to demonstrate changes in hospitalizations or emergency department (ED) use. Many of these interventions are modeled after practice-level complex care management (CCM) programs. The authors hypothesized that a national CCM program may be effective for some subgroups of HNHC patients, and the overall null effect may obfuscate subgroup-level impact. They used a previously published typology defining 6 subgroups of high-cost Medicaid patients and evaluated program impact by subgroup. The analysis used an individual-level interrupted time series with a comparison group. Intervention subjects were high-cost adult Medicaid patients who enrolled in 1 of 2 national CCM programs implemented by UnitedHealthcare (UHC) ($n=39{,}687$). The comparators were patients who met CCM program criteria but were ineligible due to current enrollment in another UHC/Optum led program ($N=26{,}359$). The intervention was a CCM program developed by UHC/Optum to provide ''whole person care'' delivering standardized interventions to address medical, behavioral, and social needs for HNHC Medicaid patients, and the outcome was probability of hospitalization or ED use in a given month, estimated at 12 months postenrollment. A reduction in risk of ED utilization for 4 of 6 subgroups was found. A reduction in risk of hospitalization for 1 of 6 subgroups was also found. The authors conclude that standardized health plan led CCM programs demonstrate effectiveness for certain subgroups of HNHC patients in Medicaid. This effectiveness is principally in reducing ED risk and may extend to the risk of hospitalization for a small number of patients.

Keywords: complex care management, high-cost high-need, Medicaid, managed care, machine learning

Introduction

The majority of patients insured through Medicaid are now managed by private organizations contracting state by state to form Medicaid-managed care organizations, instead of state-run Medicaid.[1] Complex care management (CCM) is a widely clinically implemented service at the practice level that provides individualized care plans, 24/7 access to urgent care needs, and help with medication management.[2] As insurers have developed more value-based contracting arrangements, there has been an increasing interest in CCM interventions led by health plans to reduce avoidable utilization that is concentrated in a small number of patients.

This has led to a series of quasi-national or national CCM programs implemented in the past decade.[3–8] Medicaid patients may be more likely to benefit from CCM programs than patients in other insured populations due to issues of network

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adequacy—especially challenges in obtaining timely specialty visits[9] and underlying high rates of unmet social needs,[10] both that may be effectively addressed by CCM.[11–13]

Unfortunately, many of these programs have failed to demonstrate effectiveness as highlighted by a recent comprehensive systematic review and evidence-based practice report from the Agency for Healthcare Research and Quality that concludes that while patient characteristics can be used to identify high-need high-cost (HNHC) patients, interventions must be tailored to the unique individual HNHC patient to be successful.[14] The subject study analysis builds directly on this conclusion by suggesting the use of a previously validated typology for identifying HNHC patients in Medicaid and demonstrating differential program effectiveness by the HNHC patient subgroup.

CCM programs implemented by health plans typically partner with patients following a standardized approach of identifying and meeting patient needs through in-person visits or accompaniment to other health care visits as well as phone-based support.[15] For practice-level interventions, patients may be identified through clinical judgment. When CCM is led by insurers, there is a need to identify HNHC patients through claims-based approaches, which have been shown to be imprecise. Most claims-based algorithms use the primary outcome of cost that aggregates patients who are clinically distinct into HNHC status with diverse clinical subtypes.[4,16]

Given this challenge, improving calibration for these (often proprietary) algorithms has been an area of intense focus for application of new machine learning methods.[17] As these algorithms have proliferated among health plan-led interventions, it has become imperative to learn to separate (or segment) high-cost patients into clinically distinct subgroups. To do this effectively often requires both clinical awareness of the underlying population and use of novel machine learning methods.[18–22]

In prior study, the team demonstrated the use of partitional clustering (where all patients are assigned to exactly 1 nonoverlapping cluster) to disaggregate high-cost patients eligible for a large multistate Medicaid CCM program, and previously published their methods in detail, including code snippets to describe a novel application of cluster analysis emphasizing cluster stability.[23]

In brief, demographic characteristics and patterns of previous diagnoses driving utilization were used to apply the following characteristic labels: (1) patients with relatively ‘‘few diagnoses’’ despite being high cost, (2) women with ‘‘pregnancy complications,’’ (3) patients with predominantly ‘‘behavioral health’’ conditions, (4) patients with predominantly ‘‘cardiometabolic disease,’’ as well as 2 groupings of patients with multisystem disease, (5) patients with ‘‘complex illness, lower resource use,’’ and (6) patients with ‘‘complex illness, higher resource use’’ to describe 2 levels of complex patients with varying engagement with health care utilization. This study builds on prior work by using this typology of high-cost HNHC Medicaid patients to determine the effectiveness of a CCM program by subgroup of HNHC patients.

Materials and Methods

Study population

The population consisted of 39,047 Medicaid beneficiaries 21 years of age and above who were enrolled in a CCM program implemented by UnitedHealthcare (UHC) in 15 states between January 1, 2013, and June 1, 2017. These UHC CCM programs were called Care Coordination Organizations (CCOs). The comparison population consisted of 26,359 Medicaid beneficiaries who met CCO program criteria but were ineligible due to current enrollment in another UHC/Optum led program, UHC Accountable Care Communities, or ACCs.

Patients were eligible for the UHC CCO program if they were (1) in the top 5% of spending among UHC Medicaid beneficiaries in the prior year and (2) identified by UHC’s proprietary risk algorithm as likely to persist in the top 5% of spending in the following year. This algorithm has been internally validated by UHC and is used across their enterprise. University of California, Los Angeles (UCLA) authors are blinded to all score components as well as the derivation and validation of the risk algorithm. This study was approved by the UCLA Institutional Review Board No. 16-000276.

CCM intervention and comparator

The CCO program was developed by UHC and Optum to more effectively address the needs of vulnerable patients with multiple chronic conditions, and has been previously evaluated among CCO patients with diabetes.[24] The CCO program was principally implemented by nurse (RN) case managers with limited support from community health workers (CHWs). Program enrollment was as follows—program staff would be notified by Optum of patient eligibility and RNs or CHWs would enroll patients by completing a standardized health risk assessment (including unmet social needs) that were identified using a standardized electronic platform.

RN case managers and CHW staff would call patients at least monthly throughout the time of enrollment and in some cases visited patients in their home. If medical or behavioral health needs were identified, program staff would interface with Optum clinicians to close gaps.

The CCO intervention was not the only UHC program for Medicaid patients at the time of this study, and the team used this concurrent program to identify their comparator population. Some high-cost patients were eligible for the CCO intervention but not enrolled because they were receiving care in clinics that were part of a practice-level program, ACC. The ACC consisted of several practice-based interventions utilizing clinical dashboards to improve ambulatory clinical care (ie, same day scheduling) and did not outreach to patients directly. This intervention was not specifically targeting high-cost patients within a clinic and was shown to have no effect on ED visits or hospitalizations.[25] Patients who were eligible for the CCO intervention but were enrolled in a clinic receiving the ACC program formed the comparator group for the analysis.

Defining person-month analysis

The authors arbitrarily defined month ‘‘0’’ as the month of CCO enrollment for each patient in the intervention group and defined a month ‘‘0’’ for the comparator patients who did not have an enrollment date using the method described by Harvey and Jankus, which the team called a ‘‘synthetic’’ enrollment date.[26] The ‘‘pre’’ period was defined as months

–15 to –3, a transition period from months –3 to 6 and ''post'' period months 6 to 27. These specific intervals were chosen because UHC reported it typically took 3 months for patients to be enrolled in the CCO program once eligible, and the team hypothesized the program would take 6 months to demonstrate effectiveness.

All outcomes were defined at the person-month level, specifically as the utilization of individuals in a given month relative to their enrollment date. This analytic decision reflects the substantial churn in Medicaid eligibility and in month-to-month enrollment. All eligible person-months during the study window were included in the analysis.

Covariates, measures, estimates of interest

Data included Medicaid beneficiary eligibility and demographic data, medical, pharmacy, and laboratory claims, identifying practice-level characteristics (to identify the comparator population), as well as CCO program eligibility and enrollment information. Each person-month was assigned to a cluster as defined in previous study. The principal outcome measures were indicators of whether patients had any hospital admissions or ED visits in the person-month. Importantly, obstetric hospitalizations were excluded at an early stage of analytic design.

Key covariates included the indicator for intervention group (CCO enrollment) versus comparator (ACC), and an indicator (of the level of the outcome) variable for changes in the outcome time trend. The comparisons for the outcome variable were at the beginning of month 6 (start of ''post'' period) compared with month –3 (end of the ''pre'' period). Other covariates included gender, age group, race, language, 17 comorbidity indicators, state-by-year fixed effects, an indicator for whether Medicaid expansion had been adopted in a given month, and seasonality. The authors' estimates of interest were the difference-in-difference between treatment versus comparator from preperiod to postperiod.

The 12-month postenrollment time point was chosen as the primary outcome measure of interest. The rationale for a 12-month postenrollment measure was for an expected 3-month lag from patient identification to enrollment, a 3- to 6-month average engagement with the program, and a minimum of 3 months of postprogram engagement to determine the durability of the intervention.

Statistical analyses

Segmented logistic regression was used to model the difference between treatment and comparator over the time trends. All models adjusted for zip-code level clustering (3 digit) using cluster-robust Huber-White standard errors. A significance level of <0.05 was used to determine statistical significance. All analyses were completed using SAS 9.4 and STATA 14.2 SE.

Results

The person-level demographic and clinical characteristics of the CCO-enrolled intervention compared with the ACC-assigned comparator sample are given in Table 1. Although most demographic and clinical characteristics differed between CCO and ACC-assigned comparators because of the large sample, there may not be a meaningful clinical difference between these groups. For both intervention and control groups, the largest percentage of patients was 45–54 years of age (36% and 31% for CCO and ACC-assigned comparators, respectively), and the vast majority of patients were between ages of 21 and 65 years with a small proportion of patients above the age of 65 years (7% and 8%).

Nearly all (85% and 88%) spoke English as a primary language. Although a significant portion of patients were missing race/ethnicity information (14% and 15%), compared with the US general population, patients were less frequently White (54% and 50%) or Latino/a (5% and 9%), and more likely Black (24% and 23%). The distribution of patients geographically differed between intervention states and control states. For example, 14% of patients in the intervention and 23% of controls were from Tennessee.

There was also a relatively similar distribution of patients by cluster, with the largest percentages in the ''complex illness high resource use'' cluster (24% and 19%), and in descending order the ''cardiometabolic'' (23% and 23%), ''complex illness low resource use'' (20% and 17%), ''few high-cost conditions'' (16% and 19%), and ''behavioral health'' clusters (15% and 18%), with by far the fewest patients (2% and 2%) in the ''pregnancy complications'' cluster. The intervention and comparison groups had very similar likelihood of preprogram hospitalization and ED use (Table 1).

The CCO intervention reduced the probability of emergency department (ED) visits compared with the ACC-assigned comparators across most clusters with reductions in probability of utilization ranging between 1% and 5% (Table 2). The ED probability reductions were for a clinically diverse group of clusters including the ''complex illness, higher resource use'' cluster, the ''complex illness, lower resource use'' cluster, the ''behavioral health'' cluster, and the ''few diagnoses'' despite high-cost status cluster.

There were fewer reductions in probability of hospitalization by cluster than reductions in probability of ED use, ranging from the least overall reduction in hospitalization probability in the complex illness high-resource use cluster (Fig. 1) to the behavioral health cluster where there was the only statistically significant reduction in probability of hospitalization (Fig. 2). All remaining clusters' change in hospitalization or ED utilization likelihoods are provided in Supplementary Appendix Figures A1–A4.

Discussion

The use of CCM programs to improve care for HNHC patients has been widely attempted at the practice level and increasingly also by health plans interested in improving the value of care delivered. The use of claims-based algorithms to identify HNHC patients eligible for CCM (as opposed to clinical input to practice-level interventions) has proliferated with the application of machine learning techniques, but continues to aggregate clinically distinct patients when using cost as a core criterion for eligibility.

Distinguishing among clinical subgroups of HNHC patients is crucial for appropriately targeting CCM programs to those patients most likely to benefit. The team hypothesized, aligned to a recent comprehensive systematic review, that the mixed success of CCM interventions as previously

TABLE 1. DEMOGRAPHIC AND CLINICAL CHARACTERISTICS OF THE CARE COORDINATION ORGANIZATION-ENROLLED INTERVENTION PARTICIPANTS AND THE ACCOUNTABLE CARE COMMUNITY-ASSIGNED COMPARATOR PARTICIPANTS

Characteristic	*CCO enrollees (N=39,687)*	*ACC-assigned comparators (N=26,359)*	P
Age group (years)			
21–24	902 (2)	931 (4)	<0.01
25–34	4664 (12)	4060 (15)	
35–44	7331 (18)	5198 (20)	
45–54	14,100 (36)	8147 (31)	
55–64	10,063 (25)	5919 (22)	
65+	2627 (7)	2104 (8)	
Female	24,393 (61)	15,652 (59)	<0.01
English as primary language	33,823 (85)	23,088 (88)	<0.01
Race/ethnicity			
White	21,282 (54)	13,142 (50)	<0.01
Black	9326 (24)	5971 (23)	
Latino/a	1893 (5)	2281 (9)	
Asian/Pacific Islander	1163 (3)	365 (1)	
Other	553 (1)	633 (2)	
Missing	5470 (14)	3967 (15)	
State of residence			
Arizona	3548 (9)	8711 (33)	<0.01
Delaware	799 (2)	698 (3)	
Florida	1922 (5)	779 (3)	
Hawaii	45 (<1)	210 (1)	
Maryland	3368 (8)	469 (2)	
Michigan	3828 (10)	517 (2)	
Mississippi	2560 (6)	1234 (5)	
New Jersey	3035 (8)	1847 (7)	
New Mexico	727 (2)	938 (4)	
New York	6070 (15)	553 (2)	
Ohio	1971 (5)	1048 (4)	
Pennsylvania	3460 (9)	921 (3)	
Rhode Island	1587 (4)	931 (4)	
Tennessee	5484 (14)	6011 (23)	
Washington	1283 (3)	1492 (6)	
Cluster			
Complex illness, high	9643 (24)	5113 (19)	<0.01
Few diagnoses	6490 (16)	5080 (19)	
Pregnancy complications	655 (2)	608 (2)	
Cardiometabolic	9146 (23)	6185 (23)	
Behavioral health	5968 (15)	4856 (18)	
Complex illness, low	7785 (20)	4517 (17)	
Utilization			
Any hospitalization (mean, SD)	0.04 (0.21)	0.04 (0.21)	0.98
Any ED visit (mean, SD)	0.15 (0.36)	0.15 (0.35)	0.062

ACC, accountable care community; CCO, care coordination organization; ED, emergency department.

published in the literature were due to limitations in the ability of CCM's to identify patients who would likely benefit because HNHC patients were identified as a clinically aggregated group.

The team found that a standardized intervention to address unmet social, medical, and behavioral health needs as implemented by a health plan was effective for some subgroups of HNHC patients but not for others. For a multistate uniformly implemented CCM program compared with a less-intensive practice level program, they found a reduction in ED utilization risk for 4 of 6 naturally occurring and clinically distinct clusters or subgroups of high-cost Medicaid beneficiaries, as well as a reduction in hospitalization risk for a single patient cluster at 12 months after enrollment.

The authors suggest that future CCM programs in Medicaid could be tailored to address the differentiated needs for HNHC patients that did not benefit from this standardized intervention. CCM programs could continue to lead similar interventions for those identified subgroups where there has been a demonstrated benefit, and explore tailored interventions for those who did not. Use of the team's previously published typology may support those plans interested in CCM interventions beyond the imperative to ''to just do something'' that is a common starting point for implementers.[21]

This is the first time (known to the authors) where a CCM program for HNHC Medicaid patients implemented in multiple states has been evaluated at the subgroup level, and they suggest the previously identified typology to be a

Table 2. Adjusted Difference-in-Difference 12-Month Predicted Outcomes, by Cluster

		Intervention predictions (CCO), %		*Comparator predictions (ACC), %*		*DiD at 12 months, %*		
		B	*A*	*D*	*C*	*DiD = (A − B) − (C − D)*		P
Cluster	*Predicted outcome*	*End pre*	*Begin post*	*End pre*	*Begin post*	*DiD level*	*95% CI*	*<0.05*
Complex illness higher resource use	Any hospitalization	15.1	14.4	8.2	7.6	−0.08	−1.4 to 1.2	
	Any ED visit	35.3	32.1	25.0	24.5	−2.71	−4.4 to −0.9	*
Few diagnoses	Any hospitalization	10.6	5.7	7.4	4.1	−1.58	−3.3 to −0.19	
	Any ED visit	18.5	13.0	14.1	11.2	−2.53	−4.1 to −0.9	*
Pregnancy complications	Any hospitalization	8.1	4.7	5.2	3.8	−1.98	−5.0 to 1.1	
	Any ED visit	23.6	21.2	16.5	14.3	−0.20	−5.3 to 4.9	
Cardiometabolic	Any hospitalization	9.8	6.8	6.6	3.7	−0.01	−1.1 to 1.1	
	Any ED visit	19.2	15.0	15.4	12.3	−1.11	−2.3 to 0.2	
Behavioral health	Any hospitalization	8.1	6.0	5.1	4.3	−1.27	−2.3 to −0.2	*
	Any ED visit	26.9	22.8	19.7	18.0	−2.49	−4.3 to −0.7	*
Complex illness lower resource use	Any hospitalization	9.4	7.4	5.2	3.9	−0.78	−1.8 to 0.2	
	Any ED visit	17.9	14.9	12.7	11.8	−2.04	−3.3 to −0.8	*

Predictions made using interrupted time series segmented regression analysis. Change in utilization at 12 months estimated by comparing (1) 12-month utilization amounts in the postperiod with (2) what utilization would have been at 12 months after enrollment if preperiod trends had continued. Logistic regression used for utilization outcomes. Sample is person-months eligible for complex care management (in CCO program) from 2013 to 2017.

*denotes $p < 0.05$.

ACC, accountable care community; CCO, care coordination organization; DiD, difference-in-difference; ED, emergency department.

reliable segmentation approach for others tailoring their CCM interventions for Medicaid patients.

This study is not without limitations. This is an observational study and can be affected by unmeasured confounding variables, and there are limitations to observable characteristics in medical claims, even in a large data set. Also, this program was implemented by a single insurer and may systematically differ from state-run or other managed Medicaid populations. The evaluation team has been engaged in partnered research with UHC for nearly 15 years, and through extensive discussions with these partners learned of the implementation of the CCM program but did not directly interview the personnel implementing the program.

For the clusters of patients who were high cost due to complications of pregnancy, the observed declining trajectory of their probability of ED visits or hospitalizations was not substantially impacted by their enrollment in a CCM program. It was noted that this cluster had a relatively small sample size, and the magnitude of hospitalization probability decrease was largest of the groups evaluated. Given this, the authors suggest this subgroup still be included in future CCM programs that may be tailored to the needs of this unique subpopulation.[27]

The authors further suggest that the paradoxical behavior of a cluster labeled (by the team in prior published study) ‘‘cardiometabolic’’ by demographic and clinical indicators may benefit from additional clinical indicators or social

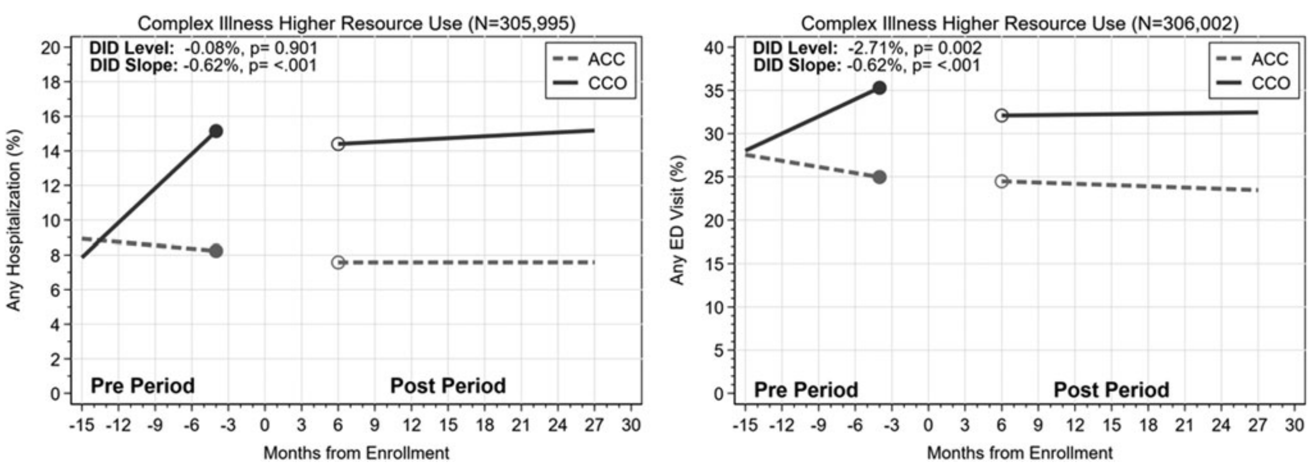

FIG. 1. Probability of hospitalization or emergency department use for patients from the complex illness higher resource use cluster in the complex care management intervention versus those ineligible due to enrollment in another program.

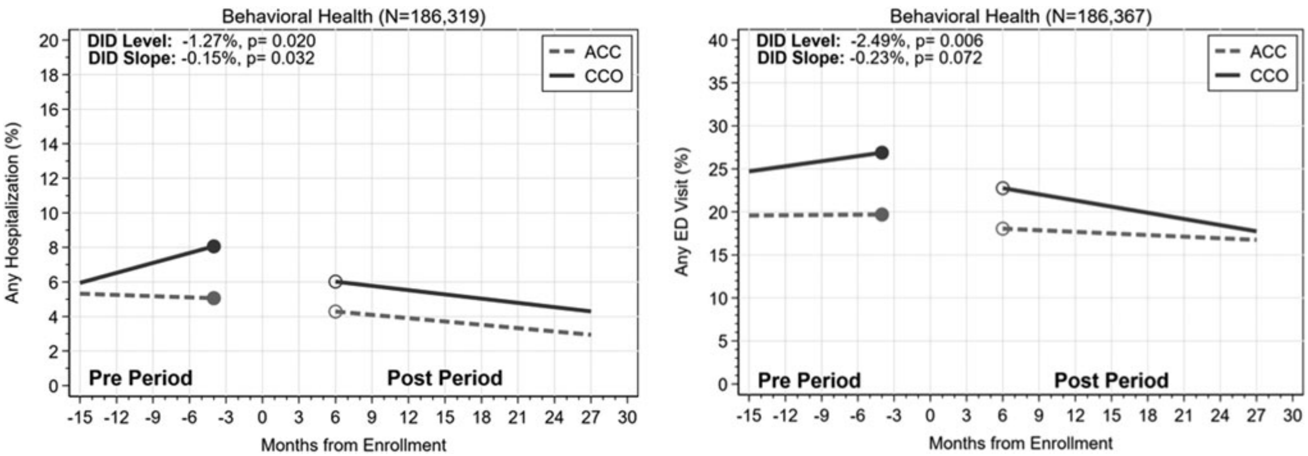

FIG. 2. Probability of hospitalization or emergency department use for patients from the behavioral health cluster in the complex care management intervention versus those eligible but currently enrolled in another program.

determinants data as their prior study suggested patients with these conditions would benefit from CCM. Given the limitations in observable variables, further studies may refine these characteristic labels or identify additional data sources to differentiate this cluster with characteristically cardiometabolic illness but with limited engagement in this RN-led CCM intervention.

The challenges associated with identifying high-cost patients who would benefit from CCM are continuously evolving. As has been suggested in a recent systematic review, there are opportunities to tailor HNHC programs to fit unique patient needs. The team believes their previous typology to be an example of a ''data informed'' approach. Using this typology, the evaluation at the subgroup level identified small but significant reductions in utilization persisting at 1 year after program enrollment.

Using a rigorously established typology of HNHC patient subgroups may be an improvement not just for overall program evaluation, but it could also be used to tailor future Medicaid CCM program design. System and plan leaders are encouraged to consider use of a typology to sort HNHC patients to the highest impact intervention tailored to their needs. This rapid evolution of available tools to improve population health is a continual challenge for this relatively nascent field and can be challenging for systems and plans to iterate in their implementation, but each improvement is a step closer to the shared goal of improving care for the most vulnerable patients in Medicaid.

Authors' Contributions

All authors contributed contributed to the design and implementation of the research, to the analysis of the results and to the writing of the manuscript.

Author Disclosure Statement

No competing financial interests exist.

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Supplementary Material

Supplementary Appendix Figure A1
Supplementary Appendix Figure A2
Supplementary Appendix Figure A3
Supplementary Appendix Figure A4

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