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ORIGINAL ARTICLE

The need for integrated clinical and administrative data models for risk adjustment in assessment of the cost transplant care

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Abstract

Introduction: Value-based purchasing requires accurate techniques to appropriately measure both outcomes and cost with robust adjustment for differences in severity of illness. Traditional methods to adjust cost estimates have exclusively used administrative data derived from billing claims to identify comorbidity and complications. Transplantation uniquely has accurate national clinical registry data that can be used to supplement administrative data.

Methods: Administrative claims from the Vizient, Inc, Clinical Data Base (CDB) were linked with clinical records from the Scientific Registry for Transplant Recipients for 76 liver and 109 kidney transplant programs. Using either or both datasets, we fitted a regression model to the total direct cost of care for 16,649 kidney and 6058 liver transplants.

Results: The proportion of variation explained by these risk-adjustment models increased significantly when combined administrative and clinical data were used for kidney (administrative only $R^2 = .069$, clinical only $R^2 = .047$, combined $R^2 = .14$, $p < .0001$) and liver (administrative only $R^2 = .28$, clinical only $R^2 = .25$, combined $R^2 = .33$, $p < .0001$).

Conclusion: Incorporating accurate clinical data into risk-adjustment methodologies can improve risk adjustment methodologies; however, as majority of variation in cost remains unexplained by these risk-adjustment models further work is needed to accuracy assess transplant value.

KEYWORDS
cost, financial, multivariable analysis, risk adjustment

1 | INTRODUCTION

The passage of the Medicare Access and Children's Health Insurance Program Reauthorization Act of 2015 accelerated the transition to value-based healthcare reimbursement in the United States.[1] Value-based care aims to achieve four major goals: cost reduction, improvement in clinical outcomes, better patient experience, and improved provider satisfaction.[2] However, implementation of effective value-based reimbursement requires accurate risk adjustment for patients' severity of illness, comorbid conditions, and socioeconomic status for *both outcomes and cost*.[3–5] While extensive methodologies have been developed to adjust outcomes assessment based on clinical characteristics, payment systems use administrative data alone for this purpose. However, these administrative data lack precise clinical details and

the models may result in inaccurate risk adjustment, limiting enthusiasm for broader application of value-based payments, particularly for high-acuity services.[6,7]

As healthcare continues to refocus reimbursement on value-based care, there is a need to improve the precision and accuracy of cost-adjustment methodologies, potentially by combining clinical and administrative data.[8] The US transplant system is uniquely positioned for this type of analysis because there is a legal mandate for universal reporting to a national clinical registry, which includes detailed data on severity of illness, characteristics of the donor organ, and process of care including time from organ recovery to transplant. Under contract from the Department of Health and Human Services, the scientific registry of transplant recipients (SRTR) uses these data to develop and report legislatively mandated center outcome performance reports for regulatory review and patient information. These reports demonstrate the dramatic differences in donor characteristics and recipient severity of illness between transplant centers that significantly affect expected outcomes.[9] These differences are the result of many factors including new organ allocation policies which prioritize broader sharing of organs over efficiency and outcomes, local organ supply, recipient socioeconomic status, and competition.[10,11] These extrinsic factors influence the characteristics of the candidates at the time of transplant, quality of the organs available, outcome of transplant, and resources required for the care of the patients. Consequently, appropriate risk adjustment is vital to accurate assessment of the "value" organ transplant care.[12]

In this analysis, we collaborated with Vizient, Inc (Irving, Texas), which produces widely used confidential reports assessing variation in the cost and hospital outcomes of procedures among leading academic and private hospitals. Vizient uses center-submitted administrative data to develop proprietary multivariate risk-adjustment models and produce risk-adjusted estimates of cost and outcomes for inpatient hospitalization, including transplant procedures. We sought to compare the accuracy of risk-adjustment models for the cost of inpatient transplant care using current Vizient models derived solely from administrative data, new risk-adjustment models for cost using solely registry data similar to current outcomes reporting by SRTR, and an integrated approach using data elements from both sets of data. Using a national data set linking hospital costs and transplant clinical registry data, we compare the accuracy of these differing risk-adjusted inpatient cost-of-care models for explaining the variation in inpatient costs. We also examine the association between risk-adjusted cost of care and publicly reported measures of "quality," including the center's transplant rate and 1-year posttransplant outcomes.

2 | METHODS

2.1 | Data source

The study population included adult (aged 18 years or older) recipients of deceased donor kidney and liver transplant (KTx, LTx, respectively) performed in US transplant centers from October 2015 through October 2018. Cost data were obtained from the Vizient Clinical Data Base (CDB) and used with permission of Vizient, Inc. All rights reserved. The CDB captured claims data from 76 LTx and 109 KTx programs. The CDB includes patient-level claims data from billing claims submissions and calculates cost data using center-specific Medicare Cost Report cost-to-charge ratios and line-item hospital charges from inpatient stays.

This study used transplant data from SRTR. The SRTR data system includes data on all donors, waitlisted candidates, and transplant recipients in the United States, submitted by the members of the Organ Procurement and Transplantation Network (OPTN), as has been described elsewhere.[13] The Health Resources and Services Administration (HRSA), US Department of Health and Human Services, provides oversight to the activities of the OPTN and SRTR contractors. As these data are used for organ allocation purposes, less than 2% of the patients had missing data elements. SRTR produces semiannual risk-adjusted observed and expected transplant rates. We obtained annual patient and graft survival rates for individual centers using publicly available data. We extracted data on center performance for 2020 from publicly available reports as the 1-year transplant survival data in the SRTR program-specific reports (PSRs) (https://www.srtr.org/reports/program-specific-reports/), which include survival from transplants analyzed in the CDB.

Data from the Vizient CDB and SRTR databases were combined using probabilistic matching based on patient age, sex, date of transplant, and transplant center Medicare ID by Vizient staff (A.H.H., S.F.H.). We excluded records from transplants that could not be matched based on this algorithm. Following linkage, all center and patient identification was removed; accordingly, we do not report individual center cost or performance data. In addition, Vizient privacy agreements prevent reporting of any single-center descriptive or outcome data. While statistical analysis was performed using identified center results, graphical presentation of the correlation between observed and expected cost are shown for aggregations of patients at five transplant programs clustered by median cost of transplant

We defined cost as the total direct cost of hospital care for the transplant episode, measured from the day of admission to discharge. We excluded high- and low-cost outliers from analysis, including LTx hospitalizations with total cost under $20,000 or over $750,000 (top .5% of total cost) and KTx hospitalizations with a total cost under $20,000 or over $300,000 (top .5% of total cost). This was done to improve functional fit and exclude patients with rare, high-cost clinical events. Additionally, KTx recipients with a calculated panel-reactive antibody (cPRA) value over 95% or plasmapheresis claims in the Vizient CDB were excluded from all models to remove biases that could arise from the use of complex immunosuppression and desensitization protocols. For LTx, we computed biologic model for end-stage liver disease (MELD) score at transplant and capped the score at a maximum value of 40, consistent with current liver allocation policy.

2.2 | Liver and kidney cost models

Three independent models were compared in this analysis. First, Vizient produced confidential risk-adjusted observed-to-expected (O:E) ratios for cost, length of stay, and in-hospital mortality using data

from the CDB. Second, we estimated new multivariate linear regression models using only clinical data from the SRTR database. Finally, we combined CDB and registry data, and used covariates from administrative and cost models after eliminating duplicative variables. For KTx, we used Vizient's current administrative claims model, which assigns patients to a "comorbidity quartile" based on analysis of administrative comorbidity codes to provide a measure of clinical complexity for the patient. For liver models, Vizient uses a proprietary claims-based model that includes recipient demographic characteristics, diagnoses, procedure codes, and discharge diagnoses to risk adjust cost comparisons. Our second set of models used transplant registry data alone to develop linear regression models to predict cost at transplant. For each model, we computed center-specific O:E cost ratios by comparing aggregated predicted costs with aggregated observed costs for all observations. Vizient data use agreements preclude the reporting of the exact components of equations used for risk adjustment. Consequently, we only report statistics describing the robustness of the model.

2.3 | Statistical analysis

We used univariate analysis to characterize the sample population and cost, assessing differences using *t*-tests, the χ^2 statistic, and analysis of variance models. We used robust multivariate linear regression models to assess characteristics associated with the cost of the transplant episode. We evaluated by log transformed and non-log transformed models and did not demonstrate a significant improvement in R^2. For ease of interpretation, non-log transformed models are reported consistent with our previous methods.[14] The regression models were constructed using only clinical data, using only administrative data, and using the combined data set. We compared goodness of fit using R^2, Akaike information criterion (AIC), and Bayesian information criterion (BIC). For both AIC and BIC, lower values represent improved goodness of fit, and both AIC and BIC assess the model's explanatory power and complexity. We assess the statistical significance of difference in model predictive ability with paired F-tests. We then compared the O:E ratios from the combined model with risk-adjusted center performance to assess the correlation between center O:E ratios for cost and O:E for performance assessed using the SRTR risk-adjustment models. All multivariate data analyses were performed using Proc GLM in SAS for Windows, version 9.4 (Cary, North Carolina).

Review: This project was reviewed and approved by the Saint Louis University Institutional Review Board.

3 | RESULTS

3.1 | Kidney cost models

We analyzed hospital cost data and transplant registry data for 16,649 KTxs. The average age of the recipients was 53 years, 33.7% were Black, 36.3% had diabetes, and 8.3% had a reported history of peripheral vascular disease (Table 1). The average recipient had 1494 days of dialysis time prior to receiving their transplant and 63% were unsensitized to human leukocyte antigens (HLA), while 7.2% had a cPRA value of 80% or greater. Deceased kidney donors had a mean age of 38 years, terminal donor creatinine value of 1.31 mg/dl, and cold ischemic time of 17.4 h. Organs were recovered after cardiac death in 21.6% of KTx, and 29.6% of all KTx recipients had delayed graft function. Most individuals (78%) had public insurance (Medicare/Medicaid) as their primary insurance. Only 7% of the observed transplants utilized a kidney from a hepatitis C virus–positive donor.

TABLE 1 Demographic and clinical characteristics of kidney transplant recipients, donors, and transplant

Variable	Value
Transplants (*N*)	16,649
Recipient characteristics	
Age (median [IQR])	55 [44-64]
Body Mass Index (median [IQR])	28 [24-32]
Days on Dialysis (median [IQR])	1420 [571-2265]
Black race	33.7%
Diabetes	36.3%
Peripheral vascular disease	8.3%
cPRA	
0%	63.3%
1%–24%	13.9%
25%–49%	7.2%
50%–79%	8.4%
80%–89%	4.1%
90%–95%	3.1%
Public insurance,	78.0%
Donor characteristics	
Death from stroke,	24.9%
DCD	21.6%
Age (median [IQR])	39 [26-51]
Creatinine (median [IQR])	.9 [.7-1.4]
Cold ischemic time (median [IQR])	16 [10-22]
En bloc transplant	1.8%
Shared donor	25.9%
HCV-positive	7.0%
History of hypertension	29.1%

Abbreviations: BMI, body mass index; cPRA, calculated panel-reactive antibody; DCD, donation after circulatory death; HCV, hepatitis C virus.

Overall median direct total cost was $74,136 (interquartile range, $62,598-$90,759). Donor and recipient factors associated with higher cost of deceased transplant included recipient age, cold ischemic time, donor diabetes, donor death from stroke, and recipient history of peripheral vascular disease (Table 2). Development of delayed graft function developed in 29.6% of KTx and was associated with a $10,148 increase in the risk-adjusted cost of KTx.

In the Vizient claims-based risk-adjustment models, each comorbidity quartile was associated with a $19,504 increment in the projected

TABLE 2 Kidney transplant cost models estimated using registry alone, administrative claims, or combined data

	Registry		Administrative		Combined	
Variable	**Beta, $**	***p*-Value**	**Beta, %**	***p*-Value**	**Beta, $**	***p*-Value**
Comorbidity quartile	**NA**	**–**	**Proprietary model**		**Proprietary model**	
Recipient age	76.11	.0044	–	–	41.84	.1008
Donor age	−114.68	<.0001	–	–	−90.69	.0001
Donor creatinine	−613.01	.0198	–	–	−143.78	.5667
Cold ischemic time	221.30	<.0001	–	–	336.40	<.0001
Recipient BMI	−65.13	.2456	–	–	−226.66	<.0001
Dialysis time	−4.99	<.0001	–	–	−3.84	<.0001
Black race	−4,201.95	<.0001	–	–	−3,058.14	<.0001
Diabetic	1,935.32	.0048	–	–	−2,065.14	.002
Donor stroke	2,163.94	.0056	–	–	2,002.91	.0072
DCD donor	−6,724.48	<.0001	–	–	−5,411.83	<.0001
Delayed graft function	10,148.28	<.0001	–	–	8,608.43	<.0001
Peripheral vascular disease	7,922.08	<.0001	–	–	6,727.25	<.0001
En bloc transplant	−11,798.10	<.0001	–	–	−9,362.52	<.0001
Shared donor	1,573.38	.0528	–	–	924.91	.2323
HCV-positive donor	5,832.99	<.0001	–	–	725.83	.5418
Donor hypertension	−2,708.30	.0004	–	–	−2,702.30	.0002
Antihypertensive use	1,623.24	.0718	–	–	1,615.77	.0601
Public insurance	−1,335.92	.0865	–	–	−1,441.83	.0523
cPRA category						
0%	.00	0	–	–	.00	.
1%–24%	−3,524.08	<.0001	–	–	−1,976.95	.0215
25%–49%	−3,024.14	.0115	–	–	−2,494.55	.0286
50%–79%	−2,422.92	.0298	–	–	−1,054.78	.3212
80%–89%	−4,052.37	.0089	–	–	−3,070.86	.0375
90%–95%	−6,638.74	.0002	–	–	−5,781.45	.0006

Abbreviations: BMI, body mass index; cPRA, calculated panel-reactive antibody; DCD, donation after circulatory death; HCV, hepatitis C virus.

cost. This model has an R^2 of .069 (BIC, 299232; AIC, 299209), suggesting that a limited amount of variation is explained by the model.

In the clinical model, recipient characteristics associated with higher direct costs included year of transplant, diabetes, peripheral vascular disease, and hepatitis C virus–positive status. In this analysis of deceased donor transplants, higher cPRA was associated with lower costs, as was Black race. Donor characteristics were significantly correlated with cost including age, cause of death, en bloc transplant procedure, and donation after cardiac death. Kidneys recovered outside of the local donor service area (a shared organ) were associated with a $2482 average increased cost of transplant. Goodness-of-fit analysis for the clinical model demonstrated an adjusted R^2 of .047 (AIC, 399848; BIC, 399632). These statistics suggest a slightly *worse* fit than the model using administrative data only.

Finally, we combined the models to include both data from administrative sources and clinical transplant registry data. In this model, risk adjustment with comorbidity quartiles was supplemented with registry data, particularly regarding donor characteristics. In the combined model, after controlling for other comorbidities, recipient age did not significantly increase the cost of care and Black race was associated with lower costs. Donor factors associated with cost include age, donor creatinine, death from stroke, en-bloc organs, and a regionally or nationally shared organ. The goodness-of-fit parameters for the combined models, demonstrated statistically significantly increased precision compared to the individual models (R^2 = .14; BIC, 398228; AIC, 397989, $p < .0001$). Using the combined models, the correlation between observed costs and those predicted by the model improved ($p < .0001$) (Figure 1).

Center-specific O:E cost ratios using the combined risk-adjustment model for blinded centers were calculated and compared to the O:E for transplant rate and posttransplant graft survival as reported in the 2020 PSR. There was no statistically significant relationship between transplant rate and risk-adjusted cost (R^2 = .01, p = not significant [NS]). These data suggest that higher transplant rates are not associated with higher transplant costs. Similarly, we examined the relationship between post-KTx outcomes. These data demonstrate no

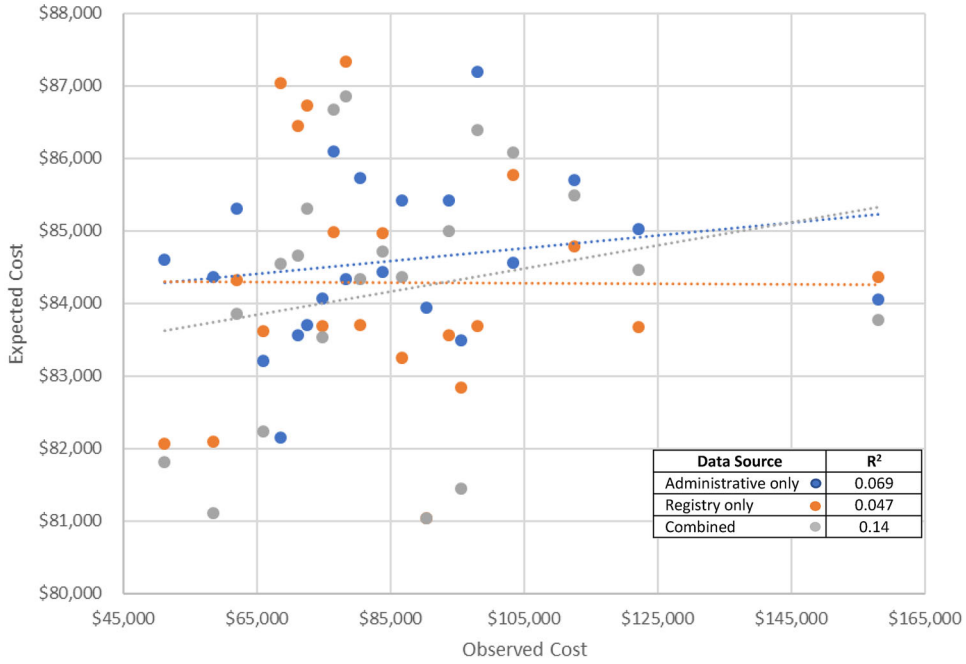

FIGURE 1 Kidney-correlation between observed and expected costs predicted using transplant registry, administrative claims, or combination models (Data shown for clusters of five or six centers per data use agreements)

statistically significant relationship between centers' O:E for cost of care and the standard O:E for 1-year graft-survival.

3.2 | Liver cost model results

Over the study period, 6058 LTx procedures were performed at Vizient centers (Table 3). The 6058 LTx recipients had the following characteristics: mean age, 56 years; laboratory MELD score at LTx, 21; and BMI, 29.4. Among LTx recipients, 8% had a portal vein thrombus, 4% had history of prior transplant, 13.2% were in an intensive care unit (ICU) prior to transplant, and 8% were on life support prior to receiving a transplant. The mean donor age was 42.2 years, and mean cold ischemic time was 6 h. Macrovesicular fat (over 10%) was found in 15.8% of all liver biopsies. Overall, 34.9% of donor organs were regional of national shares. The median total direct cost was $100,527 (interquartile range, $80,667-$127,008).

Unlike the kidney model which included only a crude complexity index, the proprietary Vizient risk-adjustment model used administrative claims to evalaute a variety of LTx recipient characteristics that were correlated with increased cost, such as ventilator dependence, extracorporeal membrane oxygenation use, and dialysis use. The model demonstrated a moderate explanation of cost variation (R^2 = .28) and reasonable goodness of fit (AIC, 149638; BIC, 149812).

We subsequently used clinical registry data to develop a cost model for LTx (Table 4). Recipient factors associated with greater cost include laboratory MELD score, recipient life support, ICU admission, portal vein thrombosis, and prior transplant. Donor factors associated with

TABLE 3 Demographic and clinical characteristics of liver transplant recipients, donors, and transplant

Variable	Value
Transplants, No.	6058
Recipient characteristics	
Age (median [IQR])	58 [50-64]
Body Mass Index (median [IQR])	28 [24-33]
MELD score, (median [IQR])	19 [13-29]
Black race	8.1%
Portal vein thrombosis	7.8%
Prior transplant	3.9%
ICU prior to transplant	13.2%
Dialysis prior to transplant	9.8%
On life support	7.9%
Donor characteristics	
Age (median [IQR])	42 [28-55]
BMI (median [IQR])	27 [23-32]
Creatinine, mean, (median [IQR])	1.1 [.8-2.0]
Cold ischemic time (median [IQR])	5.8 [4.5-7.3]
History of diabetes	12.6%
History of alcohol use	16.4%
Shared donor	34.9%
Macrovesicular fat > 10%	15.8%

Abbreviations: BMI, body mass index; ICU, intensive care unit; MELD, model for end-stage liver disease.

TABLE 4 Liver transplant cost models estimated using registry alone, administrative claims, or combined data

	Registry		Administrative		Combined	
Variable	Beta, $	*p*-Value	Beta, $	*p*-Value	Beta, $	*p*-Value
Vizient defined donor and recipient characteristics			Proprietary model	Proprietary model	Proprietary model	Proprietary model
Donor age	−16.30	.7559	–	–	−28.56	.5662
Donor BMI	−110.06	.3198	–	–	−70.76	.5006
Donor creatinine	−26.31	.947	–	–	205.25	.5855
Recipient BMI	−107.29	.3788	–	–	−205.39	.133
Diabetic donor	5,203.01	.0258	–	–	5,764.20	.0093
Shared donor	7,195.17	<.0001	–	–	5,074.49	.0014
Cold ischemic time	2,145.62	<.0001	–	–	1,895.07	<.0001
Recipient age	246.47	.0004	–	–	135.32	.0523
DCD donor	68.98	.9814	–	–	−55.01	.9844
MELD score	770.59	<.0001	–	–	323.72	.0012
Recipient life support	28,983.23	<.0001	–	–	10,962.83	<.004
Portal vein thrombosis	6,803.90	.0128	–	–	5,111.33	.0491
Macrovesicular fat	−3,449.19	.0994	–	–	2,485.00	.2117
Prior transplant	45,330.69	<.0001	–	–	64,259.92	<.0001
Donor alcohol use	1,034.72	.6034	–	–	1,448.41	.4435
Donor stroke	2,878.85	.1025	–	–	2,430.48	.1469
ICU pretransplant	34,906.12	<.0001	–	–	19,607.06	<.0001
Dialysis pretransplant	28,160.23	<.0001	–	–	10,906.58	.0012
Black race	−761.15	.7776	–	–	−1,045.23	.6843
Donor AB blood type	−4,280.25	.4575	–	–	−2,897.16	.5968

Abbreviations: BMI, body mass index; DCD, donation after cardiac death, ICU, intensive care unit; MELD, model for end-stage liver disease.

high costs include shared donors, cold ischemic time, macrovesicular fat content, and donor with diabetes. Recipient factors include age, MELD score at transplant, prior life support, portal vein thrombosis, prior transplant, ICU-level care, and need for dialysis. This model was similarly predictive (R^2 = .25) as the administrative model alone and had similar goodness of fit (AIC, 149868; BIC, 150035).

In the combined model, incorporating transplant registry data, there were small changes in the beta values from claims-based analyses. Among the registry variables, donor characteristics (diabetes, shared organ, and cold ischemic time) remained significant. Similarly, MELD score at transplant, recipient on life support, prior transplant, and dialysis remained significant. The combined model was significantly more predictive (R^2 = .33, p < .0001) and demonstrated excellent correlation between predicted and observed costs (Figure 2). Goodness-of-fit parameters were lower, suggesting that the value of the increased data elements exceeded the detrimental impact of greater model complexity (AIC, 149267; BIC, 149596).

We then compared center-specific O:E ratio for cost with SRTR-reported O:E for transplant rate and posttransplant mortality (Figure 3A,B). In the liver centers, increasing transplant rate O:E ratio was not associated with cost O:E ratio (R^2 = .0342, p = NS). Risk-adjusted 1-year posttransplant outcomes were not associated with lower mean risk-adjusted hospital costs (R^2 = .0009, p = NS). We found no significant correlation between cost and transplant volume (data not shown).

4 | DISCUSSION

The transition to quality and value-based healthcare reimbursement represents the largest change to hospital and provider reimbursement since Medicare's introduction of bundled payments. More robust measures of patient clinical complexity and cost reimbursement structures will need to be developed to achieve the value-based care aims. This analysis conclusively illustrates that clinical data and administrative claims data have a synergistic effect when developing risk models, in KTx and LTx patients. The combined dataset improves the proportion of variation explained and the goodness of fit for both KTx and LTx cost models. Using this combined model, we identified no significant correlation between risk-adjusted cost of care and center performance metrics.

Currently, clinical data are not integrated into most value-based reimbursement systems, which are based solely on administrative data sets such as Medicare claims.[6,14] Current risk-adjustment

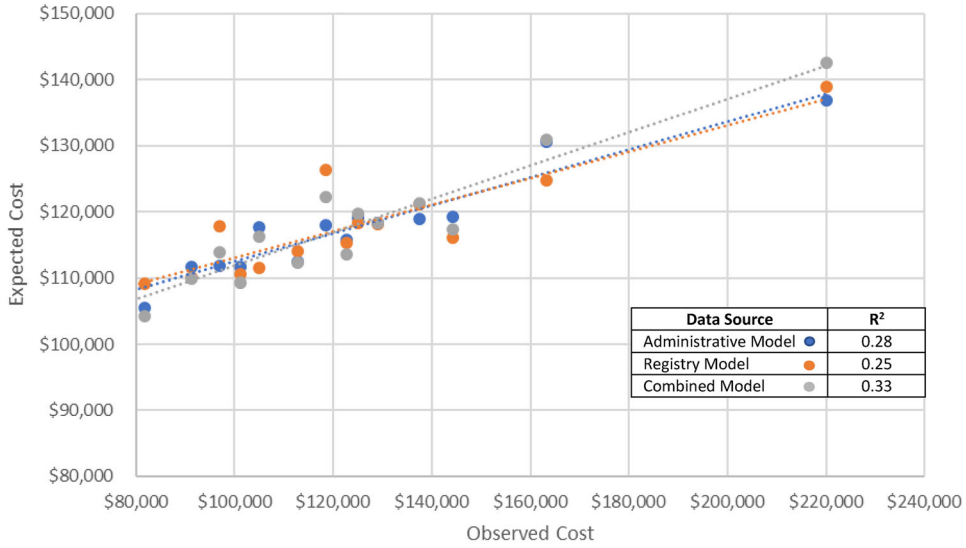

FIGURE 2 Liver-correlation between observed and expected costs predicted using Transplant Registry, Administrative claims, or Combination models. (Data shown for clusters of five or six centers per data use agreements)

methodology to determine value-based purchasing is, therefore, limited in its ability to provide accurate reimbursement concordant with the systematic differences in clinical complexity of patients. This limitation may lead to risk aversion and denial of needed services.

The cost contribution of comorbid clinical characteristics is clear for KTx. The kidney administrative claims model shows that each increase in comorbidity quartile is associated with a cost increase of $19,504. In addition, several donor and recipient characteristics known to be associated with increased KTx cost, such as greater cold ischemic time and a diagnosis of peripheral vascular disease, were shown to be significant cost contributors in the combined model. Interestingly, higher cPRA, en bloc transplants, donation-after-circulatory-death donors, Black patients, and donor hypertension—all factors reported to contribute to patient outcome—had minimal impact on cost in the combined models, although cPRA values >95% were excluded from the analysis. This may reflect the inclusion of a delayed graft function in the model which is highly correlated with these characteristics. Further research is needed to understand the findings. Additionally, the clinical registry data model shows that organs from donors recovered outside of the center's donation service area ("shared donors") increase the cost of KTx by $1573 after adjustment for cold ischemic time and other estimates of organ quality. The models include the allocated cost of organ acquisition across all transplants performed at an institution but do not include individual cost differences (e.g., cost of transportation for a specific organ).

When compared with the KTx models, a significantly greater degree of variation in observed cost of care for LTx was explained by the donor and recipient characteristics. Clinical factors in the registry model also show that utilization of life support or ICU level care pretransplant, portal vein thrombosis, history of prior transplant, increased cold ischemic time, donors with diabetes, and increased MELD scores all significantly affect costs. Liver transplants from shared donors also show significantly increased center costs, which can decrease utilization of shared donor organs. All these factors are likely to increase with the new liver allocation system, resulting in higher cost of care for LTx nationally.[15] These data, however, do not support the belief that increased transplant rate necessarily results in higher risk-adjusted costs. Similarly, achieving excellent 1-year risk-adjusted outcomes was not correlated with the adjusted cost of care. More investigations are needed to understand variation in care processes that explain observed cost differences after accounting for donor and recipient characteristics.

A significant limitation to administration claims databases for transplant cost analysis is the lack of information about donors and their impact on the cost-of-care models. It is well recognized that factors such as long cold ischemic time, donation after circulatory death, and organ import may increase length of stay. To decrease organ discards and improve access to transplant, centers are increasingly being asked to accept organs with exactly these characteristics. Yet, current financial risk-adjustment models include only recipient factors, despite the availability of data that could increase the precision of the cost estimates. A second limitation of models based solely on administrative claims is the precision of clinical coding for comorbid conditions. These data do not include objective measures, such as laboratory values and severity of illness scores such as MELD score for LTx and expected posttransplant survival score for KTx. These scores have been validated to affect perioperative complications and posttransplant survival and have been strongly associated with higher cost.[16,17] The addition of registry and claims-based data provide important additional explanatory power as demonstrated by the increase in the R^2 and lower BIC and AIC.

The substantial residual variation which is unexplained by these models is consistent with analyses of cost data and the difficulty in accurately determining the cost of care.[18,19] The Vizient CDM applies robust method to calculate costs for hospital charges and adjust for differences in care delivery. It is important to note that in spite of

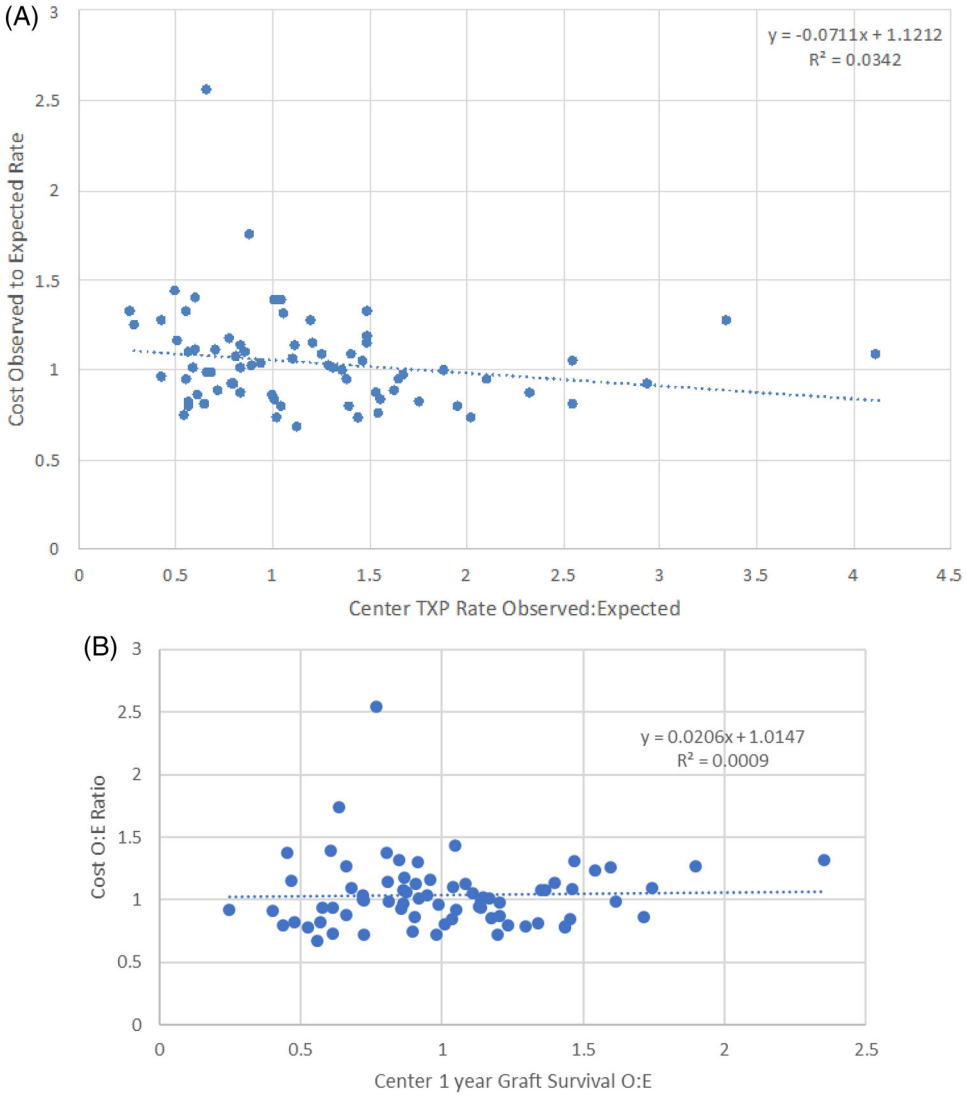

FIGURE 3 (A) Association of observed:expected transplant rate with observed:expected cost. (B) Correlation between observed:expected (O:E) 1-year patient survival and observed:expected median total cost

the significant unaccounted for variation in cost at the patient level, the correlation between observed and expected costs at the center level, shown in Figure 2, is excellent. While a significant portion of the residual variation at the individual patient may reflect practice variation, it is likely that there are significant unmeasured factors that contribute to the unexplained differences. Clinical variables which are not currently collected by the OPTN such as cardiac status, prior malignancy, and frailty need to be comprehensively reported and included. Similarly, sociodemographic characteristics (e.g., neighborhood deprivation index, literacy, and access to community resources) vary widely among transplant populations, impacting the efficiency of care delivery, but are not included in either administrative or clinical models. This is particularly problematic as transplant programs are subject to forces beyond their control (organ supply, severity of illness at the time of transplant, socioeconomic factors), and inadequate risk adjustment contributes to risk aversion in recipient section, donor acceptance, and innovation.[20]

There are several important limitations to this analysis. First, the administrative claims models used were current models used for risk adjustment today. It is possible that different models using these data would have different predictive abilities. We chose to compare the currently used administrative claims models to models combined with clinical registry data to determine incremental value of clinical data in a real-world setting. Second, we examined only the index hospitalization for this analysis. There may be additional costs from readmissions that affect the cost of care under global contracts that are not considered here. Third, we exclude high-cost outliers to improve model fit. This reflects the infrequent occurrence of high-cost, unpredictable, complications that may be unrelated to donor and recipient characteristics and impact < .5% of the population. Currently, reimbursement for these very high-cost patients includes outlier payments that partially compensate for higher-than-expected costs. Third, we were not able to look at payment data. Consequently, we cannot determine how the cost of care affected profit margins. However, because more than 70%

of KTx cases were paid for by Medicare, which historically were paid under a single diagnosis-related group (DRG), it is likely that higher cost implies lower hospital margins. For patients below outlier thresholds, higher costs often result in financial losses for transplant providers. Finally, we used publicly reported risk-adjusted O:E ratios for transplant rate and 1-year outcomes to measure center performance. It is possible that cost would be related to unadjusted outcomes or that the other measure of transplant center performance (e.g., volume) would correlate with costs. We chose to compare cost with post-transplant mortality and transplant rate as these performance metrics are currently the primary metrics used for assessment in transplant care. There was no consistent correlation between center performance and cost in this analysis at the individual center level.

Administrative claims data are helpful in cost modeling as they are widely available, relatively inexpensive, and available to payers. However, risk adjustment based on only administrative data (diagnosis codes, discharge destination, etc.) may fail to adequately capture severity of illness in complex patients that affect center costs. However, analyses using only registry data alone, such as models used to predict outcomes in the PSR, also provide limited information. Integrating clinical registry and administrative claims not only provides a more accurate measure of patient complexity but also is the only way to incorporate information on donor factors. More accurate models can guide process improvement and inform reimbursement policies to decrease risk aversion to higher cost patients and lower quality organs. Given the ubiquity of electronic medical record data, payment models can shift to integrate clinical factors into reimbursement and the residual uncertainty in these models suggests that greater insight into the factor contributing to differing cost of care is needed. Despite this improvement in explanatory power achieved by the integrated models, it is crucial to consider that less than half of the variation in liver transplant costs and 15% of kidney transplant costs is explained by the combined risk adjustment models. Yet, models based on administrative data alone are currently the basis of cost assessments used in value-based care purchasing agreements, hospital administrative decisions, and payer assessments. As allocation systems continue to mandate greater organ sharing, leading to increasing severity of illness and transplant complexity, it is vital that transplant hospitals be fairly compensated for the differences in populations they serve to preserve patient access to this lifesaving service. Accurate assessment of value will require improved models, novel data sources, and a commitment to fair and transparent reporting of both outcomes and costs.

AUTHOR CONTRIBUTIONS

David A. Axelrod, Issac R. Schwantes, Krista L. Lentine, Mark A. Schnitzler: Study design, data analysis, drafting article. Alyssa H. Harris, Samuel F. Hohmann: Study design, data analysis, critical review. Jon J. Snyder, Ramji Balakrishnan, Bertram L. Kasiske: Study design, critical review of manuscript.

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CONFLICT OF INTEREST

DAA: Consulting: CareDx, Talaris, Specialist Direct. MAS: Consulting: CareDx, OPTUM health. AHH, SFH: Employee: Vizient Corp.

DATA AVAILABILITY STATEMENT

Vizient data used in this analysis are confidential based on data use agreements. SRTR data are available upon request.

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