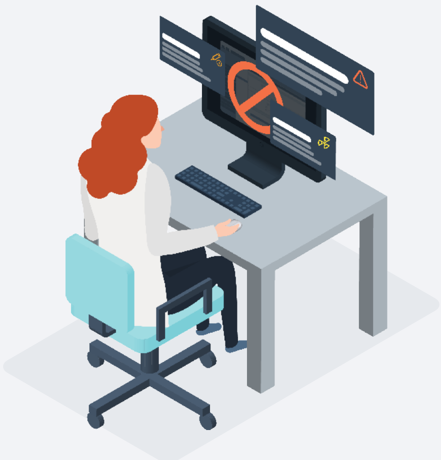

WASTEFUL BEHAVIORS PREDICT 47% OF PROVIDER SPENDING VARIATION

Study Reveals Access to Real-Time Alternatives Improve Cost Stewardship by 150%

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Sometimes little things add up to make a big difference and that's certainly true when it comes to controlling costs through the stewardship behaviors of healthcare providers, according to an 8-month study with 287 physicians we conducted using data on patient discharges. We undertook the study in order to better understand financial variation within physician inpatient ordering behavior because it's a key issue for hospital managers and physician group leaders.

Through our relationship with over 250 healthcare facilities, we were able to develop a set of provider medication and lab orders that are markers for potential wasteful behavior (e.g., a repeat daily ordering of B-type natriuretic peptide testing). What we found was that a provider's propensity to engage in these wasteful behaviors is a strong predictor of that provider being a high-cost outlier, even when controlling for patient acuity ($R^2 = .467$).

Research Highlights

An 8-month study with 287 physicians identified as a Hospitalist, Internal Medicine, or Family Medicine who placed at least 50 orders and cared for at least 15 patients.

The goal was to develop a method to directly measure behaviors that correlate with higher spending and to determine if an effective method exists to intervene on those behaviors in a way that reduces both the behaviors specifically and spending generally.

It was found that when providers are "nudged" to stop wasteful behaviors, their average spend on meds and labs goes down by an amount the exceeds the sum of the specific opportunities identified.

Analysis shows that for every 1 dollar of decrease in average savings opportunities per provider per patient, the clinician actually saves up to 1.5 times that amount per admission.

"Advanced stewards" that embrace financial stewardship opportunities are able to reduce the cost of care while maintaining the quality of care delivered.

When providers are gently "nudged" to stop these wasteful behaviors (with a clinical pearl of wisdom and its literature citation), their average spend on medications and labs goes down, surprisingly by an amount that exceeds the sum of the specific financial opportunities identified. We hypothesize that reinforcing a "stewardship ethos" causes providers to be more judicious in areas that fall outside of those that are presented overtly by IllumiCare. We also show that good stewards order fewer and less expensive tests and medicines, rather than just cost shift those orders to other providers on the case.

A Focus on Providers

IllumiCare provides a service to hospitals whereby it collects real-time clinical data about inpatients and wholesale cost data (not charges) on medications and lab tests. We use that data to calculate a real cost of every medication and lab order, attribute that cost to the ordering provider and aggregate those costs at the patient admission and DRG levels.

Unlike previous studies that have utilized highly advanced models including artificial neural networks, ridge regression models, gradient boosting, and other techniques to predict the individual patient's cost, utilizing patient demographics such as age, sex, ethnicity, and comorbidities as predictors of the individual's cost, our study shifts the focus off patient characteristics and onto physician habits.[i]

Leep Hunderfund et al. surveyed physicians and medical students, finding that 88% of respondents moderately or strongly agreed that "trying to contain costs is the responsibility of every physician." [ii] The AMA Code of Medical Ethics states, "Physicians also have a long-recognized obligation to patients in general to promote public health and access to care. This obligation requires physicians to be prudent stewards of the shared societal resources with which they are entrusted." [iii]

Despite calls for provider stewardship, studies have shown large variation in provider spending on similarly sick patients, even within the same specialty and in the same hospital. [iv] Higher spending may be an acceptable tradeoff for better outcomes, however higher spending does not correlate with better outcomes. [v]

What is needed is a method to directly measure behaviors that correlate with higher spending and to intervene on those behaviors in a way that reduces both the behaviors specifically and spending generally.

Materials and Methods

Stewardship Opportunities Considered

Over the past six years, IllumiCare has accumulated a set of medication and lab orders that represent very likely wasteful care (Stewardship Opportunities or "Opportunities"). A medication example is the use of IV Tolvaptan over oral Urea when the patient's sodium is 128 or above. A laboratory example is repeat daily ordering of B-type natriuretic peptide (BNP) whether or not the result of the test is normal or abnormal.

Some of these decisions are the responsibility of just one provider, e.g. the ordering provider for the repeated BNP. There are other decisions that may be a missed opportunity for multiple providers, e.g., an IV to PO switch opportunity where the original IV order was appropriate but later the patient commenced other PO meds and the PO medication was clinically equivalent, but multiple providers failed to make the switch. In this analysis, we included only those Opportunities that were the responsibility of a single provider. We evaluate the relationship between a provider's Opportunity per patient (calculated by summing the costs of the wasteful orders of that provider) - the independent variable denoted x - and that provider's overall medication and laboratory spend per patient - the dependent variable denoted y.

Data Collection and Preprocessing

Data on patients discharged during the period of 01 November 2020 to 30 June 2021 was collected through the subject health system's HL7 data feed. HL7 messages were parsed and processed into a normalized data warehouse. Only pharmacy-verified medication orders and resulted laboratory orders were evaluated. Costs for services were attributed at the CMS allowable rate, and cost for medications were attributed at the average wholesale price obtained from Medi-Span. Charge codes were not used in this analysis.

Only orders placed by providers registered with CMS under taxonomy code 208M00000X (Hospitalist), 207R00000X (Internal Medicine), or 207Q00000X (Family Medicine), or who was identified as a Hospitalist, Internal Medicine, or Family Medicine provider by the hospital system under the terms of an IllumiCare SmartRibbon user were included in this analysis. All included providers will be referred to as "hospitalists" in this analysis. There were 284 such providers in the analysis.

Only orders associated to a patient encounter discharged under the class "Inpatient" were included. A provider is defined as "caring for" an inpatient encounter if they placed at least 25% of the orders on the discharged patient. Only orders in which the hospitalist was the direct ordering provider as seen in the HL7 order message are included in the calculation, e.g., if a hospitalist instructed a nurse practitioner to place an order, we did not attribute that order to the hospitalist.

In sum, this analysis considered 17,032 patient encounters and 30,930 "violating" orders (28,448 lab orders and 2,482 med orders).

Independent Variable

For the cost of identified laboratory Opportunities, the entire CMS allowable cost of the order is assigned as an Opportunity. For medication orders, the Opportunity is calculated as the difference between the daily unit cost of the ordered medication and the daily unit cost of the lower-cost medication, multiplied by the timestamp interval difference between prescription start and prescription end. This Opportunity, for example, is only presented for IV to oral switches when the patient is on another oral medication. A hospitalist's Opportunity per patient is calculated as the sum of all orders that were identified as an Opportunity divided by the total number of inpatient admissions that they cared for.

Dependent Variable

Hospitalists' risk-adjusted spend per patient is calculated as $$\frac{1}{n}\sum_{i=1}^{n}(y_i/w_i)$$

Where n is the distinct number of patients treated, y is the subject hospitalist's total medication and laboratory spend on the patient, and w is the MS-DRG weight of the patient. In other words, it is the sum of the value of all medication and laboratory orders placed by that provider on a patient that they cared for divided by the assigned MS-DRG weight, divided by the total number of inpatient discharges that they cared for.

Outcome Measures

Because we are evaluating the relationship between the two variables, our outcome measures are focused on directional relationship, variation, and correlation. Our key measures are the Coefficient of Determination (R^2), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE). R^2 is calculated as $\frac{\Sigma(\hat{y}-\bar{y})^2}{\Sigma(y-\bar{y})^2}$, or the sum of squares regression divided by the sum of squares total. This value, often expressed as a percentage, gives us the proportion of variability explained in the model among the total variability.[vi] In our case, how much does a provider's opportunity per patient explain their overall spend per patient? RMSE is calculated as $\sqrt{\frac{1}{n}\sum_{i=1}^{n} e_i^2}$, where e_i is the error of samples *i*. RMSE was chosen because it is more sensitive to variances within the model error than the mean absolute error by penalizing errors with a larger absolute value.[vii] MAPE is calculated as $\frac{100}{n}\sum_{i=1}^{n}\left|\frac{\hat{y}_i-y_i}{y_i}\right|$. The resulting value is the average percentage error a predicted point was from the true value, across the data. MAPE is utilized for its intuitive interpretation on the quality of a regression model, its handling of relative variation instead of absolute variation, and its ability to handle both positive and negative errors within our model.[viii]

Statistical Analysis and Dataset Preparation

All statistical analysis were performed in R version 3.6.1. The relationship between a hospitalist's spend per patient and opportunity per patient is assessed through an ordinary least squares (OLS) regression, residuals analysis using diagnostic plots, train-test validation of the model, and comparison of time series.

In the first dataset used for the OLS regression model, the unit of analysis is an individual hospitalist. To prepare the dataset, a hospitalist's independent and dependent variables are calculated using data over the entire evaluated timespan. For a provider to be included in this dataset, they must have placed at least 50 orders and cared for at least 15 patients. Using random assignment, the hospitalist data is split into a training set (80%) and test set (20%). The training set included 215 hospitalists and the test set included 54 hospitalists. When performing a linear regression with this data, the independent variable x was right skewed, causing the model to be non-linear, resulting in the non-normal distribution of residuals. Visualization utilizing a scatterplot also indicated heteroskedasticity. OLS regression assumes $V(\varepsilon_i) = \sigma^2$ for all values i, meaning the error terms have a constant variance (homoskedasticity).[ix] To account for non-linearity and heteroskedasticity, a logarithmic transformation was performed on the independent variable x using $\log_e(x+1)_y$ adding the constant of 1, we were able to apply the logarithmic transformation to values $x=0$.

In the second dataset used for time series analysis, the unit of analysis is the mean value among hospitalists per month, i.e., the mean hospitalist opportunity per patient each month or the mean hospitalist spend per patient each month. Costs are attributed to the month in which a patient was discharged. A hospitalist's independent and dependent variables is calculated as the sum cost for that month divided by the number of patients cared for and discharged during that month. The mean value per month is calculated to achieve the monthly rate for each variable. A provider must have cared for at least five patients per month to be included.

Results

Descriptive Statistics

Table 1 describes the distribution of our dependent and independent variables. Opportunity per patient, x, is summarized in the table both before and after transformation, so that the distribution of hospitalists' opportunity can be evaluated both in real dollar terms and in the log-transformed terms used in our regression model. A two-sample t-test of the training set and test set dependent variables resulted in a p-value=0.699 and of the transformed independent variables resulted in a p-value=0.724, indicating that there are no significant differences in the means of the two datasets.

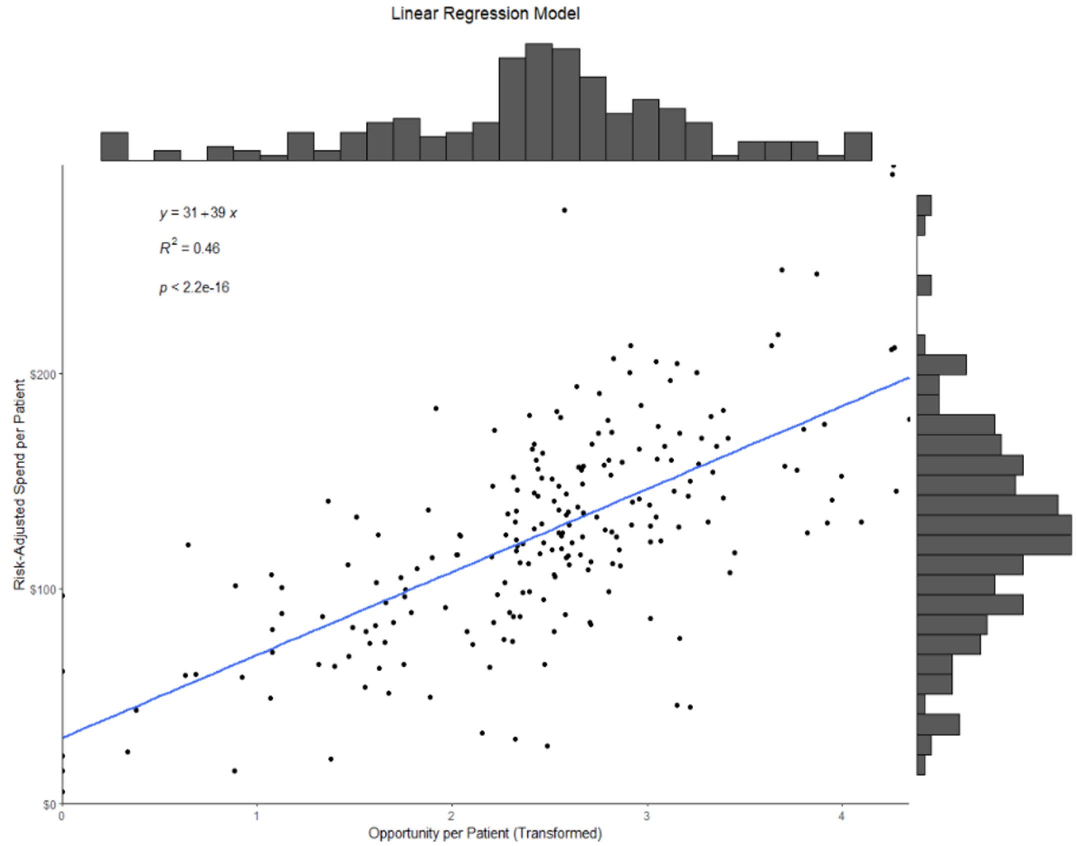
TABLE 1.

	Mean	*Std. Dev.*	*Minimum*	*Maximum*	*Median*	*Q1*	*Q3*
Training Set (n = 215)							
x (before transformation)	15.235	14.368	0.000	76.237	11.621	6.677	18.263
x (transformed)	2.448	0.878	0.000	4.347	2.535	2.038	2.958
y	125.037	50.025	5.469	296.569	124.732	92.152	155.273
Test Set (n = 54)							
x (before transformation)	13.524	9.292	0.065	50.489	11.113	6.565	15.737
x (transformed)	2.493	0.638	0.063	3.941	2.494	2.023	2.818
y	127.836	36.036	14.670	195.135	126.523	102.529	157.726

Ordinary Least Squares (OLS) Linear Regression

In Figure 1 we use the training set to depict the relationship between each provider's (n=215) independent and dependent variables, with a marginal histogram to visualize the distribution. Each point represents a hospitalist, and the blue line indicates the line of best fit. The training model resulted in a $R^2 = 0.458$, with a p-value < 0.001 and residual standard error of 36.9 on 213 degrees of freedom.

FIGURE 1. LINEAR REGRESSION USING TRAINING DATA



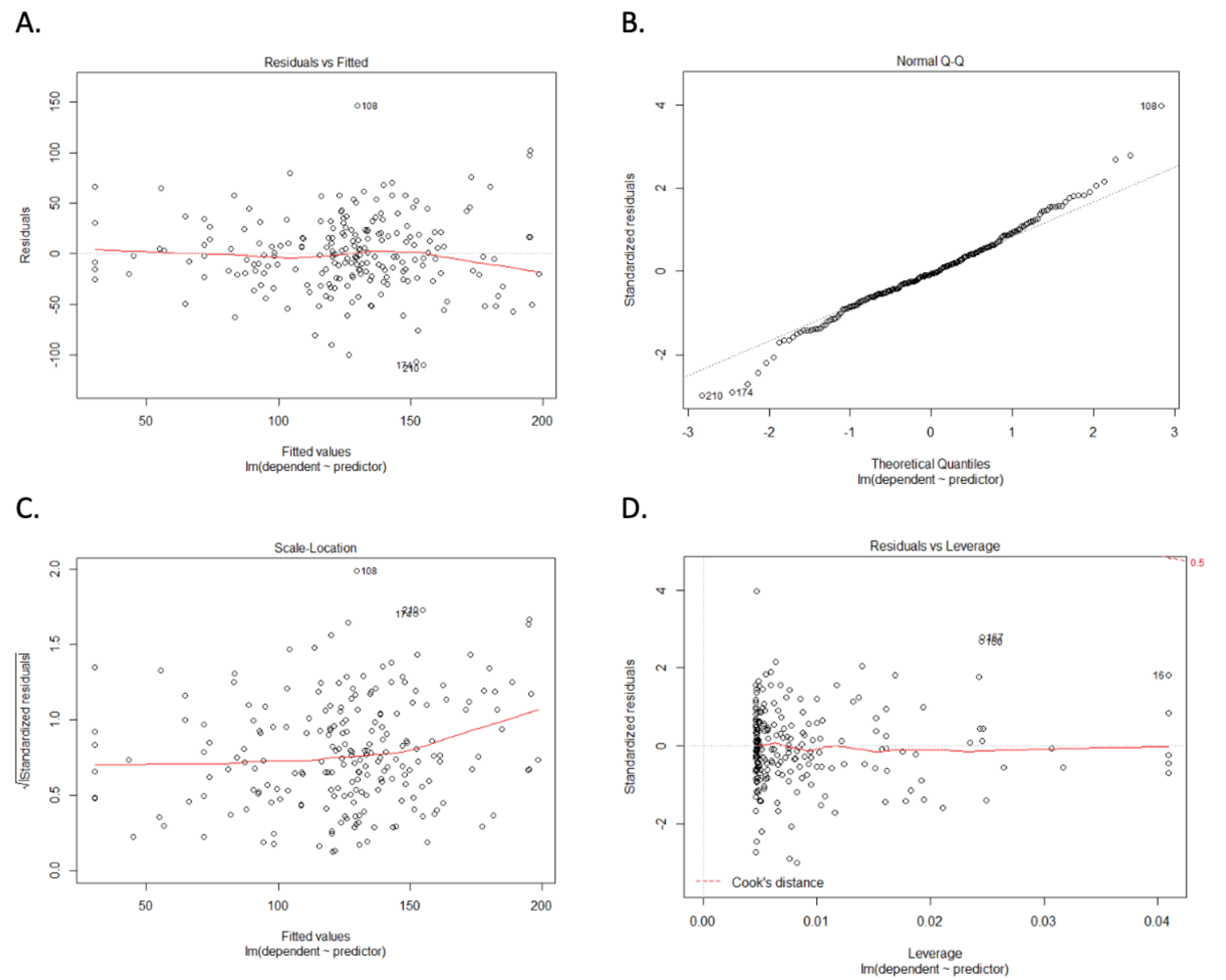
While the distribution looks linear, we analyze the residual diagnostic plots in Figure 2 using R's plot() function with defaults.

Figure 2A displays the residuals vs fitted values, where the residual on the y-axis is calculated as $r_i = y_i - \hat{y}_i$, or the observed y value minus the predicted value, and the x-axis is the fitted (predicted) value $\hat{y}_i$. If residuals do not show a trend and are spread randomly, then that is a good indication that our variables share a linear relationship and there is not an underlying non-linear trend, such as an exponential increase. [x]

Figure 2B and 2C, the normal quantile-quantile (normal q-q) plot and scale-location plot, evaluate normality and homoskedasticity of the residuals. Values in the normal q-q plot in 2B generally follow the 45-degree reference line so we can assume normality, though it does exhibit heavy tails, notably at values 210, 174, and 108. The scale-location plot is similar to the residuals vs fitted plot in that it is ideal to see a random spread, though the scale-location plot is used to evaluate the variance in errors to detect heteroskedasticity.[xi] We see in Figure 2C that our errors do not show a trend, so we fulfil the assumption that our dataset is homoscedastic, and errors ε_i have a constant variance.

Figure 2D, residuals vs leverage, is used to detect outliers and determine whether any point (a provider) significantly affects the model, known as having high leverage.[xii] Unlike the other charts in Figure 2, the residuals vs leverage plot does not look for a pattern, it looks for individual points that pass the Cook's distance line in the upper or lower right-hand corners. A point with a large Cook's distance doesn't fit well with the model and with the trend and can greatly affect the slope and R^2.[xiii] Because we do not have any points past the Cook's distance line, we can infer that no hospitalist included in our dataset is an outlier within our model or significantly goes against the trend.

FIGURE 2. RESIDUAL DIAGNOSTIC PLOTS OF THE LINEAR REGRESSION



With our model trained, we calculate RMSE and MAPE to measure the goodness of our model. When running our training data back through the model, the RMSE=36.728 and the MAPE=33.1%. When feeding new data to our model using the test dataset (n = 55), RMSE = 24.363 and MAPE = 18.7%, meaning our model's accuracy was slightly better when evaluating new hospitalists' data.

Subcategory Analysis

With our model validated, we reran the analysis in three ways. We evaluated all med/lab cost data (the dataset before randomly splitting into train/test sets), laboratory-only cost data, and medication-only cost data. We can see that the laboratory-only (R^2= .437) or medication-only (R^2= .271) models do not explain variability as well as the combined order spend (R^2= .467) although their variables are still highly correlated and their p-value shows a highly significant relationship.

TABLE 2.

	Laboratory Orders	*Medication Orders*
Mean of X (before transformation)	14.478	2.137
Mean of X (transformed)	2.482	0.888
Mean of Y	129.684	108.963
Correlation Coefficient (r)	0.661	0.520
R^2	0.437	0.271
p-value	< 0.001	< 0.001
RMSE	22.76	22.63
MAPE	24.6%	53.8%

Monthly Time Series Analysis

We observed an overall relationship in the linear model between provider spend per patient and provider opportunity per patient, so we then wanted to evaluate whether over time there was a directional relationship between opportunity and spend. Our previous independent and dependent variables were then evaluated as timeseries x_t and y_t respectively.

Monthly characteristics

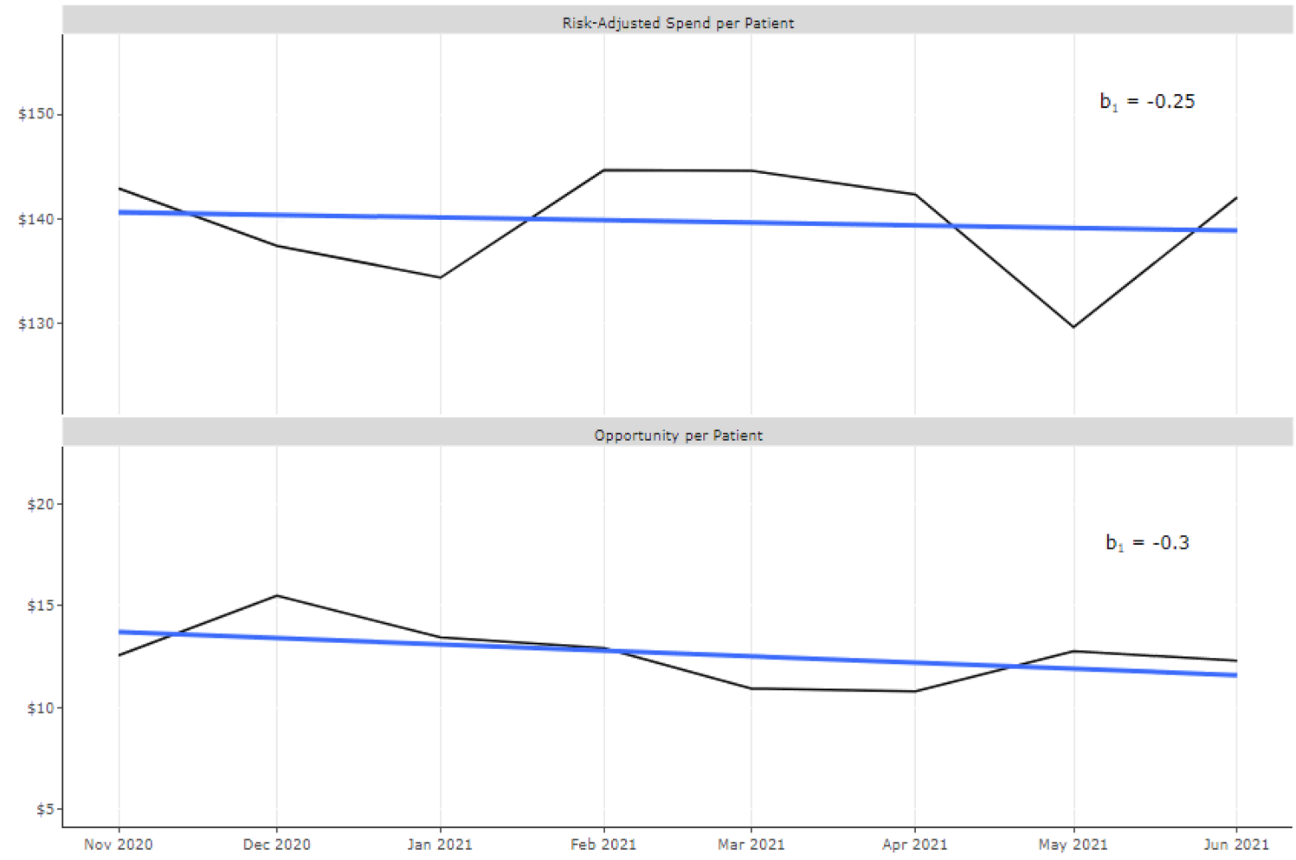
TABLE 3.

	Mean	*Minimum*	*Maximum*	*Standard Deviation*
y_t	139.769	129.695	144.665	5.407
x_t	12.660	10.797	15.503	1.481

Time Series Relationship

Figure 3 visualizes the time series with a regression trend line, with y_t appearing on top and x_t appearing on bottom. The regression slope β_1 of y_t is -0.251 and the slope β_1 of x_t is -0.303, meaning for every \$1.00 opportunity reduction per provider per patient, there was a \$0.82 decrease in average risk-adjusted hospitalist spend per patient. Using the average monthly case mix index of 1.88 of the included patients, we can extrapolate that this is a change of \$1.54 in real-dollars per patient for each dollar in opportunity reduced.

FIGURE 3. TIME SERIES



Discussion

Clinical stewardship is a mind-set that is difficult to create and even more difficult to measure. While it may be obvious that providers who spend more per admission have more opportunities to save money, the opportunities to reduce cost are not readily known at the point-of-care. IllumiCare has over 1400 clinical financial decision support opportunities in the medication and laboratory space that are markers of opportunities to make less costly decisions without compromising quality in the right clinical context. These opportunities predict 47% of the financial variation, risk-adjusted, in medication and laboratory spend in a patient's admission.

Interestingly, the ceiling for savings is greater than the sum total of the opportunities attributed to the provider per patient. This implies a flywheel effect where an interested and attentive clinician-steward begins to ponder other opportunities to save that are not directly "nudged." For example, IllumiCare may not nudge an expensive drug as an opportunity as the drug may not have an alternative. However, an astute clinician can use the IllumiCare platform to notice medications on the med list that are expensive – these medications are purposely shown at the top of the med review screen. We consider such clinicians "advanced stewards" when they order these drugs less often on future admissions. An analysis shows that for every 1 dollar of decrease in average opportunities per provider per patient, the clinician actually saves up to 1.5 times that amount per admission. This reflects the activation of the stewardship program and its maximal effect being greater than the sum of the opportunities. This is a significant development in the stewardship program.

Finally, we analyzed length of stay which remained fairly constant over the period of analysis thus a decline in length of stay would not explain declining costs or opportunities per admission. We also examined whether clinicians who were acting on opportunities and reducing their costs were merely shifting those costs to other providers. We found that not to be the case, as these savings became a net reduction in the total cost of care.

Conclusion

This novel study strongly suggests that IllumiCare has a proprietary set of clinical financial decision support rules that are markers of opportunities to reduce financial variation in clinical care. The greater the "opportunity dollar amount" attributed to a provider, the greater the variation in care attributed to this provider. Indeed, when the provider focuses on these opportunities, cost of care and financial variation decline. Of interest, the decline in overall spend per admission is steeper than the decline in dollar opportunity per provider per patient. This implies that these clinicians are on a path to stewardship and can transcend to savings beyond the sum total of these opportunities. We label these providers "advanced stewards" as they seek opportunities beyond "nudges" sent to them to reduce the cost of care while maintaining the quality of the care they deliver. There was no increase in risk adjusted morbidity and mortality in this study period.

About IllumiCare

Founded in 2014 in Birmingham, Ala. by a visionary physician and team of hospital IT experts, IllumiCare is dedicated to helping clinicians become better stewards of system and patient resources. Its Smart Ribbon® platform brings clinicians critical, patient-specific data in a focused view for expedited clinical decision making at the point of care, without disrupting clinical workflow. To learn more, visit www.illumicare.com/ereports.

Endnotes

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