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Using Bayesian Imputation to Assess Racial and Ethnic Disparities in Pediatric Performance Measures

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Abstract

Objective. To analyze health disparities in pediatric HEDIS quality of care measures and to determine how imputation has an impact on these disparities.

Data Sources. Five HEDIS measures are calculated based on 2012 administrative data for 145,652 children in two public insurance programs in Florida.

Methods. The Bayesian Improved Surname and Geocoding (BISG) imputation method is used to impute missing race and ethnicity data for 42% of the sample (61,954 children). Models are estimated using the imputed data as well as dropping observations with missing race and ethnicity data.

Principal Findings.

Using BISG, we find that age, female, enrollment in Children's Medical Services Network, and more severe illness are associated with a higher likelihood of HEDIS compliance. The effect of race and ethnicity on HEDIS compliance varies across the measures. Using the BISG imputed race and ethnicity analysis as the benchmark, dropping those individuals who do not self-report their race and ethnicity substantially alters the coefficient estimates. In particular, the race and ethnicity coefficient estimates are systematically dampened if they are positive and magnified if they are negative.

Conclusions.

These results provide further support for the importance of appropriately accounting for missing race and ethnicity data through advanced imputation methods.

Key Words. HEDIS, Disparities, Bayesian Imputation, Racial/Ethnic differences, Medicaid, Children

JEL Codes: I10, C11, I18

Introduction

In recent years there has been an increased emphasis on the importance on assessing quality of health care in pediatrics. In 2009 the Children's Health Insurance Program Reauthorization Act (CHIPRA) mandated the creation and refinement of a core set of measures, the creation of a Pediatric Quality Measures Program, and commissioned an annual report to Congress of the quality of care for children with Medicaid and CHIP coverage (Centers for Medicare and Medicaid Services 2009). Ultimately, the measures were designed to estimate quality at a national level, conduct comparative analyses, and identify disparities (Centers for Medicare and Medicaid Services 2011). The Health Information Technology for Economic and Clinical Health (HITECH) Act is another example of federal legislation that focuses on measurement. HITECH provides incentives to practices to use interoperable Electronic Health Records (EHR) and establishes meaningful use for the United States health care system. Pediatric practices participating in HITECH are required to report on several performance measures. EHR meaningful use is meant to reduce disparities, improve public health, improve coordination of care, engage patients and their families, and improve privacy.

A health disparity is defined as "a particular type of health difference that is closely linked with social, economic, and/or environmental disadvantage" (U.S. Department of Health and Human Services 2008). While there are standards by which overall healthcare quality can be measured, it can often be difficult to easily and accurately identify health disparities. This is in part due to incomplete data (Agency for Healthcare Research and Quality 2013). For example, identifying racial and ethnic disparities is complicated by the fact that these data are often missing in health care data (Bilheimer and Sisk 2008). There have been attempts to improve the collection of self-reported race and ethnicity data nationwide (Boston Public Health Commission 2006; National Health Plan Collaborative 2006). However, the process has proceeded slowly and has achieved limited success (Bilheimer and Sisk 2008). Other attempts have been made to impute the missing data using geocoding, surname analysis, or both (e.g., Fiscella and Fremont 2006; Fremont, 2008; Elliott et al. 2008; Elliott et al. 2009). Geocoding links a member's address to census data that contains the neighborhood's race and ethnicity makeup. The

Surname approach infers race and ethnicity from last names that are often associated with certain races/ethnicities. Although these approaches have been used in a wide array of analyses in the past (e.g., Jacobs and Lauderdale 2001; Fremont et al. 2005; Fiscella and Fremont 2006) they seem to have issues with differentiating Blacks from non-Hispanics Whites and identifying Hispanics or Asians, respectively.

Several studies have sought to investigate racial and ethnic disparities in the pediatric population using nationally recognized measures and large scale databases. Dougherty and colleagues used data from two reports to show that for more than 50 measures child and adolescent disparities have virtually remained unchanged over time (Dougherty et al. 2014). Shi and colleagues investigated racial disparities in self-reported health status using data from the Community Tracking Study (Shi, Green, and Kazakova 2004). Results from the study suggest that primary care and disparities are indirectly related. Although these studies are insightful, they did not comment on the accuracy of the race and ethnicity data. Several other studies have used large scale datasets to identify disparities in specific segments of the child population such as those with HIV, obesity, ADHD or who have been prescribed psychotropics (Zhang et al. 2013; Hernandez and Pressler 2014; Saloner, Fullerton, and McGuire 2013). In general, these studies do not address the issue of missing race and ethnicity data either.

Our study makes novel contributions to the literature on pediatric racial and ethnic disparities. We use large scale databases to 1) focus on plan-level disparities, 2) identify and determine the magnitude of disparities over an array of core measures, and 3) use the Bayesian Improved Surname Geocoding (BISG) imputation methodology (Elliot et al. 2009) to impute missing data and determine what effect the missing data has on the interpretation of the measures. The BISG method uses a Bayesian approach to utilize detailed data from both the individual's geographical location and the race and ethnicity distribution of an individual's last name. Several validation studies reveal that the BISG approach substantially outperforms previous race and ethnicity imputation methodologies (Elliott et al. 2009; Derose et al. 2012; Adjaye-Gbewonyo et al. 2014). Yet, this imputation methodology has not been widely used to analyze health disparities (Martino et al. 2012). Using this improved method, we aim to illustrate that failure to account for the missing race and ethnicity data could result in incorrect conclusions about health disparities. Results from our study can be used to demonstrate how improved accuracy can lead to better informed policies and interventions.

Methods

Study Sample

Data for this study came from the 2012 Healthcare Effectiveness Data and Information Set (HEDIS) measures that were reported for children in the Florida Healthy Kids program and Children's Medical Services Network (CMSN). Florida Healthy Kids serves healthy children ages 5 to 18 who are eligible for the Children's Health Insurance Program (CHIP) and meet the Title XXI income requirements. Florida Healthy Kids contracts with seven managed care plans for the delivery of medical services. CMSN is Florida's Title V program for children with special health care needs. Although children enrolled in CMSN include those eligible for either Medicaid or CHIP, this study includes only those eligible through Medicaid. At the time of the study, CMSN was in the process of procuring a statewide Third Party Administrator to collect and process claims, encounter, and enrollment data for its Title XXI population. Therefore, that data was not available.

The combined dataset used in the analysis accounted for 31,343 children in CMSN and 114,309 in Florida Healthy Kids (total =145,652).

Outcome Measures

HEDIS measures are nationally recognized standards for quality in health care and are well understood by a variety of stakeholders. The HEDIS measures used in this study are all part of the CHIPRA core measure set (Centers for Medicare and Medicaid Services 2013). In general, HEDIS measures report compliance with the measure of interest. The current analysis focuses on the following HEDIS measures: (1) Child and Adolescent Access to Primary Care Practitioners (CAP); (2) Appropriate Testing of Children with Pharyngitis (CWP); (3) Well-Child Visits in the 3rd, 4th, 5th, and 6th Years of Life (W34); (4) Adolescent Well-Care Visit (AWC); and (5) Follow-Up Care for Children Prescribed ADHD Medication (ADD). These HEDIS measures are chosen because they represent a variety of health care scenarios including availability of care (CAP), preventive care and health promotion (W34, AWC), acute care (CWP), and management of chronic conditions (ADD).

The HEDIS measures used in this study required 12 months of continuous enrollment for children to be included in the denominator. Compliance, denoted by a 1 in the numerator, indicated that a child received the prescribed care during 2011. Although HEDIS allows for supplementation of the administrative data with data gleaned from medical records for W34 and AWC, medical record data was not used in this study.

Predictor Variables

The multivariate analyses used in the current study adjusted for several child, health system, and geographic characteristics. Child's age, gender, race and ethnicity, and Clinical Risk Group (CRG) were included (Neff et al. 2004). CRG is a categorical variable that classifies an individual's burden of illness using a combination of diagnoses and procedure codes. Children are classified into one of six categories: Non-Chronic Non-Acute, Significant Acute, Minor Chronic, Moderate Chronic, or Major Chronic. A residual category labeled as Unassigned is given to children who did not have adequate diagnoses or procedure codes to be placed into one of the other categories. Geographic location is defined by eight regions: Northwest, Big Bend, North Central, Tampa, Central, Southwest, Southeast, and South Florida Counties. These eight regions have been historically used by CMSN to define its healthcare catchment areas (Florida Department of Health, 2008). Each child in the dataset was assigned to one health plan, either one of the seven Florida Healthy Kids plans or CMSN. The seven Florida Healthy Kids plan names have been masked and noted as Plan A to Plan G.

Classification and Imputation of Race and Ethnicity

Parents seeking to enroll their children in Florida's Medicaid or CHIP programs are asked to fill out an application. Applications can be submitted electronically or in person at designated locations. On the application, the self-reported choices available for ethnicity are Hispanic or Not Hispanic and Latino or Not Latino. Choices for race are American Indian/Alaskan Native, Asian or Pacific Islander, Non-

Hispanic Black, Non-Hispanic White, Hispanic, or Other. The race and ethnicity fields in the application are voluntary.

Once the race and ethnicity data are collected through the application process, the data is compiled into a statewide enrollment file. The enrollment file categorizes enrollees into five categories: White, Black, Hispanic, Asian/Pacific Islander (API), and Other. In this study if an individual self-reported their ethnicity as Hispanic, regardless of race, they were classified as Hispanic. If an individual self-identified as a non-Hispanic, they were classified as White, Black, API, or Other.

It was expected that a significant portion of individuals in this study would have missing race and ethnicity data since this field is voluntary. For those individuals who did not report race or ethnicity, the BISG imputation methodology was used to estimate the probability that an individual falls within one of five race and ethnicity categories: White, Black, Hispanic, API, or Other. The BISG imputation algorithm detailed in Elliott et al. (2008, 2009), uses a Bayesian method to combine information on an individual's race and ethnicity from their last name and their geographical location using geocoding. Geocoding links a member's address to census data that contains the neighborhood's race and ethnicity makeup (Fremont et al. 2005). Alternatively, the surname approach infers race and ethnicity from last names that are often associated with certain races and ethnicities (Abrahamse et al. 1994). After the imputation process, there may still be a small number of individuals whose race and ethnicity could not be imputed. This is due to the fact that their current address is a Post Office Box or the address field is missing. The predicted probabilities generated by the BISG algorithm are then used in place of the unobservable dichotomous race and ethnicity variables for those individuals with missing race and ethnicity data.

Analyses

Descriptive and multivariate analyses were performed. Summary statistics were calculated for each HEDIS measure as well as the characteristics' of the children in the sample. In the multivariate analyses, HEDIS measure compliance was the outcome measure. For each HEDIS measure, both linear and logistic regression models were estimated, adjusting for the previously mentioned race and ethnicity predictor variables to assess their associated with HEDIS compliance. These models adjust for a child's age and gender, race and ethnicity, CRG status, health plan, and geographic region. In each of the models the referent groups were White, CMSN, non-acute non-chronic, and Northwest for race and ethnicity, health plan, CRG status, and geographic region, respectively.

Two sets of multivariate analyses were conducted. First, linear and logistic regression models were estimated with the BISG imputed race and ethnicity data. The predicted race and ethnicity probabilities were used in place of the unobservable race and ethnicity variables for those individuals with missing race and ethnicity data. This approach outperformed the alternative approach that classifies probabilistic information about race and ethnicity into dichotomous predictor variables. This alternative approach assigned an individual into a particular race and ethnicity category if the predicted probability exceeded an arbitrarily set critical threshold. Such classification by the imputed probabilities resulted in measurement errors (McCaffrey and Elliott 2007). For those individuals without missing race and ethnicity data, their self-reported race and ethnicities were used.

Second, the same analyses were performed, but using data only from individuals who self-reported their race and ethnicities. Children with missing race and ethnicity were dropped from the analysis.

Results

Summary Statistics and Group Comparisons

Table 1 provides the summary statistics for all of the children's characteristics, those who self-reported race and ethnicity, and those with missing race and ethnicity. Most of the children did not have a chronic or acute health condition (62.3%), were in Florida Healthy Kids- Plan A (28.3%), were male (51.8%), and resided in the Southeast region (23.6%). Ranking HEDIS compliance shows that CAP had the greatest compliance followed by W34, CWP, AWC, and ADD. The p-values revealed that the children with and without reported race and ethnicity substantially differed based upon their demographics, locations, health status, and health plans. For example, children who self-reported were less likely to be compliant with the ADD measure, were older, less likely to be in CMSN, more likely to be located in a northern region, and more likely to be characterized in a more severe CRG. Given that the children whose race and ethnicity was self-reported differ from those who choose not to self-report, simply dropping them from the analyses would bias the results and would substantially reduce the sample size of this study.

HEDIS Analysis with Imputed Race and Ethnicity Data

There were 147,568 children in the original sample with 63,870 observations with missing race and ethnicity data. The BISG imputation methodology estimated the race and ethnicity probabilities for over 97% (61,954 observations) of those children. The remaining 3% (1,916 observations) were dropped from the analysis. Table 2 provides the linear regression results for the HEDIS analysis when the BISG imputed race and ethnicities were included in the analyses.[1] For brevity the logistic regressions are not included in the paper but are available from the authors upon request. The qualitative conclusions in the logistic analysis are analogous to the linear specification. Hence, the presentation of the results is only focused on the linear model.

The effect of an individual's age, gender, region, health status, and race and ethnicity varied across each HEDIS measure.[2] However, several notable trends arose. For ADD, there was not a statistically significant relationship between race and ethnicity and the probability of compliance. Alternatively, for AWC and W34, being White had a negative and statistically significant lower probability of being compliant as compared to being Hispanic, Black, or API. The effect ranges from 2.8% to 5.2% for AWC and 2.2% to 9.1% for W34. For CWP, being Hispanic or Black had a negative and statistically significant lower probability of being compliant compared to being White. Being Hispanic or Black results in a 5.2% to 5.9% lower likelihood of compliance with CWP compared to being White.

For the HEDIS measures W34, CAP, and CWP, age had a positive and statistically significant effect on the probability of compliance. Further, this effect was non-linear given that age-squared is negative and statistically significant. For HEDIS measures ADD, AWC, and CAP, males had a statistically significant lower probability of being compliant than females.

For the W34, ADD, AWC, and CAP HEDIS measures, if an individual was in the CMSN program the individual had a higher probability of HEDIS compliance than any of the other health plans. For a wide array of the non-CMSN health plans, this effect was statistically significant. For example, compared to Plan B, an individual in CMSN had a 4.8% to 21.8% higher probability of compliance across these four measures. Similarly, for these same HEDIS measures children with more severe conditions (Minor Chronic, Moderate Chronic, and Major Chronic) were associated with a higher probability of being compliant. Across these four HEDIS measures, an individual classified in the Major Chronic CRG had a 5.8% to 23.2% higher probability of compliance compared to an individual in the non-acute, non-chronic CRG.

HEDIS Analysis Dropping Those with Missing Race and Ethnicity

For each HEDIS measure, the analysis was performed again using only those individuals who self-reported their race and ethnicity. Table 3 presents the results of the linear regression analysis on this subsample. Taking the coefficient estimates from the BISG imputation presented in Table 2 as the benchmark, several notable trends arose.

Tables 2 and 3 show that for AWC, CAP, and ADD, the magnitude of the negative and statistically significant effects of being a male on the probability of compliance increased. Likewise, for AWC, CAP, W34, and ADD, being in the CMSN health plan increased the probability of compliance as compared with the other plans and the imputed results. Therefore, the positive and often statistically significant effect of being in CMSN on the probability of compliance compared to any other health plan was overestimated when those individuals who did not report race and ethnicity are dropped from the analysis.

Table 3 also reveals that for several of the HEDIS measures, the probability of compliance was higher when an individual had a more severe CRG condition compared to the non-acute, non-chronic category. Comparing the results in Tables 2 and 3, for ADD and CAP, this positive effect on the probably of compliance was dampened leading one to potentially underestimate the relationship between more severe CRG and compliance.

Dropping the individuals who did not self-report race had several impacts on the coefficient estimates for the effect of race and ethnicity on HEDIS compliance. To better interpret these effects, the percentage change in the coefficient estimates was calculated, using the BISG coefficient estimates as the reference value. For a given race and ethnicity group i and HEDIS measure j, we denoted the coefficient estimate including the BISG imputed race and ethnicity probabilities as β_{ij}^{BISG} and the coefficient estimate dropping those individuals with missing race and ethnicity as β_{ij}^{DROP}. The percentage change was then calculated by:

$$\frac{\beta_{ij}^{DROP} - \beta_{ij}^{BISG}}{\beta_{ij}^{BISG}}$$

for each $i \in \{Black, Hispanic, Asian/\ API, Other\}$ and $j \in \{ADD, AWC, CAP, CWP, W34\}$.

Table 4 summarizes the percentage changes for each race and ethnicity and HEDIS measure. If the coefficient estimate was positive, then dropping those who did not self-report race and ethnicity dampened the positive coefficient estimates potentially leading to an underestimation of the positive impact of being non-White on the probability of compliance. Alternatively, if the coefficient estimate was negative, then dropping those who did not self-report race and ethnicity amplifies the negative coefficient estimates leading one to potentially overestimate the negative impact of being non-White on the probability of compliance. For ADD, dropping those with missing race and ethnicity substantially dampened the positive coefficient estimates on Hispanic, Asian/API, and Other, and increased (becomes more negative) the coefficient estimate on Black. For ADD, CAP, CWP, and W34, focusing solely on the self-reported race and ethnicity observations systematically altered the coefficient estimates downward. Finally, dropping those who did not self-report race and ethnicity also affected the statistical significance of several coefficient estimates. In particular, the coefficient estimates became either less statistically significant or lost their statistical significance completely for all but the ADD measure.

Discussion

Identifying racial and ethnic disparities in children's health care quality is important. Without an understanding of where these disparities occur in the health care delivery process, it is difficult to make decisions on how to allocate funds and prioritize initiatives towards reducing disparities. Inaccurate information could lead to wasted time and funds. Our study focused on identifying racial and ethnic disparities at a state level, using a novel method to increase the accuracy of the identified disparities, and we demonstrated how failure to address missing data could overestimate disparities. Findings from our study are applicable to a variety of stakeholders interested in identifying and reducing disparities.

Our findings corroborate others that have identified disparities in pediatric health care quality measures. For all five measures, which evaluated a continuum of care from preventive to chronic, we found race and ethnicity disparities across all measures. A study by Berdahl and colleagues similarly found racial disparities in pediatric quality measures as assessed by two large survey datasets: the Medical Expenditure Panel Survey and the Healthcare Cost and Utilization Project (Berdahl et al. 2010). They note that Hispanics had the worst quality of care among six racial and ethnic groups (White, Black, API, Hispanic, Asian, and Other). As previously mentioned a study by Dougherty and colleagues examined disparities in 68 measures. They found that 50 had disparities while 18 did not. We found no contradictions between the 18 measures that they found had no disparity and our results. For example, the 18 measures they found that had no disparities included measures such as cancer deaths, birth trauma, alcohol and substance abuse, and ability to get prescription medications.

To our knowledge none of the studies mentioned previously that examined disparities in pediatric quality measures assessed the completeness of the race or ethnicity data. Moreover, none made an attempt to impute the race and ethnicity data. In both of these ways our study is able to contribute to this literature in a novel way. We found evidence that simply ignoring the missing race and ethnicity data has an affect on the identification and magnitude of disparities.

Our results reveal for all five measures, the coefficient estimates are biased downwards either towards zero, dampening the coefficient estimates, or more negative, exaggerating health disparities. Further, all but one measure (ADD) saw a decrease or total loss of significance in the coefficient estimates on the race and ethnicity variables. The percentage change in the coefficient estimates when the missing data is dropped ranged from about 2 to 200 percent for Asian, 22 to 108 percent for Black, 7 to 112 for Other, and 2 to 84 for Hispanic. These findings imply that failure to impute missing race and ethnicity data might lead researchers and policy makers to under-identify the presence of health disparities. This arises because of a dramatic reduction in the sample size. Alternatively, our findings imply that when missing race and ethnicity data is dropped, the negative race and ethnicity coefficient estimates that suggest the presence of potentially large health disparities, might be artificially inflated. These two confounding results make it difficult for researchers and policy-makers to disentangle when health disparities are present and the underlying magnitude of these health disparities. This lends further credence and importance to appropriately imputing missing race and ethnicity data (or something along these lines).

Given this data is at the health plan level, it is important to discuss what a health plan could infer from the findings. If health plans wish, or are mandated, to address health care disparities there are two methods whereby they can allocate resources to improve the data: increasing the number of enrollees who self-report and imputation. A 2013 report from the American Hospital Association, America's Essential Hospitals, American College of Healthcare Executives, Catholic Health Association of the United States, and the American Association of Medical Colleges provides instructions, case studies, and resources on how to collect race, ethnicity, and language (REAL) data so that it can be used in a meaningful way (Health Research & Educational Trust 2013). Regardless of whether or not health plans desire to allocate resources towards increasing self-report, they should consider employing the BISG imputation methodology. Health plans could use the imputed data and subsequent analyses to better understand their enrollee population, improve resource planning, have more accuracy in targeting subgroups for performance improvement projects, improve strategic planning, and improve targeted marketing campaigns.

Our study has implications at the policy and programmatic level as well. We demonstrated that a significant number of children in our sample did not have self-reported race and ethnicity data in the enrollment file. Our findings are consistent with data reported by other Medicaid health plans in other states (Michigan Department of Community Health 2012). Yet, without clear direction and incentives from policymakers and other decision-makers this problem will persist. NCQA does have a measure called Race/Ethnicity Diversity of Membership. Specifications call for plans to report on the percentage of their members by racial and ethnic category. Unknown is one of the categories that members can be classified into and the percentage of members in that category widely varies. The 90th percentile benchmark for members in the unknown category is about 80%. Having health plans report on these measures is a first step, but our results suggest that if plans are not allowed to impute for the unknown category, either because this is not allowed by the HEDIS specifications or at the direction of the state, then decisions made based on these numbers might be misguided. Beyond just reporting the results health plans could be incentivized for improving the diversity of their membership, the accuracy of their race and ethnicity data, and ultimately the ability to reduce disparities. NCQA has a Multicultural Health Care Distinction Program and many states require health plans to have a cultural competency program that could be incentivized (National Committee for Quality Assurance 2011).

Every study has limitations and ours is no exception. First, we focused on six HEDIS measures when many other HEDIS and non-HEDIS pediatric quality measures exist. We chose these because they align with current national initiatives and assess a continuum of preventive, acute, and chronic care. We also chose them because they are in the core CHIPRA measure set. There are noticeable gaps in the CHIPRA core measure set across the health care delivery continuum. For example there are few adolescent measures and none on end of life care. It is unclear if our results would be similar if we focused on other measures. Second, race and ethnicity data that was self-reported might still not be representative from the individual’s perspective. Forcing people into classify themselves into one group is not satisfactory as it does not allow them to identify with more than one race or ethnicity. Third, we made no attempt to validate the self-reported or imputed race and ethnic data. We did not match the administrative data to other datasets such as a birth vital statistics or an immunization registry. As previously mentioned we also did not compare the data to data found in medical records. From our experience the missingness of race and ethnicity data in medical records is significant and may not prove to be a good source for validation. Third, there are certainly other factors that could contribute to compliance with quality of care measures that we have not accounted for. Future research could match administrative data to survey data for example that has collected information that might help to explain variation in compliance. Finally, we used data from two large public health insurance programs in

Florida. Results may not be generalizable to other states or even other programs within Florida’s public healthcare delivery system.

Despite these limitations, our study contributes to the literature on pediatric health disparities. By improving the ability to identify, quantify, and target disparities there can be more progress made towards decreasing and ultimately eliminating them.

Table 1. Summary Statistics and Comparisons by Availability of Race and Ethnicity Information

Variables	All (n=145,652)	Self-Reported (n=83,698)	Missing (n= 61,954)	p-value
HEDIS Measures				
ADD	37.4	39.9	32.8	<1%
AWC	54.5	54.4	54.8	0.204
CAP	92.0	92.1	91.9	0.203
CWP	65.8	65.9	65.6	0.771
W34	71.0	70.7	71.5	0.319
Clinical Risk Groups				
Non-Chronic, Non-Acute	62.3	63.4	60.8	<1%
Sign. Acute	7.6	7.8	7.3	<1%
Minor Chronic	6.6	9.0	8.1	<1%
Moderate Chronic	13.4	13.3	13.5	0.259
Major Chronic	7.1	5.3	9.5	<1%
Unassigned	1.0	1.2	0.8	<1%
Health Plan				
CMSN	21.4	21.9	20.7	<1%
Plan A	28.3	27.9	28.8	<1%
Plan B	2.3	2.6	2.0	<1%
Plan C	9.4	8.6	10.5	<1%
Plan D	1.9	1.7	2.1	<1%
Plan E	0.4	0.5	0.3	<1%
Plan F	14.2	15.0	13.1	<1%
Plan G	22.1	21.8	22.4	0.01
Demographics				
Age	11.1	11.0	11.4	<1%
Male	51.8	51.3	52.5	<1%
Northwest	4.1	4.5	3.6	<1%
Big Bend	1.8	1.9	1.5	<1%
North Central	15.1	16.0	13.8	<1%
Tampa Bay	15.1	15.4	14.8	<1%
Central	11.9	12.0	11.8	0.136
Southwest	9.9	10.3	9.3	<1%
Southeast	23.6	22.7	24.7	<1%
South	18.6	17.2	20.6	<1%

Note: For all variables except age, the numbers represent percentages.

Table 2. Linear Regression Results with BISG Race and Ethnicity Data

	ADD Compliance	AWC Compliance	CAP Compliance	CWP Compliance	W34 Compliance
Variables	(1)	(2)	(3)	(4)	(5)
Demographics					
Age	-0.0032	0.0016	0.0098 ***	0.0352 ***	0.1314 ***
	(0.0788)	(0.0116)	(0.0007)	(0.0069)	(0.0301)
Age Squared	-0.0010	-0.0012 ***	-0.0005 ***	-0.0019 ***	-0.0226 ***
	(0.0042)	(0.0004)	(0.0003)	(0.0003)	(0.0042)
Male	-0.0687 ***	-0.0206 ***	-0.0086 ***	-0.0057	0.0061
	(0.0243)	(0.0033)	(0.0016)	(0.0097)	(0.0074)
Black	-0.0190	0.0292 ***	-0.0015	-0.0516 ***	0.0223 **
	(0.0414)	(0.0056)	(0.0026)	(0.0183)	(0.0109)
Hispanic	0.0206	0.0279 ***	0.0082 ***	-0.0589 ***	0.0337 ***
	(0.0205)	(0.0042)	(0.0021)	(0.0118)	(0.0096)
Asian/API	0.0331	0.0519 ***	0.0042	-0.0154	0.0911 ***
	(0.1491)	(0.0149)	(0.0073)	(0.0449)	(0.0355)
Other	0.1188	0.0440	-0.0092	-0.2655 ***	-0.0353
	(0.1491)	(0.0330)	(0.0198)	(0.0889)	(0.0831)
Clinical Risk Groups					
Sign. Acute	-0.0648	0.1010 ***	0.0736 ***	0.0218	0.0762 ***
	(0.0724)	(0.0062)	(0.0024)	(0.0184)	(0.0139)
Minor Chronic	0.0858 ***	0.0834 ***	0.0736 ***	0.0086	0.0883 ***
	(0.0279)	(0.0059)	(0.0002)	(0.0178)	(0.0147)
Moderate Chronic	0.1525 ***	0.0886 ***	0.0755 ***	0.0089	0.0853 ***
	(0.0376	(0.0054)	(0.0019)	(0.0154)	(0.0101)
Major Chronic	0.2324 ***	0.0719 ***	0.0835 ***	0.0097	0.0579 ***
	(0.0674)	(0.0082)	(0.0019)	(0.0231)	(0.0119)
Unassigned	0.0351	-0.0267	-0.0543	-0.0307 *	-0.3756 **
	(0.0338)	(0.0458)	(0.0425)	(0.0166)	(0.1642)
Health Plan					
Plan A	-0.1169 **	-0.0145 **	-0.0469 ***	0.0608 ***	-0.0412 ***
	(0.0536)	(0.0062)	(0.0025)	(0.0161)	(0.0148)
Plan B	-0.1084	-0.1240 ***	-0.0482 ***	-0.1056 ***	-0.2175 ***
	(0.0824)	(0.0121)	(0.0063)	(0.0290)	(0.0376)
Plan C	-0.0938	-0.0095	-0.0323 ***	0.0929 ***	-0.0543***
	(0.0649)	(0.0076)	(0.0034)	(0.0199)	(0.0419)
Plan D	-0.1481	-0.0102	-0.0158 **	0.0883 **	-0.0506
	(0.1038)	(0.0134)	(0.0063)	(0.0435)	(0.0419)
Plan E	-0.3876 ***	-0.0202	-0.0377 **	0.0983	0.0106
	(0.0608)	(0.0256)	(0.0145)	(0.0737)	(0.0687)
Plan F	-0.0630	-0.0191 ***	-0.0175 ***	0.0183	-0.0349 **
	(0.0548)	(0.0068)	(0.0028)	(0.0205)	(0.0163)
Plan G	-0.1137 **	-0.0955 ***	-0.0618 ***	0.0392 **	-0.0961 ***
	(0.0522)	(0.0064)	(0.0027)	(0.0166)	(0.0159)
Regional Dummies	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
No. of Observations	1933	87,833	111,641	9,411	14,705

Note: Stars indicate statistical significance where * if p≤0.10, ** if p≤0.05, and *** if p≤0.01. Values in the parentheses are robust standard errors. All models also include location (Region) covariates.

Table 3. Linear Regression Results when Missing Race and Ethnicity Data is Dropped

Variables	ADD Compliance (1)	AWC Compliance (2)	CAP Compliance (3)	CWP Compliance (4)	W34 Compliance (5)
Demographics					
Age	0.0486	0.0152	0.0111 ***	0.0478 ***	0.1459 ***
	(0.0997)	(0.0154)	(0.0009)	(0.0087)	(0.0398)
Age Squared	-0.0039	-0.0018 ***	-0.0006 ***	-0.0026 ***	-0.0236 ***
	(0.0053)	(0.0005)	(0.0001)	(0.0004)	(0.0056)
Male	-0.0768 **	-0.0288 ***	-0.0089 ***	-0.0047	-0.0029
	(0.0306)	(0.0044)	(0.0022)	(0.0122)	(0.0095)
Black	-0.0395	0.0357 *	-0.0019	-0.0702 *	0.0166
	(0.0462)	(0.0186)	(0.0030)	(0.0420)	(0.0130)
Hispanic	0.0033	0.0384 ***	0.0061 **	-0.0599 ***	0.0237 ***
	(0.0313)	(0.0053)	(0.0026)	(0.0139)	(0.0119)
Asian/API	0.0129	0.0648 ***	0.0039	-0.0478	0.0886 **
	(0.1566)	(0.0168)	(0.0081)	(0.0500)	(0.0381)
Other	0.1005	0.0384	-0.0187	-0.2851 ***	-0.0748
	(0.3767)	(0.0346)	(0.0213)	(0.0925)	(0.0871)
Clinical Risk Groups					
Sign. Acute	-0.2112 **	0.1008 ***	0.0738 ***	0.0394 *	0.0637 ***
	(0.0837)	(0.0084)	(0.0030)	(0.0228)	(0.0169)
Minor Chronic	0.0598 *	0.0912 ***	0.0725 ***	0.0291	0.0984 ***
	(0.0361)	(0.0078)	(0.0029)	(0.0221)	(0.0177)
Moderate Chronic	0.1038 **	0.0922 ***	0.0728 ***	0.0212	0.0876 ***
	(0.0473)	(0.0072)	(0.0025)	(0.0189)	(0.0124)
Major Chronic	0.1586 *	0.0662 ***	0.0793 ***	0.0090	0.0589 ***
	(0.0851)	(0.0110)	(0.0025)	(0.0320)	(0.0177)
Unassigned	0.0248	-0.0511	-0.0713	-0.0355 *	-0.1132
	(0.0425)	(0.0582)	(0.0628)	(0.0204)	(0.3313)
Health Plan					
Plan A	-0.1411 **	-0.0398 ***	-0.0582 ***	0.0576 ***	-0.0784 ***
	(0.0697)	(0.0078)	(0.0032)	(0.0195)	(0.0186)
Plan B	-0.1598	-0.1629 ***	-0.0559 ***	-0.0992 ***	-0.2288 ***
	(0.0999)	(0.0154)	(0.0081)	(0.0347)	(0.0451)
Plan C	-0.1309	-0.0420 ***	-0.0372 ***	0.0879 ***	-0.0875***
	(0.0846)	(0.0101)	(0.0045)	(0.0249)	(0.0261)
Plan D	-0.2812 **	-0.0295	-0.0298 ***	0.1463 **	-0.1193 **
	(0.1283)	(0.0183)	(0.0093)	(0.0579)	(0.0556)
Plan E	-0.4448 ***	-0.0418	-0.0529 ***	0.0934	-0.0008
	(0.0791)	(0.0320)	(0.0181)	(0.0933)	(0.0763)
Plan F	-0.1061	-0.0420 ***	-0.0268 ***	0.0165	-0.0599 ***
	(0.0709)	(0.0085)	(0.0036)	(0.0248)	(0.0198)
Plan G	-0.1191 *	-0.1092 ***	-0.0660 ***	0.0639 ***	-0.1297 ***
	(0.0677)	(0.0080)	(0.0035)	(0.0199)	(0.0197)
Regional Dummies	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
No. of Observations	1257	48,885	61,046	5,922	8,874

Note: Stars indicate statistical significance where * if p≤0.10, ** if p≤0.05, and *** if p≤0.01. Values in the parentheses are robust standard errors. All models also include location (Region) covariates.

Table 4. Percent Change in Coefficient Estimates Dropping Those with Missing Race and Ethnicity Data

Variables	ADD Compliance	AWC Compliance	CAP Compliance	CWP Compliance	W34 Compliance
Black	107.9 ↓	22.3 †	26.7 ↓	36.1 ↓ †	-25.6 ↓ ††
Hispanic	-84.0 ↓	37.6	-25.6 ↓ †	1.7 ↓	-29.7 ↓
Asian/API	-61.0 ↓	24.9	2.4	210.4 ↓	-2.7 ↓ †
Other	-15.4 ↓	-12.7 ↓	103.3 ↓	7.4 ↓	111.9 ↓

Note: The numbers reflect the percent change in the coefficient estimates. ↓ reflects a reduction in the coefficient estimates either towards zero (if coefficient is positive) or more negative (if coefficient is negative).
† reflects a reduction in the degree of statistical significance. †† reflects a loss of statistical significance.

Notes

1. To test for specification errors the Ramsey Regression Equation Specification Error Test (RESET) and Link Test were performed on each regression (Wooldridge, 2010). These tests revealed that the null hypotheses in our regression analyses were properly specified and supported.

2. Martino et al. (2012) focused their analysis on the effect of the interaction between race and ethnicity and the health plan. The qualitative conclusions in this article were robust to the addition of interactions between race and ethnicity and health plan. Further, the interaction terms were systematically statistically insignificant in our analysis.

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