

# How well does diagnosis-based risk-adjustment work for comparing ambulatory clinical outcomes?

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**Abstract** This paper examines the empirical consistency of the Diagnosis Cost Groups/Hierarchical Condition Categories (DCG/HCC) risk-adjustment method for comparing 7-day mortality between hospital-based outpatient departments (HOPDs) and freestanding ambulatory surgery centers (ASCs). We used patient level data for the three most common outpatient procedures provided during the 1997–2004 period in Florida. We estimated base-line logistic regression models without any diagnosis-based risk adjustment and compared them to logistic regression models with the DCG/HCC risk-adjustment, and to conditional logit models with a matched cohort risk-adjustment approach. We also evaluated models that adjusted for primary diagnoses only, and then for all available diagnoses, to assess how the frequently absent

secondary diagnoses fields in ambulatory surgical data affect risk-adjustment. We found that risk-adjustment using both diagnosis-based methods resulted in similar 7-day mortality estimates for HOPD patients in comparison with ASC patients in two out of three procedures. We conclude that the DCG/HCC risk-adjustment method is relatively consistent and stable, and recommend this risk-adjustment method for health policy research and practice with ambulatory surgery data. We also recommend using risk-adjustment with all available diagnoses.

**Keywords** Risk-adjustment · Ambulatory · Administrative data · Mortality · Diagnosis Cost Groups/Hierarchical Condition Categories (DCG/HCC)

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## 1 Introduction

Accurate risk-adjustment of patient-related medical conditions is essential when comparing quality outcomes between two or more healthcare providers. Yet, researchers using administrative data face difficulties in risk-adjustment given the known limitations of such datasets [1–3]. Given that conclusions about comparative outcomes may be sensitive to the risk-adjustment method, caution about risk-adjustment is especially important when studies influence government policy, reimbursement and, potentially, patient access to care.

Due to the significant growth in the number of ambulatory surgical procedures provided in the U.S. and associated overall costs [4], researchers have begun to examine differences in quality outcomes for procedures performed in freestanding ambulatory surgical centers (ASCs) and hospital-based outpatient departments (HOPDs) [5–15]. Overall, these studies have utilized

varying risk-adjustment approaches and have generally produced mixed results. In this paper we argue that the inconclusive findings from this body of literature may be partially attributed to differences and limitations in risk-adjustment methods.

The purpose of this paper is to examine the empirical consistency of one such risk-adjustment methodology that is currently being used by the Centers for Medicare and Medicaid Services (CMS) to adjust capitation payments for the Medicare + Choice (Advantage) program [4, 11, 16]. Specifically, we examine the consistency of the Diagnosis Cost Groups/Hierarchical Condition Categories (DCG/HCC) methodology as a risk-adjustment tool when using ambulatory surgical data for comparing clinical outcomes for two different types of providers, hospital-based outpatient departments (HOPD) and freestanding ambulatory surgery centers (ASC). While the DCG/HCC instrument has been validated using inpatient data [17, 18], and has certain characteristics suitable for use with ambulatory data [19], this method has not been empirically tested using ambulatory surgical data, but has had a limited use in previous ambulatory research [11, 15]. As part of our study, we also assess how missing secondary diagnoses fields, common in ambulatory surgery administrative data, may affect risk-adjustment and the conclusions drawn about quality performance of HOPDs and ASCs.

## 2 Methods

### 2.1 Background and research questions

In the current study, we use ambulatory surgical datasets to evaluate the performance of the DCG/HCC risk-adjustment methodology. We also compare risk-adjustment for patient severity of illness using the DCG/HCC risk-adjustment methodology with risk-adjustment using the matched cohort approach. The later approach involves risk-adjustment by matching patients with the same demographic and clinical characteristics [20, 21], and compares the clinical outcomes of those treated in a HOPD compared to an ASC using only information from matched groups who had at least one member with the adverse outcome (7-day mortality). Hence, our research questions are as follows: Are there differences in conclusions regarding comparative clinical outcomes for HOPDs and ASCs between a model with no risk-adjustment for patient severity and a model with the DCG/HCC risk-adjustment for patient severity? Are there differences in conclusions regarding comparative clinical outcomes for HOPDs and ASCs between the DCG/HCC and matched cohort risk-adjustment approaches?

Administrative data are used primarily for billing and managerial purposes, thus the data accuracy and complete-

ness for research has been questioned [1, 2, 22]. In our ambulatory data, we found that fewer secondary diagnoses were reported among ASCs compared to HOPDs. Moreover, some ASCs did not report secondary diagnoses at all in some years during the 1997–2004 period. On the one hand, ASCs may treat a healthier case mix of patients with fewer comorbid conditions [11]. On the other hand, ASCs may fail to report patients' secondary diagnoses because major payers, such as Medicare, providing reimbursements to ASCs, do not adjust for patient clinical similarities [23]. Under the ASC payment system, procedures are assigned to one of the nine payment groups that contain procedures with similar costs. The HOPD system, however, pays for procedures bundled in groups with similar costs and clinical characteristics [23]. Given the limitations in how administrative data are originally collected, we cannot definitively say when and whether secondary diagnoses are reliably reported.

In our study, we address the problem of potential non-reporting of comorbidities by comparing estimates with and without incorporating information on secondary diagnoses in ambulatory data. Hence, our third and final research question is: To what extent does incorporation of information on secondary diagnoses in risk-adjustment affect conclusions regarding the relative quality performance of HOPDs and ASCs?

### 2.2 Data sources

Two patient-level databases, representing the 1997–2004 time period, were used in this study. The ambulatory discharge dataset, obtained from the Florida Agency for Health Care Administration (AHCA), contains information on patient personal identification numbers, demographic characteristics, the primary and up to four secondary diagnoses as classified by ICD-9 codes, procedure codes based on Current Procedural Terminology (CPT), and payer type for all ambulatory procedures performed in licensed ASCs and HOPDs in Florida. The vital statistics dataset, obtained from the Florida Department of Health, includes the state's death registry.

For this study, we considered the three most common ambulatory procedures (colonoscopy, upper gastrointestinal endoscopy, and cataract removal) for all patients between the ages of 20 and 99, during the years 1997–2004. Together these procedures represented 33% of all ambulatory procedures performed at HOPDs or ASCs in Florida during the eight year study period. This study received Institutional Review Board approval.

### 2.3 Outcome variable

Using patient identifiers, the ambulatory discharge dataset was merged with the vital statistics data in order to

calculate 7-day mortality rates. Mortality is a quality indicator commonly used in the inpatient setting [24]. Even though mortality related to the ambulatory surgical setting is rare, this indicator has been used to flag potential quality problems associated with ambulatory surgery [6, 7, 9, 25]. Other researchers have also used mortality as an outcome for comparing quality of care provided in the outpatient setting [8, 12, 26, 27]. We used 7-day indicators since, as a shorter measure, it can reduce the effects of extraneous factors unrelated to outpatient procedures [6]. In order to partially account for unrelated deaths following a given ambulatory procedure, we excluded suicides and homicides.

We treated each procedure as a separate event performed on that encounter. In order to distinguish between mortality outcomes, as well as between different types of procedures, we created an individual dataset for each outcome for each of the three procedures. We also counted multiple adverse outcomes only once in those cases where the same patient had more than one encounter for the same procedure. For example, if a patient had two cataracts removed and later died within a 7-day period, this would be represented in the same dataset as one encounter and the mortality outcome counted only once. However, if a patient had a colonoscopy and also a cataract surgery, this would be represented in two separate datasets, and any subsequent mortality would be counted as an adverse outcome for both procedures.

#### 2.4 Analytical approach

The critical parameter of interest was the odds ratio for 7 day mortality for the ASC variable. A value of one was assigned to all patient encounters at ASCs; while those treated at an HOPD were assigned 0 (the reference category). We compared the estimates of the ASC odds ratios generated from three logistic regressions incorporating different risk-adjustment approaches and with the ASC estimates from the conditional logit model. All logistic regressions included the identical independent variables. Patient age was included through indicator variables for 16 groups representing five-year intervals for patients aged 20–99 (the reference group was patients aged 65–69) in order to capture the expected complex, non-linear relationship between age and risk of adverse outcomes. Race/ethnicity was included via binary variables as White (the reference group), African American, Hispanic, or other (including unknowns). We also included a binary variable for gender (female as reference). Patient insurance types included Commercial/PPO, Medicare (the reference group), Medicare HMO, Medicaid, Medicaid HMO, HMO, charity, self-pay, or other. We also controlled for changes over time common to both ASCs and HOPDs by including a set of dummy variables for each year between 1997 and 2004 in our analyses.

#### 2.5 Models without DCG/HCC risk-adjustment for patient severity

To establish a baseline, we estimated a model that did not include any variable as an adjuster for patient severity. That is, the model did not adjust for differential risk, due to burden of illness, except through the inclusion of the above-mentioned indicator variables for sex, age, and patient insurance type (Estimate Set 1).

#### 2.6 Models with risk-adjustment for patient severity using the DCG/HCC method

In order to assess the empirical consistency of the DCG/HCC methodology, we utilized a continuous measure of severity (i.e., risk scores) that was generated by *RiskSmart Stand Alone V.2.1* software, using the DCG/HCC methodology [28]. The DCG/HCC risk-adjustment methodology uses all available diagnosis codes (ICD-9-CM) and classifies them in clinically homogeneous and meaningful groups named condition categories (CCs) [16–18, 28]. The CCs are then hierarchically grouped by severity (HCC) and ranked according to their historical and empirically determined diagnostic cost (i.e., DCG/HCC). Each patient with multiple diagnoses gets assigned into a single group with the highest hierarchy, where higher group number indicates increasing severity [11, 16–18, 28]. These groups are then translated into risk scores. The DCG/HCC also adjusts for patient age and sex.

In our study, all outpatient encounters in Florida were used to compute risk scores for 1997–2004. The generated risk scores predicted the severity burden for each patient relative to that of the average ambulatory patient in Florida. Thus, relative risk scores above the average represented increased complexity related to comorbidities, and scores below the average represented decreased complexity [11, 28].

We constructed our risk scores in two ways in order to evaluate the impact of including the information from secondary diagnoses on perception of quality performance for HOPDs and ASCs. The first set of risk scores adjusted for primary diagnosis only (this variable was labeled as RRPM, standing for relative risk predictive model) (Estimate Set 2), while the second set of risk scores adjusted for primary and all available secondary (up to four) diagnoses (RRPM5DX, standing for relative risk predictive model with up to five diagnoses) (Estimate Set 3).

#### 2.7 Models with risk-adjustment for patient severity using the matched cohort method

Comparing estimation results (Estimate Sets 1–3) allows us to gauge the impact of risk adjustment by (1) the inclusion

of the above-mentioned indicator variables for sex, age, and patient insurance type versus (2) risk adjustment using RRPM versus (3) incorporating secondary diagnoses using RRPM5DX. A matched cohort design and conditional logistic regression model was used to assess consistency of the DCG/HCC methodology as an alternative approach for risk-adjustment to the use of RRPM5DX (i.e., with conditional logistic regression risk adjustment via matching by observable characteristics including secondary diagnoses).

This risk adjustment via matching in conditional logistic regression allows us another view to assess risk adjustment using DCG/HCC methodology. The units of analysis were groups of patients who underwent the same procedure and who had the same clinical (primary and secondary diagnoses) and demographic (sex, age, and insurance type) characteristics. The odds ratio for patients who received their procedures at the ASC was estimated using information only from the matched groups with one or more patients suffering the adverse outcome; matched groups containing no patients suffering the adverse outcome and unmatched individuals did not provide information to form the estimates [29, 30]. Note, that in the matched cohort design, the size of the matched groups varied from cohort to cohort. Note also, that the conditional logistic regression is equivalent to a Cox proportional hazards regression if the exact marginal or exact partial likelihoods are applied to tied survival times [31, 32].

To evaluate the impact of including the information from secondary diagnoses, we report ASC odds ratios from a conditional logistic regression from matching patients by principal diagnosis (ICD-9-CM code), up to four secondary diagnoses reported as ICD-9-CM codes, primary procedure (CPT-4 code), sex, four race/ethnicity categories, nine payer groups, and 16 age categories (Estimate Set 4).

Given the matching on all observable characteristics, we draw conclusions based on the conditional logit models with the dummy variable for ASC and yearly dummy variables to control for time-specific effects. Thus, odds ratio for the ASC variable, represented a risk-adjusted comparison in outcomes between the two settings of care, was then compared with the ASC mortality odds ratios generated in the logistic regression models with and without DCG/HCC risk-adjusters.

Table 1 summarizes the juxtaposition of risk-adjusters and inclusion/exclusion of secondary diagnoses for the DCG/HCC and the matched cohort methodologies we utilized in each of our analyses.

## 2.8 Specification of models

Let  $y = 1$  indicate the adverse outcome of death within 7 days of the outpatient procedure. We apply the standard

**Table 1** Description of the comparisons: use of information in secondary diagnoses and risk-adjustment method

Estimate set	Regression model	Risk adjustment using DCG/HCC	Risk adjustment via matched cohort	Incorporate secondary diagnoses
1	Logistic	No	No	No
2	Logistic	Yes	No	No
3	Logistic	Yes	No	Yes
4	Conditional logistic	No	Yes	Yes

logit model assuming that the index  $\mathbf{x}\beta$  is mapped to the conditional probability of death by the function

$$P(y = 1|\mathbf{x}) = \frac{\exp(\mathbf{x}\beta)}{1 + \exp(\mathbf{x}\beta)}$$

The index function contains different regressors for each estimate set 1–3. In estimate set 1, risk adjustment occurs only through indicator variables for sex, age, race, and insurer/payer.

$$\mathbf{x}\beta = \beta_0 + \theta_t + \beta_1 asc + \beta_2 female + \beta_3 \mathbf{A} + \beta_4 \mathbf{R} + \beta_5 \mathbf{P}$$

where  $\theta_t$  represents fixed effects for year of surgery (that is, a set of dummy variables for each year from 1998 to 2004, with 1997 being the base or reference year) and controls for a potential influence of time,  $\mathbf{A}$  indicates a set of 15 indicator variables for patient age,  $\mathbf{R}$  indicates a set of three indicator variables for race of patient, and  $\mathbf{P}$  indicates a set of either indicator variables for patient insurance type.

In estimate set 2, we add to this index function information from the DCG/HCC risk scores adjusted for primary diagnosis only (RRPM).

$$\mathbf{x}\beta = \beta_0 + \theta_t + \beta_1 asc + \beta_2 female + \beta_3 \mathbf{A} + \beta_4 \mathbf{R} + \beta_5 \mathbf{P} + \beta_6 RRPM$$

In estimate set 3, we add instead the information from the DCG/HCC risk score adjusted for primary and all available secondary diagnoses (RRPM5DX). We report the *ASC odds ratios* =  $\exp(\beta_1)$  as the critical parameter of comparisons of estimate sets 1–4.

Estimate set 4 is quite different in that patient demographic information as well as information on primary and secondary diagnoses are used to establish cohorts of patients and we apply the conditional logit model or, alternately, logit model with fixed effects for cohorts. The index model becomes

$$\mathbf{x}_{i,s}\beta = c_i + \theta_t + \beta_1 asc_{i,s}$$

where  $c_i$  represents the fixed effect for cohort  $i$  and the subscript  $s$  indicates patients within cohort  $i$ . That is,

**Table 2** Summary statistics for colonoscopy, Upper Gastrointestinal (UGI) endoscopy, cataract removal procedure by facility type

	Colonoscopy		UGI Endoscopy		Cataract	
	N=2,761,636		N=1,308,080		N=2,031,487	
	<sup>a</sup> HOPD	ASC	HOPD	ASC	HOPD	ASC
Percentage of sample	47.67	52.33	53.42	46.58	15.61	84.39
Death (%)	0.01	0.01	0.04	0.03	0.01	0.01
Secondary DX reported (%)	88.29	44.72	89.25	47.34	59.64	8.65
RRPM	1.17	1.18	1.25	1.27	1.53	1.55
RRPM5DX	1.51	1.32	1.68	1.45	2.05	1.66
Female (%)	54.31	54.46	59.67	59.79	60.93	60.00
Hispanic (%)	8.53	7.60	11.42	9.62	14.25	5.02
Black (%)	6.79	4.39	8.37	4.93	6.11	2.45
Other non-white (%)	4.10	10.83	4.05	11.84	3.87	17.27
Medicare (%)	36.82	42.20	36.45	44.26	63.87	72.91
Private insurance (%)	29.19	37.18	27.56	34.66	10.63	12.49

<sup>a</sup>HOPD stands for hospital-based outpatient department

ASC ambulatory surgery center; RRPM relative risk predictive model; RRPM5DX relative risk predictive model with up to five diagnoses.

patients are separated into cohorts matched by every characteristic *except* the location of the outpatient surgery. Specifically, they are matched to a cohort based on principal diagnosis (ICD-9-CM code), up to four secondary diagnoses reported as ICD-9-CM codes, primary procedure (CPT-4 code), sex, four race/ethnicity categories, nine payer categories, 16 age categories, and we also controlled for year of outpatient surgery through inclusion of the set of year dummies in both logit and conditional logit models. In the conditional logit model, no information is obtained from cohorts where all or none of the patients suffered the adverse outcome; in such cohorts the outcome is not determined by  $\theta_i$  or  $\beta_1$ . The  $c_i$  cannot be estimated consistently, at least when some cohort sizes are small. The conditional logit solves this problem by conditioning on the total number of deaths within a cohort, eliminating the  $c_i$  [34] [30].

### 3 Results

#### 3.1 Major descriptive findings

Table 2 contains summary statistics for the three procedures by location of outpatient surgery (HOPD and ASC). For the sake of brevity, we report only the most important summary information.<sup>1</sup> For example, for payers we only included percentage Medicare and percentage private insurance, since these two payers accounted for two-thirds or more of patients.

The percent of patients treated in HOPDs and ASCs varied by the type of procedure. For example, the percent of colonoscopy and gastrointestinal endoscopy patients were fairly evenly distributed in HOPDs and ASCs, splitting

patients relatively near a 50% mark. Only 15.61% of cataract removal patients, however, were treated in HOPDs. Overall, seven-day unadjusted mortality was rare, and comparable for HOPDs and ASCs.

HOPDs reported secondary diagnoses more frequently than ASCs. Nearly 90% of colonoscopy and upper gastrointestinal endoscopy patients had secondary diagnoses reported by HOPDs, while only about 45% of colonoscopy, and 47% of upper gastrointestinal endoscopy, ASC patients had secondary diagnoses reported. There were 59.64% of cataract removal patients with secondary diagnoses reported by HOPDs in comparison with only 8.65% of patients in ASCs.

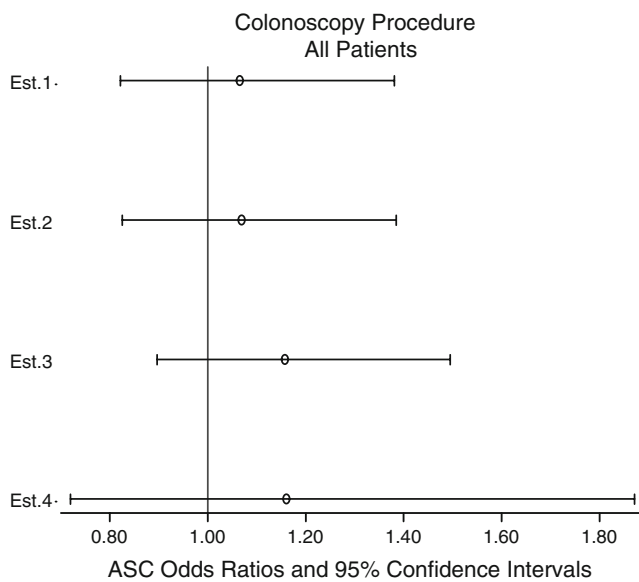
Given these differences in the percentage of patients for which there were secondary diagnoses reported, not surprisingly, mean values of RRPM5DX were higher at HOPDs than at ASCs. Of note, mean values of RRPM were slightly higher at ASCs in comparison with HOPDs. This indicates that some differences in patient comorbidities exist between HOPDs and ASCs even when risk-adjustment was restricted to only one primary diagnosis.

In terms of key patient demographic and insurance characteristics, there were similar percentages of women treated in HOPDs and ASCs. More Hispanic and Black patients were treated in HOPDs. Other non-White patients (including patients with unknown race) were more frequently treated in ASCs. More Medicare and privately insured patients received outpatient services at ASCs.

#### 3.2 Comparing the odds ratios for ASCs using no adjustment for patient severity, the DCG/HCC, and the matched cohort risk-adjustment methods

Figures 1, 2 and 3 present the ASC odds ratios and the confidence intervals for the four comparisons (Estimate

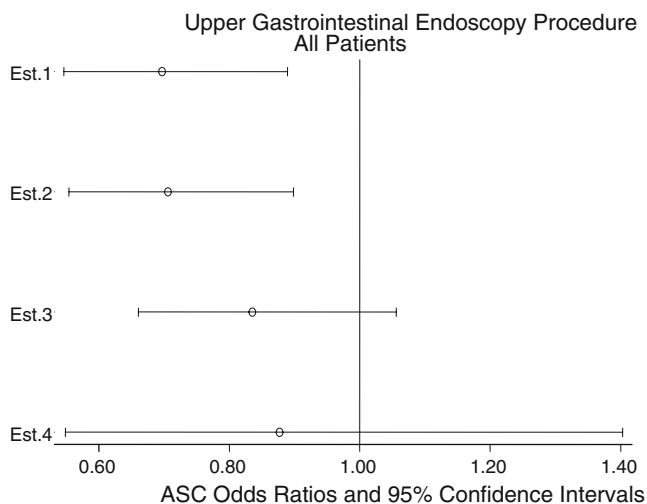
<sup>1</sup> Complete estimation results are available in the [appendix](#).



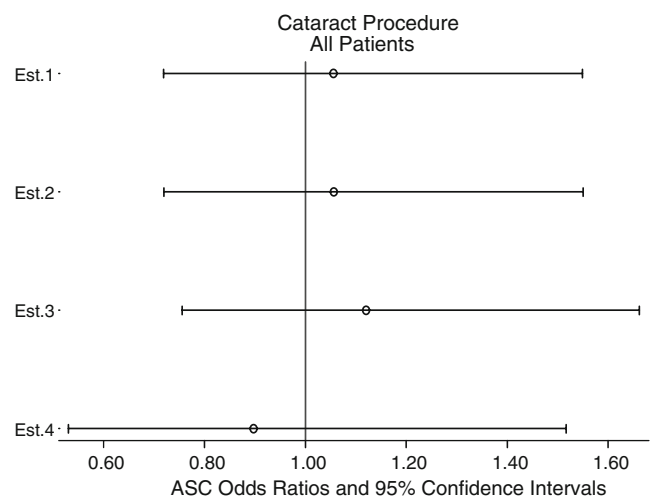
**Fig. 1** ASC odds ratios and 95% confidence intervals by risk-adjustment method for colonoscopy procedure

Sets 1–4) and each of the three procedures. We present the ASC odds ratio estimates in graphical form in order to focus on the general question of comparability of estimates by risk-adjustment method.

For all three procedures, the ASC odds ratios (and even the 95% confidence intervals) in both estimate sets 1 and 2 are remarkably similar (i.e., models with no risk-adjustment for patient severity, and with the DCG/HCC risk-adjustment for primary diagnosis only). The ASC odds ratio estimates for colonoscopy were 1.07 and 1.07, for upper gastrointestinal endoscopy—0.70 and 0.71, and for cataract removal—1.06 and 1.06, for estimate sets 1 and 2, respectively.



**Fig. 2** ASC odds ratios and 95% confidence intervals by risk-adjustment method for upper gastrointestinal endoscopy procedure



**Fig. 3** ASC odds ratios and 95% confidence intervals by risk-adjustment method for cataract removal procedure

For estimate set 2 compared to estimate set 3, the estimates are dissimilar, and the ASC odds ratios substantially increased. For example, the ASC odds ratio estimates increased from 1.07 to 1.16 for colonoscopy; for upper gastrointestinal endoscopy an increase was seen from 0.71 to 0.84; and for cataract removal, from 1.06 to 1.12.

For estimate set 3 compared to estimate set 4, the similarity of the estimates varies by procedure. For colonoscopy and upper gastrointestinal endoscopy, the difference is quite small, the conditional logit odds ratios (estimate set 4) being the same for colonoscopy (1.16 versus 1.16) and only slightly large for upper gastrointestinal endoscopy (0.88 versus 0.84) in comparison with the logistic regression models with RRPM5DX (estimate set 3). The largest difference occurred with estimate set 4 for cataract removal where the conditional logit's ASC odds ratio estimate was 0.90 compared to the estimate of 1.12 from the logistic regression models with the DCG/HCC risk-adjustment for all available diagnoses (estimate set 3).

The differences we observe in odds ratios between the methods may be attributable to differences in the reporting of, and risk-adjustment for, secondary diagnoses. The ASC odds ratios were essentially unchanged for estimate sets 1 vs. 2 (note that estimate set 2 used information from primary diagnoses only). The ASC estimates increased substantially for estimate sets 2 vs. 3, and 2 vs. 4, where estimate sets 3 and 4 used information from all available diagnoses. For example, the ASC odds ratios estimates for colonoscopies in estimate set 2 was 1.07 compared to 1.16 in estimate sets 3 and 4. Similar patterns were observed in other procedures and comparisons.

For cataract removal procedures, however, the ASC odds ratio estimates were 1.06 in estimate set 2, 1.12 in estimate set 3, and 0.90 in estimate set 4, when risk-adjusted using

matched cohorts, and this estimate was considerably smaller than in sets 2 and 3. This difference may be attributable to a high percent of absent secondary diagnoses for this procedure. Specifically, data in Table 2 shows that the majority of cataract removal procedures (84.39%) were provided by ASCs which had only 8.65% secondary diagnoses reported. HOPDs reported secondary diagnoses for 59.64% of cataract patients, but only 15.61% of all cataract patients were treated in HOPDs. Thus, for estimate set 4, the majority of matched cohorts were for patients with no secondary diagnosis, these groups primarily affect odds ratio estimates in conditional logit model. As a result, the DCG/HCC risk-adjustment may be more reliable in this case.

#### 4 Discussion

To our knowledge, the current study is the first to empirically assess the consistency of the DCG/HCC risk-adjustment method for comparisons of clinical outcomes for outpatient surgery providers, and for use with ambulatory surgery data. We used all-payer, patient level data for the three most common outpatient procedures provided in Florida during the 1997–2004 period. We estimated the mortality outcomes with both no risk-adjustment for patient severity and with two types of diagnosis-based risk-adjustment (comparing logistic regressions with the DCG/HCC risk-adjustment method, and matched cohort models), to evaluate the consistency of comparative outcomes.

Referring to our research questions of whether there were differences between the two risk-adjustment methods, we conclude that risk-adjustment via the DCG/HCC method in logistic regressions, and risk-adjustment via matching in cohort models, provided comparable results in assessment of clinical outcome as represented in the ASC odds ratios. Hence, the DCG/HCC risk-adjustment method can be used with a reasonable degree of consistency with ambulatory surgical data. Given that our empirical results are relatively consistent and stable, and incorporating the fact that the DCG/HCC method is easy to implement and use in practice [28], it is reasonable to recommend this risk-adjustment method for health policy research and practice with ambulatory surgery data.

Referring to our other research question of whether there were effects of the secondary diagnoses reporting on risk-adjustment and comparative quality performance in HOPDs and ASCs, we attempted to address the issue of potential non-reporting of comorbidities by comparing the ASC estimates with and without incorporating information on secondary diagnoses in risk-adjustment. We demonstrated that reporting of secondary diagnoses is important for risk-adjustment and for conclusions on comparative quality

performance in the outpatient settings. We found that risk-adjustment for all available diagnoses increased the ASC odds ratios in the majority of models and changed the direction of comparative outcomes in select models. The magnitude of these effects was noticeable and depended on the level of reporting of secondary diagnoses and the type of outpatient procedure. Thus, it is advisable to use all comorbidity information available in administrative data for risk-adjustment and comparative analyses.

Uncertainties about the accuracy of administrative data present serious challenges to healthcare payers, policy makers, providers, and researchers [1–3] [22]. For example, the Agency for Healthcare Research and Quality (AHRQ) promotes research on ambulatory surgery services and currently provides the State Ambulatory Surgery Databases (SASD) to interested researchers. Many states, including Florida, continuously collect ambulatory data and participate in AHRQ's SASD project. Federal and state agencies should recommend or even mandate outpatient surgical centers to provide comprehensive information on all important fields including secondary diagnoses when submitting administrative data.

Outpatient surgical clinics also should take a proactive approach in providing uniform, reliable, and valid information to payers that increasingly incorporate the diagnoses-based risk-adjustment tools, such as the DCG/HCC, in their payment mechanisms. For example, the CMS has recently proposed a change in the ASC payment system designed to better align with the existing payment mechanism used with HOPDs.[23] The proposed changes aim to improve transparency and eliminate differences between these two payment systems [23, 34, 35]. Our study demonstrated that accuracy of the reporting of administrative data may have become even more relevant to outpatient surgical centers, if the diagnosis-based risk-adjustment tools were used for aligning the payment systems. The use of incomplete administrative data for risk-adjustment may actually expand distortions in the payment systems.

Despite the new information presented in our study, several limitations exist. Previous research has demonstrated that serious coding bias exists in the administrative data for hospitals [1–3, 22]. Thus, accuracy of coding of diagnoses, procedures, and other data fields is of concern in the outpatient setting as well. Thus, future research should incorporate, where possible, primary data collection via medical chart abstraction in order to evaluate whether coding bias is also present in outpatient surgical settings. Another limitation potentially affecting our study is that we did not have access to financial data to assess consistency of the DCG/HCC risk-adjustment used for payment purposes. In addition, there is no consensus in the research community on valid, reliable, and variable quality of care measures for the outpatient setting. Future studies should

develop and validate new measures of quality for ambulatory surgery providers. We also had no access to data on ambulatory procedures that could potentially have been performed in physicians' offices. Thus, health care policy makers should make an effort to streamline data collection processes that include physician information in the administrative datasets as well. Finally, despite the robustness of

our data, our study is limited to a single state, so future research should validate the current findings using data from additional geographic locations. In conclusion, we believe that this study provides important validation of one of the common risk-adjustment methods and demonstrated potential effects of non-reporting that may exist in administrative ambulatory surgery data on comparative quality outcomes.

## Appendix

**Table 3** Full estimation results for colonoscopy procedure<sup>a,b</sup>

Variable	Estimate set <sup>c</sup>			
	1	2	3	4
<i>Ambulatory surgery center</i>	0.063 (0.132)	0.067 (0.132)	0.147 (0.130)	0.149 (0.244)
<i>Year 1998</i>	-0.234 (0.258)	-0.232 (0.258)	-0.228 (0.258)	-0.388 (0.355)
<i>Year 1999</i>	-0.084 (0.248)	-0.081 (0.248)	-0.090 (0.248)	-0.219 (0.341)
<i>Year 2000</i>	-0.177 (0.200)	-0.172 (0.200)	-0.183 (0.201)	-0.197 (0.322)
<i>Year 2001</i>	-0.342 (0.227)	-0.335 (0.226)	-0.354 (0.226)	-0.102 (0.323)
<i>Year 2002</i>	-0.551* (0.232)	-0.540* (0.232)	-0.567* (0.232)	-1.117** (0.391)
<i>Year 2003</i>	-0.619** (0.237)	-0.607* (0.236)	-0.639** (0.237)	-0.780* (0.355)
<i>Year 2004</i>	-0.495* (0.249)	-0.483 (0.248)	-0.516* (0.248)	-0.915* (0.368)
<i>Female</i>	-0.633*** (0.113)	-0.596*** (0.115)	-0.583*** (0.114)	
<i>Hispanic</i>	-0.000 (0.253)	0.003 (0.252)	0.023 (0.252)	
<i>Other minority</i>	-0.077 (0.205)	-0.073 (0.205)	-0.069 (0.205)	
<i>Black</i>	0.287 (0.259)	0.286 (0.259)	0.280 (0.258)	
<i>Medicare HMO</i>	0.111 (0.198)	0.115 (0.198)	0.118 (0.198)	
<i>Medicaid</i>	0.400 (0.585)	0.381 (0.585)	0.358 (0.584)	
<i>Medicaid HMO</i>	0.008 (1.033)	0.005 (1.032)	0.002 (1.029)	
<i>Private insurance</i>	-0.549* (0.245)	-0.536* (0.243)	-0.511* (0.243)	
<i>Private HMO</i>	-0.139 (0.238)	-0.126 (0.238)	-0.099 (0.236)	
<i>Self Payer</i>	0.217 (0.579)	0.227 (0.579)	0.249 (0.580)	

**Table 3** (continued)

Variable	Estimate set <sup>c</sup>			
	1	2	3	4
<i>Charity Care</i>	0.943 (0.860)	0.932 (0.862)	0.952 (0.856)	
<i>Other Payer</i>	-0.246 (0.451)	-0.235 (0.450)	-0.219 (0.449)	
<i>Age 30–34</i>	-0.233 (0.737)	-0.044 (0.742)	-0.026 (0.737)	
<i>Age 35–39</i>	-0.785 (0.745)	-0.587 (0.759)	-0.572 (0.746)	
<i>Age 40–44</i>	-1.296 (0.739)	-1.092 (0.743)	-1.080 (0.740)	
<i>Age 45–49</i>	-0.487 (0.482)	-0.329 (0.480)	-0.324 (0.478)	
<i>Age 50–54</i>	-0.229 (0.364)	-0.065 (0.367)	-0.057 (0.365)	
<i>Age 55–59</i>	-0.322 (0.369)	-0.229 (0.369)	-0.228 (0.366)	
<i>Age 60–64</i>	0.412 (0.291)	0.495 (0.294)	0.488 (0.290)	
<i>Age 70–74</i>	0.523* (0.239)	0.508* (0.240)	0.501* (0.239)	
<i>Age 75–79</i>	1.204*** (0.209)	1.183*** (0.211)	1.171*** (0.210)	
<i>Age 80–84</i>	1.605*** (0.212)	1.581*** (0.213)	1.566*** (0.212)	
<i>Age 85–90</i>	1.924*** (0.248)	1.897*** (0.251)	1.877*** (0.249)	
<i>Age 90–94</i>	2.467*** (0.346)	2.434*** (0.348)	2.408*** (0.348)	
<i>Relative risk prediction model</i>		0.279* (0.116)		
<i>Relative risk prediction model with Secondary diagnosis information</i>			0.287*** (0.052)	
<i>Constant</i>	-8.879*** (0.252)	-9.311*** (0.284)	-9.439*** (0.274)	
Number of observations	2,761,636	2,761,636	2,761,636	71,605
Pseudo R-squared <sup>d</sup>	0.049	0.050	0.052	0.014
Percent correctly classified <sup>e</sup>	99.97	99.98	99.98	–

<sup>a</sup> Logit (or conditional logit) coefficient estimates and standard errors (in parentheses) are reported. An odds ratio can be obtained by exponentiating a coefficient estimate.

<sup>b</sup> Significance levels: \*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$

<sup>c</sup> The Estimate Sets are described in Table 1 of the manuscript.

<sup>d</sup> The Pseudo R-squared for the conditional logit estimates, Estimate Set 4, is not comparable to that for the logit models, Estimate Sets 1–3, because the Pseudo R-squared is based only the ambulatory surgery center dummy variables, and the seven yearly dummy variables (the information on sex, race, payer, age, and primary and secondary diagnoses having been conditioned out in the fixed effect for cohorts).

<sup>e</sup> For the three logit models, Estimate Sets 1–3, the cut-off value to calculate the percent correctly classified was selected so that predicted number of adverse events was approximately equal to the number of adverse events in the estimate sample. Note that in the conditional logit model, Estimate Set 4, the focus is on the parameter estimates; no specific prediction for a given cohort is calculable since the fixed effect for the cohort is conditioned out to obtain consistent estimates of the relevant parameters.

**Table 4** Full estimation results for Upper Gastrointestinal (UGI) endoscopy procedure <sup>a,b</sup>

Variable	Estimate set <sup>c</sup>			
	1	2	3	4
<i>Ambulatory surgery center</i>	-0.361** (0.124)	-0.349** (0.123)	-0.180 (0.120)	-0.131 (0.240)
<i>Year 1998</i>	0.094 (0.157)	0.090 (0.158)	0.089 (0.158)	0.182 (0.316)
<i>Year 1999</i>	-0.075 (0.161)	-0.076 (0.161)	-0.107 (0.160)	-0.424 (0.368)
<i>Year 2000</i>	-0.102 (0.188)	-0.101 (0.188)	-0.134 (0.189)	-0.299 (0.346)
<i>Year 2001</i>	-0.424* (0.189)	-0.422* (0.189)	-0.466* (0.190)	-0.375 (0.347)
<i>Year 2002</i>	-0.294 (0.167)	-0.293 (0.166)	-0.355* (0.167)	-0.013 (0.333)
<i>Year 2003</i>	-0.315 (0.196)	-0.311 (0.195)	-0.390* (0.194)	-0.232 (0.343)
<i>Year 2004</i>	-0.636** (0.219)	-0.634** (0.218)	-0.711** (0.217)	-0.633 (0.380)
<i>Female</i>	-0.463*** (0.090)	-0.401*** (0.092)	-0.344*** (0.093)	
<i>Hispanic</i>	-0.484* (0.238)	-0.464* (0.235)	-0.399 (0.232)	
<i>Other minority</i>	-0.094 (0.185)	-0.083 (0.184)	-0.077 (0.184)	
<i>Black</i>	0.563*** (0.168)	0.566*** (0.167)	0.547** (0.167)	
<i>Medicare HMO</i>	-0.252 (0.213)	-0.243 (0.213)	-0.215 (0.210)	
<i>Medicaid</i>	0.806* (0.340)	0.768* (0.342)	0.693* (0.343)	
<i>Medicaid HMO</i>	-0.088 (0.699)	-0.102 (0.699)	-0.110 (0.697)	
<i>Private insurance</i>	-0.058 (0.205)	-0.033 (0.203)	0.046 (0.197)	
<i>Private HMO</i>	-0.358 (0.240)	-0.333 (0.239)	-0.252 (0.236)	
<i>Self payer</i>	0.617 (0.408)	0.627 (0.406)	0.664 (0.403)	
<i>Charity care</i>	0.126 (0.634)	0.114 (0.624)	0.153 (0.646)	
<i>Other payer</i>	0.779** (0.273)	0.791** (0.271)	0.824** (0.268)	
<i>Age 25–29</i>	-2.259* (1.038)	-1.977 (1.047)	-1.857 (1.039)	
<i>Age 30–34</i>	-2.735** (1.029)	-2.465* (1.036)	-2.367* (1.032)	
<i>Age 35–39</i>	-1.749** (0.546)	-1.478** (0.555)	-1.403** (0.541)	
<i>Age 40–44</i>	-0.692* (0.321)	-0.439 (0.326)	-0.389 (0.317)	
<i>Age 45–49</i>	-0.669* (0.321)	-0.491 (0.326)	-0.495 (0.317)	

**Table 4** (continued)

Variable	Estimate set <sup>c</sup>			
	1	2	3	4
<i>Age 50–54</i>	(0.300) -0.653* (0.316)	(0.299) -0.477 (0.315)	(0.293) -0.488 (0.309)	
<i>Age 55–59</i>	(0.307) -0.762* (0.307)	(0.308) -0.656* (0.308)	(0.303) -0.667* (0.303)	
<i>Age 60–64</i>	(0.270) -0.275 (0.270)	(0.269) -0.179 (0.269)	(0.265) -0.204 (0.265)	
<i>Age 70–74</i>	(0.186) 0.223 (0.186)	(0.185) 0.209 (0.185)	(0.185) 0.200 (0.185)	
<i>Age 75–79</i>	(0.182) 0.621*** (0.182)	(0.183) 0.606*** (0.183)	(0.182) 0.593** (0.182)	
<i>Age 80–84</i>	(0.176) 1.153*** (0.176)	(0.176) 1.141*** (0.176)	(0.176) 1.129*** (0.176)	
<i>Age 85–90</i>	(0.186) 1.654*** (0.186)	(0.186) 1.638*** (0.186)	(0.186) 1.617*** (0.186)	
<i>Age 90–94</i>	(0.229) 2.330*** (0.229)	(0.229) 2.325*** (0.229)	(0.229) 2.311*** (0.229)	
<i>Relative risk prediction model</i>		0.328*** (0.058)		
<i>Relative risk prediction model with Secondary diagnosis information</i>			0.385*** (0.027)	
<i>Constant</i>	(0.210) -7.456*** (0.210)	(0.228) -8.041*** (0.228)	(0.219) -8.424*** (0.219)	
Number of observations	1,308,080	1,308,080	1,308,080	21,397
Pseudo R-squared <sup>d</sup>	0.059	0.063	0.078	0.008
Percent correctly classified <sup>e</sup>	99.92	99.93	99.93	–

<sup>a</sup> Logit (or conditional logit) coefficient estimates and standard errors (in parentheses) are reported. An odds ratio can be obtained by exponentiating a coefficient estimate.

<sup>b</sup> Significance levels: \*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$

<sup>c</sup> The Estimate Sets are described in Table 1 of the manuscript.

<sup>d</sup> The Pseudo R-squared for the conditional logit estimates, Estimate Set 4, is not comparable to that for the logit models, Estimate Sets 1–3, because the Pseudo R-squared is based only the ambulatory surgery center dummy variables, and the seven yearly dummy variables (the information on sex, race, payer, age, and primary and secondary diagnoses having been conditioned out in the fixed effect for cohorts).

<sup>e</sup> For the three logit models, Estimate Sets 1–3, the cut-off value to calculate the percent correctly classified was selected so that predicted number of adverse events was approximately equal to the number of adverse events in the estimate sample. Note that in the conditional logit model, Estimate Set 4, the focus is on the parameter estimates; no specific prediction for a given cohort is calculable since the fixed effect for the cohort is conditioned out to obtain consistent estimates of the relevant parameters.

**Table 5** Full estimation results for cataract procedure <sup>a,b</sup>

Variable	Estimate set			
	1	2	3	4
<i>Ambulatory surgery center</i>	0.054 (0.196)	0.055 (0.196)	0.114 (0.201)	-0.109 (0.268)
<i>Year 1998</i>	-0.017 (0.222)	-0.017 (0.222)	-0.016 (0.222)	-0.099 (0.249)
<i>Year 1999</i>	-0.134	-0.135	-0.139	-0.219

Table 5 (continued)

Variable	Estimate set			
	1	2	3	4
	(0.242)	(0.242)	(0.242)	(0.258)
<i>Year 2000</i>	0.112	0.111	0.106	0.028
	(0.196)	(0.196)	(0.196)	(0.249)
<i>Year 2001</i>	-0.200	-0.201	-0.210	-0.262
	(0.240)	(0.240)	(0.240)	(0.269)
<i>Year 2002</i>	-0.373	-0.374	-0.386	-0.600*
	(0.236)	(0.236)	(0.234)	(0.291)
<i>Year 2003</i>	-0.087	-0.088	-0.102	-0.278
	(0.255)	(0.255)	(0.254)	(0.267)
<i>Year 2004</i>	-0.118	-0.119	-0.133	-0.213
	(0.210)	(0.209)	(0.207)	(0.265)
<i>Female</i>	-0.288*	-0.270*	-0.258*	
	(0.118)	(0.130)	(0.125)	
<i>Hispanic</i>	-0.053	-0.051	-0.048	
	(0.229)	(0.228)	(0.227)	
<i>Other minority</i>	0.019	0.019	0.020	
	(0.198)	(0.198)	(0.198)	
<i>Black</i>	-0.593	-0.593	-0.601	
	(0.507)	(0.507)	(0.506)	
<i>Medicare HMO</i>	-0.473	-0.471	-0.469	
	(0.276)	(0.277)	(0.276)	
<i>Medicaid</i>	0.313	0.313	0.313	
	(0.543)	(0.543)	(0.543)	
<i>Private insurance</i>	-0.126	-0.124	-0.117	
	(0.292)	(0.291)	(0.291)	
<i>Private HMO</i>	-0.182	-0.181	-0.176	
	(0.258)	(0.258)	(0.258)	
<i>Self Payer</i>	-0.102	-0.097	-0.086	
	(0.545)	(0.543)	(0.542)	
<i>Other payer</i>	-0.634	-0.633	-0.628	
	(0.558)	(0.557)	(0.557)	
<i>Age 35–39</i>	0.850	0.928	0.941	
	(0.982)	(0.989)	(0.981)	
<i>Age 40–44</i>	-0.009	0.071	0.090	
	(1.048)	(1.052)	(1.048)	
<i>Age 45–49</i>	-0.735	-0.675	-0.661	
	(1.049)	(1.089)	(1.058)	
<i>Age 50–54</i>	0.250	0.308	0.320	
	(0.517)	(0.516)	(0.518)	
<i>Age 55–59</i>	-0.555	-0.523	-0.519	
	(0.568)	(0.569)	(0.569)	
<i>Age 60–64</i>	-0.878	-0.847	-0.844	
	(0.461)	(0.483)	(0.466)	
<i>Age 70–74</i>	-0.277	-0.280	-0.281	
	(0.233)	(0.233)	(0.233)	
<i>Age 75–79</i>	0.212	0.209	0.208	
	(0.247)	(0.247)	(0.247)	
<i>Age 80–84</i>	0.574**	0.571**	0.572**	
	(0.203)	(0.203)	(0.203)	

**Table 5** (continued)

Variable	Estimate set			
	1	2	3	4
Age 85–90	1.018*** (0.227)	1.017*** (0.227)	1.019*** (0.227)	
Age 90–94	1.377*** (0.296)	1.377*** (0.296)	1.381*** (0.296)	
Relative risk prediction model		0.102 (0.163)		
Relative risk prediction model with Secondary diagnosis information			0.132 (0.085)	
Constant	–8.869*** (0.297)	–9.042*** (0.426)	–9.166*** (0.388)	
Number of observations	2,031,487	2,031,487	2,031,487	913,403
Pseudo R-squared <sup>d</sup>	0.016	0.016	0.017	0.002
Percent correctly classified <sup>e</sup>	99.94	99.97	99.97	–

<sup>a</sup> Logit (or conditional logit) coefficient estimates and standard errors (in parentheses) are reported. An odds ratio can be obtained by exponentiating a coefficient estimate.

<sup>b</sup> Significance levels: \*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$

<sup>c</sup> The Estimate Sets are described in Table 1 of the manuscript.

<sup>d</sup> The Pseudo R-squared for the conditional logit estimates, Estimate Set 4, is not comparable to that for the logit models, Estimate Sets 1–3, because the Pseudo R-squared is based only the ambulatory surgery center dummy variables, and the seven yearly dummy variables (the information on sex, race, payer, age, and primary and secondary diagnoses having been conditioned out in the fixed effect for cohorts).

<sup>e</sup> For the three logit models, Estimate Sets 1–3, the cut-off value to calculate the percent correctly classified was selected so that predicted number of adverse events was approximately equal to the number of adverse events in the estimate sample. Note that in the conditional logit model, Estimate Set 4, the focus is on the parameter estimates; no specific prediction for a given cohort is calculable since the fixed effect for the cohort is conditioned out to obtain consistent estimates of the relevant parameters.

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