New Study Illuminates the Ongoing Road to ICD-10 Productivity and Optimization

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To quantify the impact of ICD-10-CM/PCS (ICD-10) on coding productivity, Ciox Health, in partnership with the University of Pittsburgh's Department of Health Information Management, School of Health and Rehabilitation Sciences, conducted a previous study published in the August 2016 issue of the *Journal of AHIMA* on ICD-10 inpatient coding productivity, and examined average inpatient coding times using a total of 157,248 cases discharged from October 2015 to February 2016. Through this study, Ciox's goal was to create realistic and dynamic productivity expectations for better management of coding operations.

This article discusses a second study, an extension of the first study, which includes cases discharged more recently from March 2016 to July 2016 and examined the impact of ICD-10 on inpatient coding productivity over time. Like the first study, the most recent study demonstrates that inpatient coding productivity with ICD-10-CM/PCS continues to improve over time.

This is an important finding since better coding productivity helps to ensure an optimized revenue cycle. Also, there are other reasons for continuing to examine coding productivity in ICD-10. First, the healthcare industry is still working with old standards that reflect ICD-9—not ICD-10—productivity, and most of those standards were based on antiquated perceptions of coding productivity that were largely anecdotal in nature.

Ciox's study addresses these shortcomings and improves on previous models through its use of large data sets, including actual measured coding times for each record. As a coding service provider, Ciox has captured key attributes of each coded inpatient record (over 165,000 cases in the second study) including DRG, length of stay (LOS), principal diagnosis, and principal procedure, among other data elements. Collecting these attributes allowed Ciox researchers to measure their influence on coding productivity time.

Primary Goals of the Studys

The primary goal of this study was to create realistic and dynamic productivity expectations for better management of a coding business. Other goals for the study included:

- Understand the impact of ICD-10 on inpatient coding productivity
- Understand the impact of variables like LOS and case mix index (CMI) on productivity
- Create a formula that allows organizations to factor these variables into their own productivity expectations

Figure 1: Breakdown of Studied Cases, by Month (March 2016 to July 2016)

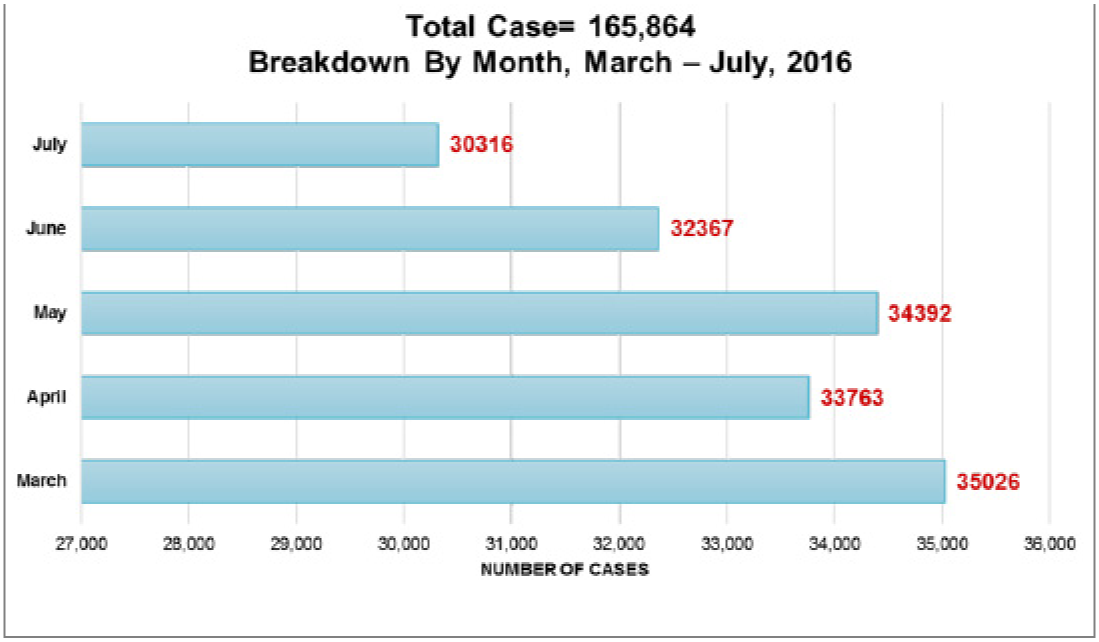


Figure 2: Distribution of Coding Time, LOS, and CMI							
	N	**Mean**	**Trimmed Mean**	**Standard Deviation**	**Median**	**Minimum**	**Maximum**
Coding Time (Minutes)	165,864	38.1	34.3	34.2	29.7	0.1	593.8
Length of Stay (LOS)	165,864	5	4.1	7	3	1	331
Case Mix Index (CMI)	165,864	1.57	1.54	0.40	1.51	0.68	10.47

Data Set for the Study

The data set for this study uses data compiled by Ciox for a five-month period (March 2016 to July 2016). This data set was selected specifically so researchers could focus on coding productivity after ICD-10 was in use for a longer period of time than the first study. The data was analyzed, organized, and stripped of influential outliers. Examples of influential outliers include LOS greater than 365 days and coding time greater than 10 hours.

The following attributes are examples of what were included in the final data set derived from inpatient encounters coded by Ciox coding professionals:

- 2016 MS-DRG-based relative weight (RW) and CMI along with facility attributes such as number of beds
- Teaching status
- Trauma level

A breakdown of the number of cases by month is available in Figure 1, above.

Inpatient Coding Productivity Observations

The mean coding time shown in the study was 38.1 minutes, with a standard deviation of ± 34.2. Coding time ranged from 0.1 to 593.8 minutes representing minimum and maximum values, respectively. Average LOS was five days ± seven days (range = 330). Average CMI was 1.57 ± .4. Furthermore, trimmed means were 34.3 minutes for coding time, 4.1 days for LOS, and 1.54 for CMI. The trimmed mean, just like the mean, is a measure of central tendency. It is calculated by discarding the extreme values (highest and/or lowest) and taking the mean of the remaining data. The trimmed mean is less sensitive to the effect of influential outliers and therefore is a robust estimator of central tendency in the study where extreme values are more common in terms of LOS, CMI, and DRG relative weight. The distribution of coding time, LOS, and CMI is provided in Figure 2, above.

Figure 3: Average Coding Time (in Minutes) by Month

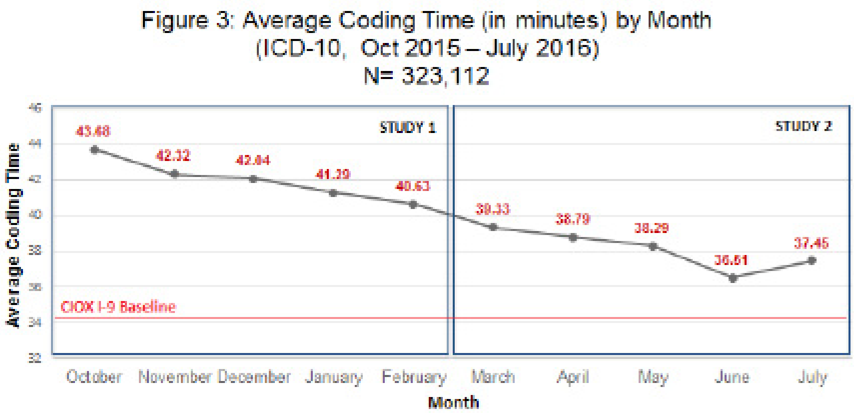


Figure 4: Comparing Standard Coding Productivity Times				
Inpatient Coding	ICD-9 Sample Standard AHIMA	ICD-9 May 2015 – Sept. 2015 Baseline Study Ciox Health N = 84,627 cases	ICD-10 Oct. 2015 – Feb. 2016 Sample 1 Ciox Health N = 157,248 cases	ICD-10 March 2016 – July 2016 Sample 2 Ciox Health N = 165,864 cases
Records/day	24	14	11.5	12.6
Records/hour	3	1.8	1.4	1.6
Minutes/Record	20 minutes	34.2 minutes	41.9 minutes	38.1 minutes
Productivity Impact *(Based on average time per record)*			-22% (compared to Ciox Baseline ICD-9 Study	-11% (compared to the Ciox Baseline ICD-9 Study)

Coding Productivity Over Time

Productivity continues to trend steadily towards the ICD-9 baseline. While pre-implementation training efforts helped avoid catastrophic productivity impact out of the gate, it's interesting to note the steady gains made since then. In this case, familiarity and exposure has bred efficiency.

Coding productivity has improved consistently over the 10-month research period when examining both the first study's data set and the second study's data set together (N = 323,112 cases). Average coding time in minutes per record in October 2015, when ICD-10 first went live, was 43.68 minutes, and by July 2016 average coding time decreased to 37.45 minutes. See Figure 3 above for a visual representation of this data.

Figure 5: Average Coding Time (in Minutes) by LOS

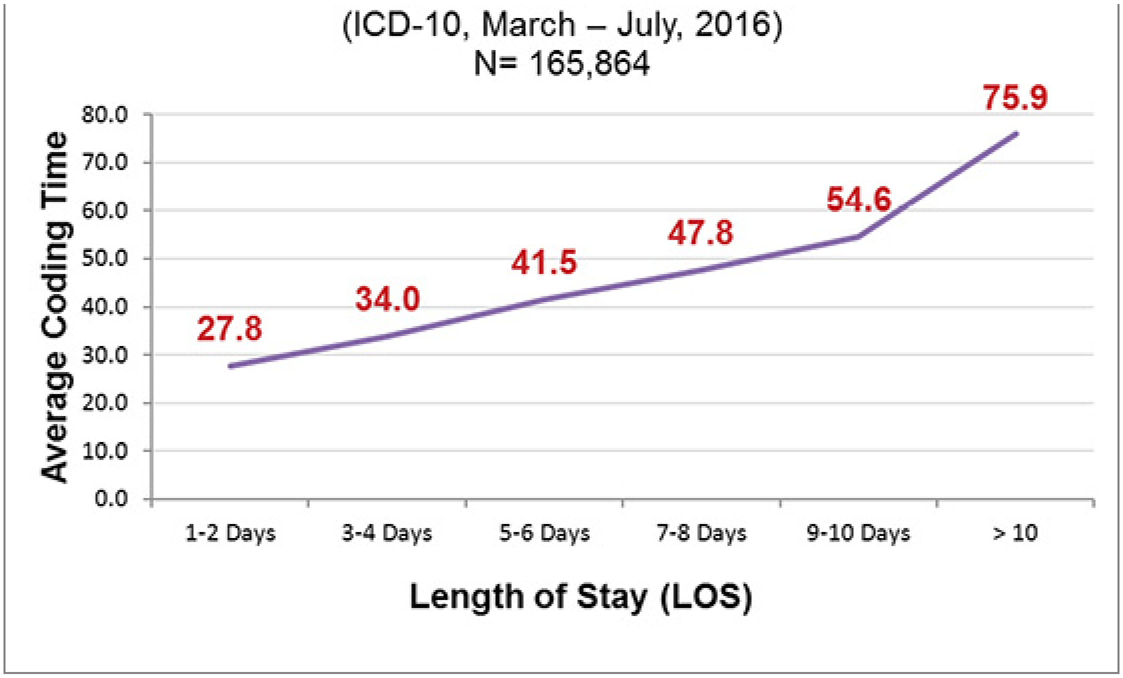
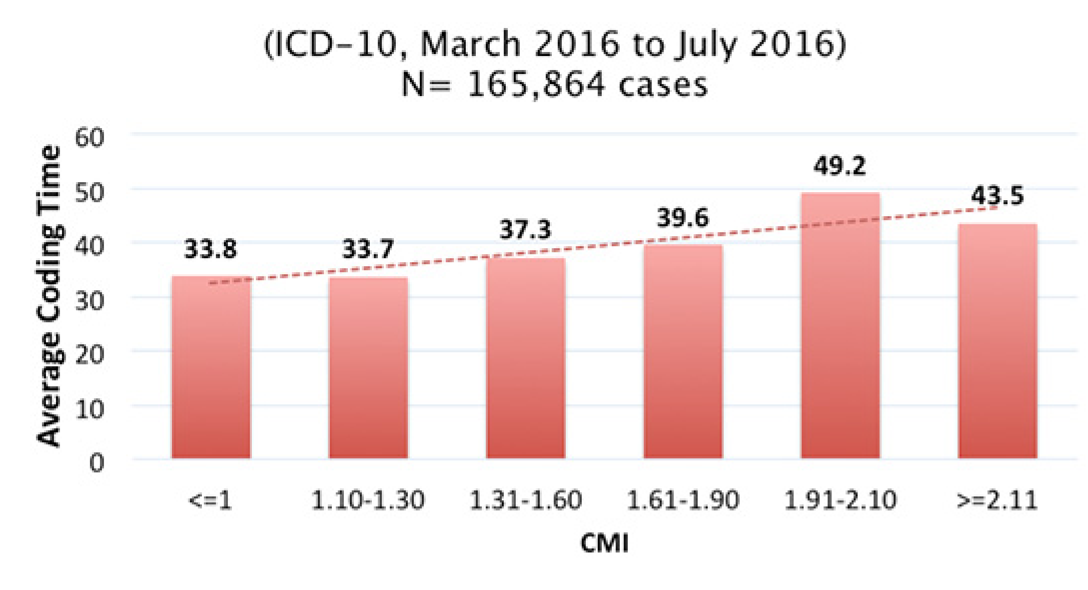


Figure 6: Average Coding Time (in Minutes) by CMI



Comparing to Standard Coding Times

Coding productivity with ICD-10 has decreased by nearly 22 percent when compared to ICD-9 productivity for the first five months of the new code set's use (October 2015 to February 2016). When compared to ICD-9, however, coding productivity has only decreased by 11 percent for the next five months (March 2016 to July 2016). In fact, researchers saw consistent improvement of ICD-10 coding productivity over time in terms of the number of coded records and average coding time. Further details are provided in Figure 4, above.

Coding Time by LOS

Approximately 80 percent of the cases in the March 2016 to July 2016 data set had a LOS of six days or less. The lowest coding time was 27.8 minutes (LOS = one to two days) while the highest coding time was 79.5 minutes (LOS > 10 days). Distribution of coding time by six LOS categories is provided in Figure 5 above. One can see that as LOS increases, coding productivity times increase as well, which is to be expected.

Coding Productivity by CMI

Also as expected, the average coding time increased as the CMI increased. See Figure 6 above for a chart graphing this with cases studied between March 2016 and July 2016.

CMI and Coding Time by Months

It was observed that productivity gains did not come at the cost of CMI. This is a very important observation since CMI is a key indicator or metric in organizations. Otherwise stated, as productivity time continued to improve, CMI was observed to increase (see Figure 7 below).

Top DRGs by Month

Normal newborn (DRG weight = 1.649) was the highest DRG for three consecutive months (April 2016 to June 2016) while septicemia (DRG weight = 1.7926) and vaginal delivery (DRG weight = 0.5865) were the top DRGs for the months of March 2016 and July 2016 respectively. The three highest DRGs for each month and their sample of cases are provided in the table in Figure 8 below.

Correlations Between Coding Time and LOS, CMI, and DRG Weight

Significant moderate positive correlations were found between coding time and LOS (r=.347) and between coding time and DRG weight (r=.324). Based on this data the researchers can conclude that as the DRG weight and LOS increase, the coding time increases accordingly.

Even though DRG weight has a stronger correlation with coding time than CMI, that is understandable since the CMI is an average of the DRG weights. Therefore, it is best to use the CMI and LOS to get a quick predictive formula for predicting coding times in a facility, since CMI is at the facility level while DRG weight is at the patient level.

Figure 7: CMI and Coding Time by Month

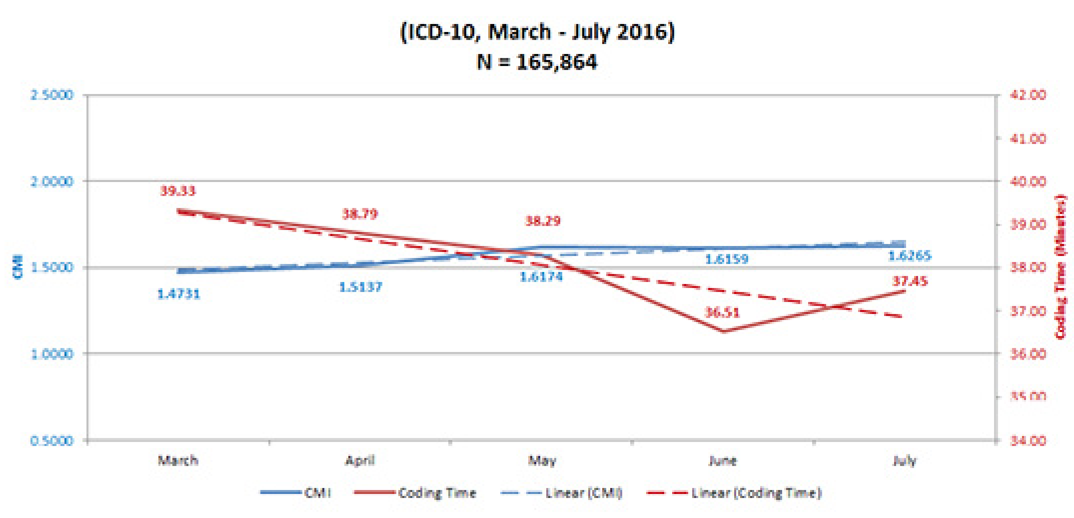


Figure 8: Top Three DRGs by Month			
2016 Month	**DRG Weight**	**DRG**	**N**
March	**1.7926**	**SEPTICEMIA OR SEVERE SEPSIS W/O MV 96+ HOURS W MCC**	1,453
	0.5865	VAGINAL DELIVERY W/O COMPLICATING DIAGONSES	1,365

	0.1649	NORMAL NEWBORN	1,223
April	**0.1649**	**NORMAL NEWBORN**	1,443
	0.5865	VAGINAL DELIVERY W/O COMPLICATING DIAGONSES	1,337
	1.7926	SEPTICEMIA OR SEVERE SEPSIS W/O MV 96+ HOURS W MCC	1,257
May	**0.1649**	**NORMAL NEWBORN**	1,416
	0.5865	VAGINAL DELIVERY W/O COMPLICATING DIAGONSES	1,415
	1.7926	SEPTICEMIA OR SEVERE SEPSIS W/O MV 96+ HOURS W MCC	1,294
June	**0.1649**	**NORMAL NEWBORN**	1,314
	0.5865	VAGINAL DELIVERY W/O COMPLICATING DIAGONSES	1,300
	1.7926	SEPTICEMIA OR SEVERE SEPSIS W/O MV 96+ HOURS W MCC	1,195
July	**0.5865**	**VAGINAL DELIVERY W/O COMPLICATING DIAGONSES**	1,315
	0.1649	NORMAL NEWBORN	1,204
	1.7926	SEPTICEMIA OR SEVERE SEPSIS W/O MV 96+ HOURS W MCC	1,061

Predicting Coding Productivity Based on LOS and CMI

As a predictive analysis, multiple linear regression is used to explain the relationship between one continuous dependent variable from two or more independent variables. Multiple linear regression was calculated to predict coding time based on LOS and CMI for inpatient encounters coded using ICD-10. A significant regression equation was found; LOS and CMI combined account for 12.7 percent of the variability in coding productivity times. Also, for each additional day in LOS, the coding time increases by approximately two minutes on average, controlling for all other effects in the model. Finally, the coding time increases by approximately seven minutes on average for each unit increase of the CMI controlling for all other effects in the model. The regression equation is provided below in Figure 9.

While a standard error of 31.95 may seem high, standard errors of this magnitude are to be expected for a sample involving more than 165,000 measures. This has been confirmed with consultation of multiple statisticians. Based on this model, one can then predict the coding time for a facility as the example below demonstrates.

Example: Predicting coding time when CMI = 1.3 and ALOS = 3.0

Regression equation: Coding Time = 19.166 + 6.650(CMI) + 1.743(ALOS)

> If CMI = 1.3 and ALOS = 3.0
> Coding Time = 19.166 + 6.650(1.3) + 1.743(3.0)
> **Coding Time= 33.04 minutes/chart or 1.82 charts/hour**

Other Models for Predicting Coding Productivity

Nearly 13 percent of the variability within our model can be attributed to LOS and CMI. But there are other factors that may affect coding productivity as well. In addition to LOS and CMI, other predictors can be used for predicting coding productivity and enhancing the model's performance. Some of these predictors include facility-related attributes such as number of beds, teaching status, and trauma status. Adding these predictors to the model can increase its predictivity by approximately 10 percent.

Furthermore, Ciox researchers are working to collect other factors that are specific to coder characteristics, such as coder education, coder credential, and years of experience, and link it directly to each coded record so that it can be added to the model to further enhance its performance. Certainly, this model is a great first step to provide HIM professionals with a benchmark derived from real ICD-10 data for coding productivity.

Figure 9: Multiple Linear Regression (Coding Time, LOS and CMI)				
Model	**Predictors**	**Regression Equation**	**R2**	**SE**
1	LOS CMI	Coding Time = 19.166+ 1.743(ALOS)+ 6.650(CMI)	0.127	31.95

Measurement is Just the First Step

Unfortunately, measurement in and of itself will not improve coding productivity—but measurement is a critical first step on the path to optimization, and use of the model above may help an organization get there. Some recommendations from the researchers to follow when moving forward with this process include:

1. Identify the baseline productivity for your facility
    a. Most abstraction systems can produce productivity statistics
    b. Adjust for “downtime” if necessary
2. Calculate the target productivity for your facility
    a. Baseline > Target: Looking good—Keep monitoring
    b. Baseline < Target: Identify challenges
3. Repeat steps 1 and 2 at the coding professional level
    a. Baseline > Target: Looking good—Keep monitoring
    b. Baseline < Target: Identify challenges, Remediate

The Ciox/University of Pittsburgh study allows HIM professionals to understand the impact of ICD-10 on inpatient productivity and create dynamic and realistic productivity expectations. Furthermore, monitoring productivity allows one the ability to identify variance, create accountability, remediate accordingly, and staff appropriately. Monitoring productivity can empower healthcare organizations to perform optimally.

Acknowledgements: Research Partnership

This research study was supported by a unique research partnership between Ciox Health and the University of Pittsburgh, Department of Health Information Management, School of Health and Rehabilitation Sciences.

Their partnership focuses on conducting research and objective analysis in the field of healthcare data quality and health information management to determine innovative best practices that when adopted can improve the efficiency and effectiveness of the US healthcare system.

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Article citation:
Alakrawi, Zahraa M; Watzlaf, Valerie J.M.; Nemchik, Scot; Sheridan, Patty Thierry. "New Study Illuminates the Ongoing Road to ICD-10 Productivity and Optimization" *Journal of AHIMA* 88, no.3 (March 2017): 40-45.
