Quantifying Trends in Florida Hospital Medical Malpractice Claims Using a Mixed Effects Approach

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This study examines the relative quality of healthcare services delivery in acute care hospitals within the State of Florida. Closed medical malpractice claims were chosen as the primary performance metric due to their standardized reporting requirements. Using a mixed-effect model, we prove that there was a significant yearly downward trend of malpractice claims from 2011 to 2016. And the downward trend after 2011 is significantly stronger than that before 2010. It can be suggested that healthcare quality in acute care hospitals in Florida has significantly improved over the ten years from 2006 through 2016.

INTRODUCTION

Though the issues of patient safety and medical malpractice have been extensively studied, the use of such studies to inform healthcare organizational management has received much less attention. The development of quantifiable outcome indicators of healthcare quality are vital additions to existing knowledge and necessary implements for the pursuit of improved quality in healthcare (Bij & Vissers, 1999). This study undertakes an examination of closed medical malpractice claims from the State of Florida for the years 2006-2016 (inclusive) in order to establish benchmarks and examine potential trends.

Generalizing from marketing and services marketing literature, as well as healthcare administration literature, suggests that reduction of medical malpractice claims may be expected to result in a lessening of the human and financial costs to patients and providers that result from disputes concluded through a third-party complaint resolution processes, and in particular, the filing and prosecution of medical malpractice claims (Young & Williams, 2010).

Marketing literature suggests a primary cause of medical malpractice claims is disconfirmation of patient expectations and dissatisfaction with service quality. The intangible nature of service provider interactions with customers makes it difficult to measure the factors comprising the service operation. Smith and Houston (1983) state, "…satisfaction with services is related to confirmation or disconfirmation of expectations", and when consumers do not perceive services as meeting or exceeding their expectations they have feelings of dissatisfaction with the service operation, technical service quality, or treatment outcomes, often referred to in services marketing literature as negative disconfirmation of expectations (Szymanski 2001). Virshup and Oppenberg opine that "Many malpractice suits are brought not because of malpractice nor even because of complaints about the quality of medical care but as an expression of anger about some aspect of patient-doctor relationships and communications" (Virshup, Oppenberg, & Coleman, 1999).

Providing quantitative measures, and quantitative peer-based data-driven comparative benchmarks is a principal and accepted tool in the study of healthcare outcomes and performance. Such measures and benchmarks provide constructive information to healthcare managers in their efforts to realize organizational objectives (Young, 2005).

Over the past two decades there has been a major focus on the quality and cost of healthcare in the United States. According to Hartman (Hartman, et al, 2018), the United States spends about 18% of its gross domestic product (GDP) on healthcare, which represents approximately $3.3 trillion annually. A significant concern is that such high healthcare expenditures could cause negative impacts on the overall U.S. economy.

Given the vast sums the United States spends on healthcare, healthcare quality has become a persistent concern as waste in the U.S. health care system contributes to the high cost of medical care and deflects resources from other desirable societal goals. (Bentley, Effros, Palar, & Keeler, 2008); Nordgren, Johnson, Kirschbaum, & Peterson, 2004). Leape et al. (Lucian L. Leape, Brennan, Laird, & al., 1991) stated that in 1984, 3.7% of the patients admitted to hospitals in the state of New York sustained some type of injury. Nearly 28% of the injuries were due to negligence. A combined study of 4,000 patients at Brigham and Women's Hospital and at Massachusetts General Hospital in Boston sought to investigate the relationship between systems failures and the occurrence of medical errors (Bates et al., 1995). In the study, 334 medication errors that led to 264 adverse drug effects were identified.

The Harvard Medical Practice Study declared that more than one million preventable medical errors occur in hospitals throughout the United States each year resulting in 180,000 preventable deaths (Brennan, Hebert, & al, 1991; Lucian L Leape & Brennan, 1991). The Institute of Medicine (Institute of Medicine, 1999) in its publication "To Err is Human: Building a Safer Health System", estimated the annual number of preventable deaths between 44,000 and 98,000. James (James, 2013) concluded both the Harvard and the IOM studies above underestimated the number of premature deaths associated with preventable harm to patients, and determined it at more than 400,000 per year, with serious harm 10- to 20-fold more common than lethal harm. Zhan and Miller (Zhan & Miller, 2003) found medical error rates in teaching hospitals are greater than in nonteaching hospitals (3.61 per 1,000 patients versus 2.08 per 1,000 patients). Further, larger hospitals with 200 or more beds had a higher medical error rate than smaller hospitals. They also found that serious medication errors decrease when physician work hours are reduced.

Reason (Reason, 1990) discovered that individual human errors are a major cause of medical errors. Many of the human errors were caused by faults that existed in the design of work and the conditions that people work in. For instance, work conditions that mandated high workloads and caused fatigue induced errors in the workplace. Improper training of employees also leads to accidents. Reason stated that these errors could be prevented by changing systems, which involves designing tasks that are fool-proof. Fool-proofing requires standardizing tasks, simplifying tasks, and avoiding a reliance on memory to successfully complete tasks.

In response to the troubling number of medical errors, many hospitals have undertaken initiatives targeted toward patient safety (Barry & Smith, 2005). According to Stock (Stock, McFadden, & Gowen, 2007) hospitals have implemented quality programs that have led to a reduction in the frequency and severity of medical errors. Hospitals have implemented a set of Patient Safety Indicators (PSI) developed by the Agency for Healthcare Research and Quality (AHRQ); Gray et al (Gray, et al 2016) states their study "demonstrated a clear association between clinically validated PSIs and patient outcomes—LOS, 30-day unplanned readmission, and mortality. These findings have important implications in policy and practice as health care reform dictates improvement in the experience of care, improvement in the health of populations, and reduction in per capita cost of health care—also known as the Triple Aim."

Errors in medical practice often bring about medical malpractice claims. Medical malpractice has an adverse impact on the healthcare delivery system, increasing healthcare delivery cost and forcing some practitioners into bankruptcy; a consequence is a reduction in access to healthcare services (Young, 2005). According to Williams (Williams, 2008), Florida patients sue for medical malpractice far more often than average for any other state. Hence, it is important to assess the quality of the healthcare delivery to ensure that medical errors that lead to malpractice claims are eliminated.

Young and Williams (Young & Williams, 2010) analyzed hospital susceptibility as it relates to the skill set of human resources (physicians and nurses) and the hospital propensity to medical malpractice claims. Their focus was on 118 acute-care hospitals in the State of Florida. Young's (Young, 2005) results show that the skill sets of hospital human capital had a significant impact on the number of malpractice claims. Hospitals with a larger number of employed physicians tend to have a lower number of medical malpractice claims than do hospitals with a larger number of resident physicians. Further, hospitals with a higher number of registered nurses had a lower number of claims than do hospitals with a larger number of licensed practical nurses.

The elemental rationale for the existence of healthcare organizations is to deliver healthcare services that are intended to improve health. Medical malpractice is an outcome of this care delivery process and represents a failure to adequately deliver healthcare (Hickson et al., 2002). Occasionally this produces not a benefit, but a detriment to health outcomes. As a malfunction of the hospital health services delivery process, malpractice does not contribute to the organization's efforts to meet its goals (Mello & Gallagher, 2010). The negative aspects of medical malpractice detract from the ability of hospitals to optimize the access, quality, and cost of healthcare. Malpractice is an indication of ineffectiveness and viewed from this perspective hospital malpractice claims are one metric that may be used to evaluate this negative organizational performance (Young & Qu, 2018).

This study focused on the assessment of healthcare quality over the decade 2006-2016. The objective was to determine if healthcare quality had improved based on a readily available quantitative peer-based metric, i.e. the number of medical malpractice claims in Florida acute care hospitals. Hospitals should be able to explore relationships between their performance as developed by this study and other internally and externally developed performance measures (Bell, Delbanco, Anderson-Shaw, McDonald, & Gallagher, 2011); such studies will inform management's strategic planning, goal setting, and resource allocation decisions.

DATA DESCRIPTION

In this study, data from the Florida Department of Insurance's Medical Professional Liability Closed Claims were analyzed. The sample consisted of general, non-federally owned, acute care hospitals in the State of Florida. The original data set contained 107,413 records. We focused on identifying trends in medical malpractice claims from 2006 to 2016, which reduced the sample size to 39,049 observations. After removing duplicate observations to insure that each medical malpractice claim was counted only once, 21,692 unique medical malpractice claims remained.

The malpractice claims are categorized by cities in Florida. We observed that in total 313 cities have at least one malpractice claim from 2006 to 2016. Of these, 142 cities have at least 7 years of malpractice claims, and account for 96.7% of the total claims. To ensure the reliability of the trend analysis, cities in our study sample should have an adequate number of years that include malpractice claims. Therefore, we focus on these 142 cities in presenting our findings.

Our data also includes the patient severity outcomes (i.e. the degree of harm or injury) from the malpractice claims (Table 1). Understandably, the "Death (D)" outcome is the most severe and the "Emotional Only (EO)" would be the least severe. We seek to determine if trends in medical malpractice claims may be a proxy measure for healthcare quality over time for all levels of outcomes severity, with a particular emphasis on the rate of wrongful deaths.

The use of administrative data has proven to be revealing in previous studies and is accepted practice in healthcare research. Administrative data has the notable advantages of lower cost, easier acquisition, large data sets, and in this instance where statutorily mandated data is reported, consistency of reported information and has been the subject of significant development for use in the study of healthcare and adverse events.

TABLE 1
SEVERITY OF PATIENT OUTCOMES RESULTING FROM MEDICAL MALPRACTICE

Severity	Severity Description
Death (D)	Permanent: Death.
Emotional Only (EO)	Emotional Only - Fright, no physical damage
Permanent Grave (PG)	Permanent: Grave - Quadraplegia, severe brain damage, lifelong care or fatal prognosis.
Permanent Major (PMJ)	Permanent: Major - Paraplegia, blindness, loss of two limbs, brain damage.
Permanent Minor (PMN)	Permanent: Minor - Loss of fingers, loss or damage to organs. Includes non-disabling injuries.
Permanent Significant (PS)	Permanent: Significant - Deafness, loss of limb, loss of eye, loss of one kidney or lung.
Temporary Major (TMJ)	Temporary: Major - Burns, surgical material left, drug side effect, brain damage. Recovery delayed.
Temporary Minor (TMN)	Temporary: Minor - Infections, misset fracture, fall in hospital. Recovery delayed.
Temporary Slight (TS)	Temporary: Slight - Lacerations, contusions, minor scars, rash. No delay.

Heterogeneity between Cities

To display the heterogeneity of malpractice claims between cities, we calculate the total number of malpractice claims from 2006-2016 for each of the 142 cities in the data sample. Shown in the histogram plot (Figure 1), although most of the cities (85 cities, 59.8%) have less than or equal 100 malpractice claims from 2006-2016, the number of malpractice claims can be very dissimilar between cities. For instance, Miami has in total 1798 malpractice claims and is ranked as the top city for malpractice claims. Tampa is the next city with the highest number of malpractice claims and has 1409 claim records. The bottom city for malpractice claims is Arcadia which has only 8 malpractice claims from 2006-2016. Since we are interested in examining the trend of total malpractice claims, the result from the histogram plot suggests that we need to account for the heterogeneity between cities when evaluating the trend of malpractice claims.

Trend of Malpractice Claims

In this section, we show model-free evidence of the trend of malpractice claims. For each year from 2006 to 2016, we compute the total number of malpractice claims across all 142 cities (Figure 2). We find that, the number of malpractice claims fluctuated from 2006 to 2010, then continuously decrease after 2011. And the downward trend of malpractice claims appears to be stronger since 2013. For example, the number of malpractice claims across all cities started at 2,612 in 2006, and increased to 2,811 in 2007 then dropped to 2,596 in 2008. From 2011 to 2016, the total malpractice claims continuously decreased from 2,363 to 140. The annual decreasing rates are 50.1% (e.g. (1235-619)/619=50.1%) and 77.4% (e.g. (619-140)/619=77.4%) in 2015 and 2016 respectively.

FIGURE 1
HISTOGRAM OF TOTAL NUMBER OF MALPRACTICE CLAIMS FROM 2006-2016 PER CITY (142 CITIES)

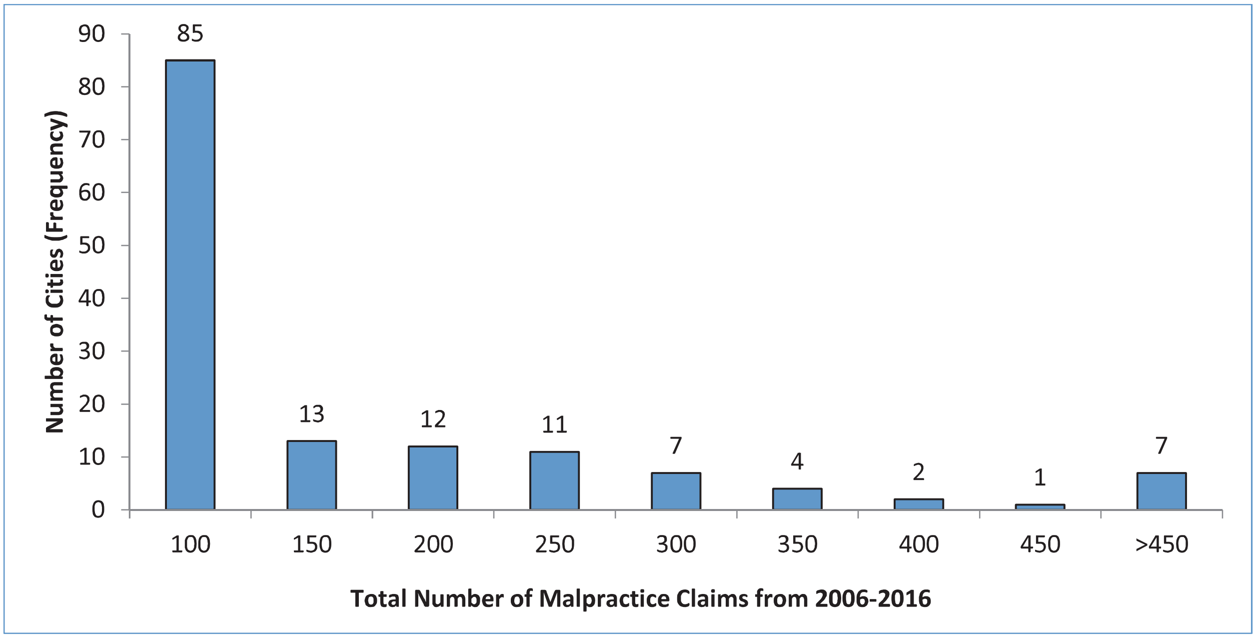
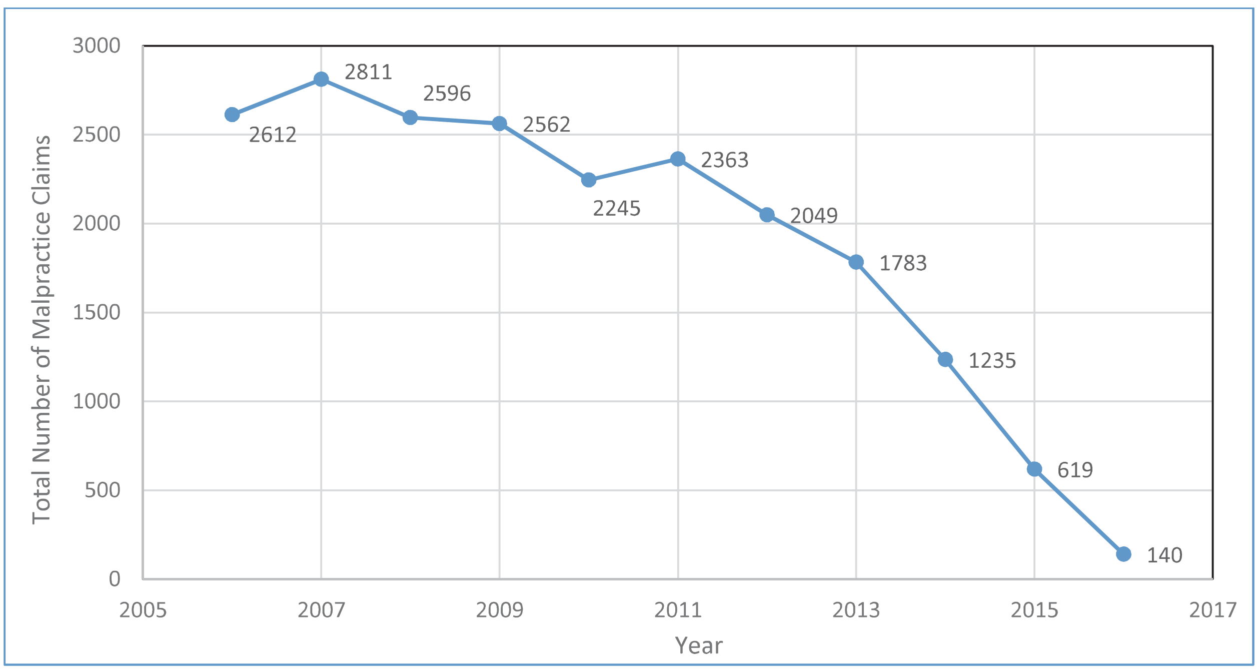


FIGURE 2
TOTAL NUMBER OF MALPRACTICE RECORDS PER YEAR



Next, we examine the total number of malpractice claims per year for each severity level (Table 2). We find that, the largest category of medical claims is "Death" which represents about 29% of the total medical claims (e.g. 6,098/21,015=29.0%). The next largest category is "TMN" which takes about

18.7% of the total claims (e.g. 3,935/21,015=18.7%). "PG" has the lowest number of medical claims which is about 3.5% of the totals (e.g. 725/21,015=3.5%).

In general, we observe a potential decreasing trend of malpractice claims for all severity levels. But both the pattern and degree of the trend can be different between severity levels. For example, the peak of malpractice claims (bold-faced numbers in Table 2) happens at different years between severity levels. Only "TMN" showed a continuously downward trend of malpractice claims from 2016 to 2016. For most of the severity levels, the number of malpractice claims fluctuated from 2006 to 2010, then continuously decrease after 2011.

TABLE 2
TOTAL NUMBER OF MALPRACTICE CLAIMS ACROSS ALL CITIES BY YEAR FOR EACH SEVERITY LEVEL

year	Severity Level									
	Death	PG	PMJ	PMN	PS	TMJ	TMN	TS	EO	Totals
2006	789	80	140	285	214	272	***487***	138	207	2612
2007	***822***	89	169	***335***	***221***	***286***	466	***174***	***249***	2811
2008	715	82	169	302	213	279	477	151	208	2596
2009	713	***117***	158	326	219	293	422	130	184	2562
2010	685	100	171	272	209	255	399	93	61	2245
2011	693	74	***175***	251	213	345	411	107	94	2363
2012	617	78	145	237	178	254	398	66	76	2049
2013	525	41	108	212	123	233	392	78	71	1783
2014	322	48	73	114	88	194	297	39	60	1235
2015	179	13	42	48	36	95	142	35	29	619
2016	38	3	1	8	5	19	44	9	13	140
Totals	6098	725	1351	2390	1719	2525	3935	1020	1252	21015

*Bold number shows the largest number of malpractice claims for each severity level.

In summary, the results provide preliminary evidence of the potential downward trend in the malpractice claims from 2006 to 2016. And we observe city-level heterogeneity in the number of malpractice claims which should be considered when performing the trend analysis.

METHODOLOGY

We chose a mixed-effect model to statistically quantify the trend of malpractice claims in Florida. A mixed-effect model is applied to situations where the variables in the data are grouped according to one or some classification factors (Pinheiro and Bates, 2000). In our study, the malpractice claims were categorized by individual city in Florida, thus the data is "grouped" by the classification factor of city. When the data is grouped, omitting the "group" effect can cause bias in the parameter estimation result, because the group variation merges the relationship between the response variable and covariates. We observe the "group" effect in the data because there is a considerable variability in the total malpractice claims between different cities (Figure 1). In our study, the primary interest is to quantitatively identify the relationship between the number of malpractice claims and the year, e.g. the trend of malpractice. To reach an unbiased estimation result, we need to consider the "group" effect in the model.

The "group" effect can be treated in two ways. One is the fixed effect model where we obtain a fixed or non-random estimation of model parameter for each individual group to demonstrate its effect on the response variable (Greene, 2011; Gardiner, et. al, 2009). The fixed-effect model is used when we have a finite number of groups, such as female vs. male, or control vs. experimental groups etc. The "group" effect can also be treated as "random" where the model parameters are considered as random variables from a population (Fisher, 1918; Pinheiro and Bates, 2000). In a random-effect model, we view the groups in the data as a randomly selected sample from a population thus focusing on estimating the distribution of the "group" population. In our data, the malpractice claim records come from 142 cities in Florida thus treating the "group" as random sample from a population is more reasonable. A mixed-effect model means that the model contains both "fixed" and "random" parameters therefore it is a combination of both fixed-effect and random-effect models. Mixed-effect model is well-established method and has been widely applied in multiple disciplines including Economics (Greene, 2011; Arauzo, 2005), Biology (Fisher, 1918; Dingemanse and Dochtermann, 2013), Engineering (Heegaard et.al, 2005; Bukoski, et.al, 2017), Public Health (Oskrochi et.al, 2016), Education (Dupuis et. al, 2013) and Management (Cherrington et. al, 2008) etc.

We demonstrate the mixed-effect model as following:

$$Y_{it} = \mu + \alpha_i + \beta t + \varepsilon_{it} \tag{1}$$

where:

- Yit is the number of malpractice claims in the city (i) at year (t).
- t is the indicator of year. We use t = 1 to 11 to represent the year from 2006 to 2016 in our data.
- μ is the intercept of the model. It represents the average number of malpractice claims per year per city for the entire (city) population in Florida when t equals 0.
- α_i is the city-specific random effect (e.g. the group effect). It measures the difference between the number of malpractice claims per year in city (i) and the average (e.g. μ) score of the entire city population. As described before, the random-effect parameter α_i is considered as a random variable from a population, therefore, it is assumed to follow a normal distribution ($N(0, \sigma_\alpha^2)$). σ_α^2 is the variance of the random-effect parameter α_i and will be estimated by the model.
- ε_{it} is the model residuals which follows the normal distribution assumption of ($N(0, \sigma_\varepsilon^2)$).
- β is the coefficient of year (t). It captures the relationship between the number of malpractice claims and year (t). In our study, we view the relationship as a fixed-effect function, e.g. the parameter β is treated as a fixed-effect.

To formalize the relationship, we include two sources of variance, e.g. the two random effects of α_i and ε_{it} to account for both the between-group and the unobserved variation (e.g. variance not captured by the model) in the malpractice claims data. The estimation of β provides us two important pieces of information on the trend of malpractice claims. The sign of β shows the direction of the trend. If β is estimated to be significantly negative, we statistically prove that the number of malpractice in Florida is decreasing from 2006 to 2016 and vice versa. And the value of β indicates the degree of the trend, e.g. the annual reduction rate of the malpractice claims per city.

RESULT

Total Malpractice Claims

We first fit the mixed-effect model via the total malpractice claims records including all severity levels. The model estimation results (Table 3) shows that, all the parameters are statistically significant (e.g. p-value < 0.0001). The city-level variance (σ_α^2) is estimated to be 476.59 (e.g. p-value < 0.0001) indicating a significant dispersion of the malpractice claims between cities in Florida. Therefore, it is necessary to account for the "group" effect when evaluating the "trend' of malpractice claims.

In the model estimation result, we have special interests in the coefficient β as it indicates the "trend" of total malpractice claims over time. From Table 3, we can see that the β is estimated to be significantly negative (p-value < 0.0001). This result statistically proves that there is a significant downward trend of total malpractice claims from 2006 to 2016 in Florida. Moreover, β has a value of -1.95 which suggests that, the annual reduction rate of the malpractice claims is approximately -1.95 per city.

TABLE 3
MIXED-EFFECT MODEL PARAMETER ESTIMATION RESULT FOR TOTAL MALPRACTICE CLAIMS

Parameters	Estimates	Std. Error	P-value
μ	24.92	1.97	<0.0001
β	-1.95	0.11	<0.0001
σ_α^2	478.59	58.71	<0.0001
σ_ε^2	153.55	6.20	<0.0001

Malpractice Claims by Each Severity Level

As shown in Table 2, the trend of malpractice claims can be different between malpractice severity levels. To examine such difference, we fit the mixed-effect model on the malpractice claim records for each severity level separately.

From the model estimation result (Table 4), we observe that coefficient (β) of the "Death" (D) malpractice is significantly negative (β=-0.64, p-value < 0.0001). This means that there is a significant downward trend of "Death" malpractice claims from 2006 to 2016. The value of β suggests that the annual reduction rate of the "Death" malpractice claims is approximately 0.64 per city, which is the largest among all the severity level.

The "EO" malpractice claims category has the second largest decreasing trend over time. The β estimation is statistically significant and has a value of -0.38. This suggests that, on average, the annual reduction rate of "EO" malpractice claims is about 0.38 per city. The "TMN" malpractice claims category follows the "EO" and presents the third level decreasing trend over time. The β is estimated to be -0.32 with p-value less than 0.0001.

The "PG" malpractice claims category has the smallest decreasing trend (e.g. β =-0.07). The p-value of coefficient β is greater than 0.05, meaning that, the decreasing trend of "PG" malpractice claims is not statistically significant at 0.05 significance level.

The city-level variance (σ_α^2) is statistically significant (e.g. p-value < 0.0001) for all severity levels. This result further indicates that, for each severity level, the malpractice can vary significantly between cities.

In summary, we quantitatively demonstrate that, for most of the severity levels, the malpractice claims significantly decrease over time. The degree of the decreasing trend is different between severity levels and the "Death" malpractice claim has the largest annual reduction rate.

Malpractice Claims before 2010 vs. after 2011

Shown in our preliminary analysis (Figure 2), the number of malpractice claims fluctuated from 2006 to 2010, then continuously decreased after 2011. To quantitatively evaluate whether the changes of malpractice claims can be different between the two time frames, we perform the mixed-effect model on the data before 2010 and after 2011 separately, and examine both the total malpractice claims and the malpractice claims of each severity level.

Table 5 only shows the model estimation results of the coefficient (β), which are our primary interests here. The complete model estimation including both the intercept (μ) the variance terms of σ_α^2 and σ_ε^2 is provided in Appendix A. We utilize the Z-score (Equation 2) and the associated p-value to statistically compare the parameter estimation outcomes between the two time frames (Clogg, et. al., 1995; Paternoster, et.al, 1998).

$$Z = \frac{\beta_2 - \beta_1}{\sqrt{SE(\beta_1)^2 + SE(\beta_2)^2}} \quad (2)$$

where β_2 is the parameter estimation after 2011 and β_1 is that before 2010, and SE is the standard error estimation of the two parameters.

TABLE 4
MIXED-EFFECT MODEL PARAMETER ESTIMATION RESULT FOR MALPRACTICE CLAIMS OF EACH SEVERITY LEVEL

Parameters	Estimates	Std. Error	P-value	Parameters	Estimates	Std. Error	P-value
Severity: D				Severity: PG			
μ	8.20	0.65	<0.0001	μ	2.25	0.24	<0.0001
β	-0.64	0.06	<0.0001	β	-0.07	0.04	0.0586
σ_α^2	42.24	5.42	<0.0001	σ_α^2	1.09	0.23	<0.0001
σ_ε^2	25.98	1.25	<0.0001	σ_ε^2	2.92	0.25	<0.0001
Severity: PMJ				Severity: PMN			
μ	2.79	0.27	<0.0001	μ	3.90	0.31	<0.0001
β	-0.11	0.04	0.0033	β	-0.27	0.04	<0.0001
σ_α^2	2.87	0.47	<0.0001	σ_α^2	7.69	1.05	<0.0001
σ_ε^2	4.58	0.32	<0.0001	σ_ε^2	6.23	0.35	<0.0001
Severity: PS				Severity: TMJ			
μ	3.21	0.24	<0.0001	μ	3.52	0.28	<0.0001
β	-0.18	0.03	<0.0001	β	-0.16	0.03	<0.0001
σ_α^2	3.01	0.46	<0.0001	σ_α^2	6.08	0.84	<0.0001
σ_ε^2	4.21	0.26	<0.0001	σ_ε^2	5.12	0.29	<0.0001
Severity: TMN				Severity: TS			
μ	5.09	0.43	<0.0001	μ	2.55	0.18	<0.0001
β	-0.32	0.04	<0.0001	β	-0.17	0.03	<0.0001
σ_α^2	16.89	2.21	<0.0001	σ_α^2	1.22	0.21	<0.0001
σ_ε^2	12.98	0.65	<0.0001	σ_ε^2	0.48	0.18	<0.0001
Severity: EO							
μ	4.03	0.6728	<0.0001				
β	-0.38	0.10	<0.0001				
σ_α^2	12.51	2.38	<0.0001				
σ_ε^2	38.07	2.67	<0.0001				

We first examine the estimation result of the total malpractice claims (Table 5). We find that, the total malpractice claims has significantly decreasing trends both before 2010 and after 2011 (p-values of β estimation < 0.001 for both time frames). Further, we obtain a Z-score of -8.95 with the associated p-value less than 0.0001. This means that the downward trend after 2011 is statistically stronger than that before 2010. Specifically, we observe an annual reduction rate of 4.06 per city after year 2011 which is 5.37 times of the reduction rate of 0.76 before 2010 (e.g. 4.06/0.76 = 5.37).

Next, we look at the estimation results of each severity level (Table 5). In the first time frame (e.g. before 2010), only "Death" and "TMN" malpractice have significantly negative β estimation outcomes (e.g. p-value < 0.05). All other severity levels show no significant trends in their malpractice claims. And the direction of trend is inconsistent between severity levels. We observe both positive and negative, although non-significant, trend of malpractice claims. For example, the β is positive for severity level of "PG", "PMJ" and "PMN" and is negative for "PS", "TMN", "TMJ" and "EO". The inconsistent and non-significant trends in most of the severity levels can be due to the fluctuation of the malpractice claims from 2006 to 2010 as shown in both Figure 2 and Table 2.

The trend of malpractice claims is clear and consistent after 2011. Except for "PG", we observe a significantly negative trend of malpractice claims for all severity levels (e.g. p-values of β estimations < 0.05). The trend of "PG" malpractice is also negative but non-significant (e.g. β= -0.18, p-value=0.150). One possible reason of the non-significant trend in "PG" could be the relatively low quantities of observations in the "PG" malpractice claim. Shown in Table 2 that, the largest number of "PG" malpractice including all 142 cities is 117 in year 2009, while in most of the years, the number "PG" malpractice claims are below 100. With the low benchmark level of the "PG" claim records, it is reasonable to get a non-significant downward trend because there is less potential for the number of malpractice claims to decrease further. In summary, the estimation results tell us that, after 2011, cities in Florida observed significantly decreasing malpractice claims in all severity levels.

When we compare the results before 2010 and after 2011 for each severity level, we realize that, except for "TS" and "EO", the β estimations are significantly more negative after 2011 than those before 2010. This suggests that, for most of severity levels, we observe significantly stronger downward trend after 2011 than before 2010. For "TS", the β estimation is more negative after 2011 (e.g. β=-0.18) than that before 2010 (e.g. β=-0.10) but the difference is not statistically significant. And for "EO", the β estimation is less negative after 2011 than before 2010. In summary, we are able to statistically prove that, for most of the severity levels, the downward trend of malpractice claims after 2011 is significantly stronger than that before 2010.

TABLE 5
MIXED-EFFECT MODEL PARAMETER (β) ESTIMATION RESULT FOR COMPARING THE MALPRACTICE CLAIMS BEFORE 2010 AND AFTER 2011

Estimates	Std. Error	P-value	Estimates	Std. Error	P-value	Z-value	P-value
All Severity Levels (2006-2010)			All Severity Levels (2011-2016)			All Severity	
-0.76	0.21	0.0003	-4.06	0.31	<0.0001	-8.95	<0.0001
Severity: D (2006-2010)			Severity: D (2011-2016)			Severity: D	
-0.33	0.13	0.0121	-1.46	0.172	<0.0001	-5.19	<0.0001
Severity: PG (2006-2010)			Severity: PG (2011-2016)			Severity: PG	
0.18	0.09	0.0502	-0.18	0.12	0.15	-2.36	0.009
Severity: PMJ (2006-2010)			Severity: PMJ (2011-2016)			Severity: PMJ	
0.15	0.09	0.0923	-0.54	0.14	0.0002	-4.18	<0.0001
Severity: PMN (2006-2010)			Severity: PMN (2011-2016)			Severity: PMN	
0.01	0.08	0.853	-0.57	0.11	<0.0001	-4.30	<0.0001
Severity: PS (2006-2010)			Severity: PS (2011-2016)			Severity: PS	
-0.05	0.08	0.5524	-0.62	0.11	<0.0001	-4.38	<0.0001
Severity: TMJ (2006-2010)			Severity: TMJ (2011-2016)			Severity: TMJ	
-0.01	0.07	0.9016	-0.68	0.09	<0.0001	-5.69	<0.0001
Severity: TMN (2006-2010)			Severity: TMN (2011-2016)			Severity: TMN	
-0.21	0.09	0.0186	-0.80	0.14	<0.0001	-3.71	<0.0001
Severity: TS (2006-2010)			Severity: TS (2011-2016)			Severity: TS	
-0.10	0.07	0.1425	-0.18	0.07	0.0142	-0.81	0.208
Severity: EO (2006-2010)			Severity: EO (2011-2016)			Severity: EO	
-0.52	0.29	0.0773	-0.16	0.06	0.0079	1.19	0.117

LIMITATIONS

This study has several limitations. While we believe that the legal environment for the data utilized was relatively consistent, factors such as the Affordable Care Act and other potential environmental variables are unaccounted for. Hospital characteristics other than those used in this study may have affected outcomes performance but were not evaluated in this study. Given the limitations of existing risk-adjustment techniques and data sources, hospital outcomes measures represent an approximation for comparing hospital quality. This study was based on administrative databases, and although this strategy has worked well in other studies, it is not known that the characteristics described by the data encompass the majority of the significant sources of variation in outcomes performance.

The limitation of generalizability is certainly present in this study, as it is composed only of Florida general acute care hospitals. It is anticipated that there will be significant variation between the malpractice claims rates of differing states, given that there is little uniformity in tort law from state to state. Further study is needed to determine if the study's methodology and findings may apply to hospitals in other states, and types of hospitals other than the ones encompassed by this study.

Medical malpractice closed-claims data provides a limited view of patient experiences with errors, adverse outcomes, and patient safety. Previous studies have raised the concerns that most negligence never leads to a malpractice claim and most claims are not the result of negligence.

It is not yet advisable to judge quality on administrative data alone in studying comparative hospital performance. Administrative data may well be used for preliminary quality control and evaluation, but until administrative information systems develop further in capturing significant factors responsible for performance variations, no definitive conclusions should be drawn.

DISCUSSION AND CONCLUSIONS

This study makes several contributions to the literature, and to the knowledge base of healthcare administration and management scholars. The study's results corroborate the belief that there was heterogeneity between the malpractice claims performance of the subject healthcare cities. The study established a scientifically-based methodology for the measurement of trends in Florida healthcare districts' malpractice claims performance and shed light on variations between city-to-city performances on relative healthcare quality. Further research is needed to better explain the characteristics of these variations. The study results do give a plausible explanation for the underlying resource-based view assumption that Florida hospitals and healthcare cities possess distinctive characteristics and capabilities and that further studies of the relationship between hospital characteristics and outcomes is warranted.

This research sought to assess the quality of the healthcare delivery systems within the State of Florida using data from the Florida Department of Insurance's closed medical malpractice claim files. Medical malpractice claims were used as the primary performance metric and we focus on the 142 cities with at least 7 years of malpractice claims to statistically test the trend of malpractice claims over time. The data analysis showed that from 2006 to 2011, the number of malpractice claims oscillated with the highest claims of 2,811 happening in 2007. Using a mixed-effect model, we statistically prove that there was a significant yearly downward trend from 2011 to 2016. And the downward trend of malpractice claims after 2011 is significantly stronger than that before 2010. If the number of (a) malpractice claims and (b) deaths from malpractice can be used to represent healthcare quality, it can be concluded that healthcare quality in the State of Florida slightly fluctuated from 2006 to 2011 and has significantly improved since 2012.

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APPENDIX A

MIXED-EFFECT MODEL PARAMETER ESTIMATION RESULTS BEFORE 2010 AND AFTER 2011

Parameters	Estimates	Std. Error	P-value	Estimates	Std. Error	P-value
All Severity Levels (2006-2010)				All Severity Levels (2011-2016)		
μ	20.46	2.48	<0.0001	23.10	1.76	<0.0001
β	-0.76	0.21	0.0003	-4.06	0.31	<0.0001
σ_α^2	804.69	97.22	<0.0001	278.42	36.50	<0.0001
σ_ε^2	57.19	3.47	<0.0001	149.59	9.05	<0.0001
Severity: D (2006-2010)				Severity: D (2011-2016)		
μ	6.89	0.83	<0.0001	8.50	0.71	<0.0001
β	-0.33	0.13	0.0121	-1.46	0.17	<0.0001
σ_α^2	68.32	8.71	<0.0001	25.84	4.01	<0.0001
σ_ε^2	17.84	1.24	<0.0001	25.98	2.00	<0.0001
Severity: PG (2006-2010)				Severity: PG (2011-2016)		
μ	1.52	0.34	<0.0001	2.28	0.35	<.0001
β	0.18	0.09	0.0502	-0.18	0.12	0.1499
σ_α^2	1.84	0.41	<0.0001	0.74	0.28	0.0044
σ_ε^2	2.77	0.33	<0.0001	2.51	0.37	<.0001
Severity: PMJ (2006-2010)				Severity: PMJ (2011-2016)		
μ	1.99	0.34	<0.0001	3.60	0.43	<0.0001
β	0.15	0.09	0.0923	-0.54	0.14	0.0002
σ_α^2	3.48	0.62	<0.0001	2.91	0.67	<0.0001
σ_ε^2	3.62	0.36	<0.0001	5.91	0.66	<0.0001
Severity: PMN (2006-2010)				Severity: PMN (2011-2016)		
μ	2.97	0.40	<0.0001	3.77	0.38	<0.0001
β	0.01	0.08	0.853	-0.57	0.11	<0.0001
σ_α^2	11.93	1.64	<0.0001	5.28	0.92	<0.0001
σ_ε^2	4.76	0.38	<0.0001	6.23	0.58	<0.0001
Severity: PS (2006-2010)				Severity: PS (2011-2016)		
μ	2.73	0.31	<0.0001	3.88	0.36	<0.0001
β	-0.05	0.08	0.5524	-0.62	0.11	<0.0001
σ_α^2	3.47	0.58	<0.0001	3.16	0.61	<0.0001
σ_ε^2	3.93	0.35	<0.0001	4.38	0.46	<0.0001
Severity: TMJ (2006-2010)				Severity: TMJ (2011-2016)		
μ	2.93	0.35	<0.0001	4.67	0.37	<0.0001
β	-0.01	0.07	0.9016	-0.68	0.09	<0.0001
σ_α^2	7.94	1.15	<0.0001	5.67	0.96	<0.0001
σ_ε^2	3.80	0.32	<0.0001	5.82	0.52	<0.0001

APPENDIX A (Continued)

MIXED-EFFECT MODEL PARAMETER ESTIMATION RESULTS BEFORE 2010 AND AFTER 2011

Parameters	Estimates	Std. Error	P-value	Estimates	Std. Error	P-value
Severity: TMN (2006-2010)				Severity: TMN (2011-2016)		
μ	4.50	0.48	<.0001	5.44	0.58	<0.0001
β	-0.21	0.09	0.0186	-0.80	0.14	<0.0001
σ_α^2	19.80	2.62	<.0001	18.00	2.69	<0.0001
σ_ε^2	6.80	0.50	<.0001	16.94	1.31	<0.0001
Severity: TS (2006-2010)				Severity: TS (2011-2016)		
μ	2.28	0.26	<.0001	2.16	0.24	<0.0001
β	-0.10	0.07	0.1425	-0.18	0.07	0.0142
σ_α^2	2.25	0.39	<.0001	0.61	0.19	0.0006
σ_ε^2	2.36	0.23	<.0001	1.92	0.23	<0.0001
Severity: EO (2006-2010)				Severity: EO (2011-2016)		
μ	4.05	1.08	0.0003	1.99	0.20	<0.0001
β	-0.52	0.29	0.0773	-0.16	0.06	0.0079
σ_α^2	41.54	6.92	<0.0001	0.47	0.14	0.0003
σ_ε^2	33.94	3.49	<0.0001	1.47	0.17	<0.0001