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Predicting Kidney Transplantation Using Prior Disease Diagnosis From Medicare Claims Data

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PREDICTING KIDNEY TRANSPLANTATION USING PRIOR DISEASE DIAGNOSIS FROM MEDICARE CLAIMS DATA

by

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Jeffrey Daniel Dischinger
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ABSTRACT

Kidney transplant prevalence and costs have been increasing steadily in the past few decades and this trend is anticipated to continue for years to come. Patient outcomes are heavily influenced by the amount of time they are waiting for a transplant and by the quality of care they are receiving up to the transplant. This paper intends to increase positive patient outcomes and decrease costs by identifying potential kidney transplant patients earlier than traditional methods. I use medical claims data to determine common risk factors of all patients who have received a kidney transplant. For the control group I include all patients who have not received a kidney transplant. I used a binary logistic regression utilizing common risk factors determined by the claims data to determine what factors are significant and which ones have a larger impact on predicting kidney transplantation. This approach attempts to predict patient health outcomes using claims data instead of clinical data which is often used in other research methods.

The results of my analysis were that the risk factors found in clinical research of kidney transplantation were the same risk factors found using medical claims data. I determined diabetes, hypertension and end stage renal disease were strong indicators of potential kidney transplantation using claims data alone. My conclusion is that medical claims data can be used in place of clinical data when clinical data is not available or does not exist.

CHAPTER I

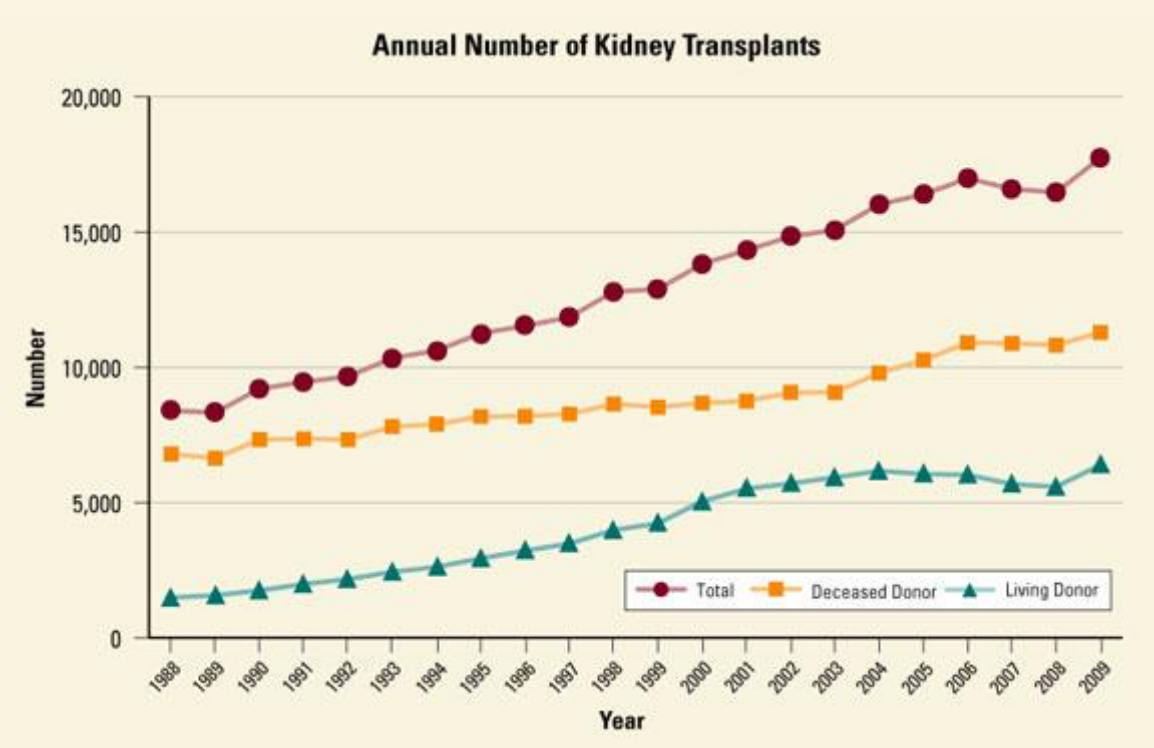
INTRODUCTION

Kidney transplantation is a life changing procedure that is expensive and has the potential for serious complications. To increase the patient's survival time after a kidney transplant it is important to intervene with the patient early on in the diagnosis to ensure proper treatment is given leading up to the transplant. This intervention will likely lead to the best outcome for the patient and help reduce any unnecessary procedures. It will also reduce costs because much of the costs associated with kidney transplant can occur before the transplant actually takes place. According to (Laupacis, 1996) the expenses associated with pre-transplant costs such as dialysis can cost more than the transplant itself and the quality of life of the patient decreases the longer the patient is on dialysis (Meier-Kriesche, 2002). These expenses can range from $7,000 for home dialysis to over $24,000 or more for annual dialysis costs (Hoffstein, 1976). These costs are higher today although the disparity between treatment options remains. This is why it is important to intervene with the patient early and ensure they are getting care from quality and cost effective providers.

Not only have costs been increasing but kidney transplant prevalence has also been increasing. As shown in the chart below (Figure 1) the annual number of kidney transplants has been increasing steadily since 1988 when there were fewer than 10,000 transplants per year to

2009 when there were almost 18,000 transplants. This trend will continue as long as long as kidney transplantation is the only option for those with end stage renal disease.

Figure 1: Annual Number of Kidney Transplants From 1988 to 2009



Even if all the proper steps are taken to ensure the patient is receiving the best care given by the highest quality clinics there is still a shortage of kidneys available for transplantation. Because of this, some patients can be on the kidney transplant waiting list for years waiting for a matching donor kidney. By intervening early in the diagnosis it is possible to inform the patient of their best and most cost effective treatment options early and get them on the waiting list at the earliest possible time. Even a simple thing like having the patient on

home dialysis can save thousands of dollars and possibly lead to better health outcomes for the patient.

Health care costs have been rising steadily for many years and a part of this increase is due to inefficient or unnecessary care. By steering patients to high quality and low cost providers it is possible to increase the likelihood of successful treatments and eliminate unnecessary expenses for the patient. High quality providers are more likely to reduce overall costs by eliminating unnecessary procedures and increasing their patient's health to prevent more doctor visits in the future. Kidney transplantation is just a small part of total healthcare costs but this is one area where it is possible to intervene in care and help reduce costs and increase health outcomes if the potential for kidney transplantation is identified early.

Using claims data in place of clinical data can benefit researches in many ways and has the potential increase the identification of various diseases. The use of claims data can help eliminate selection bias that often occurs in research using clinical data. For example, in my research I am making no decisions on whom to include or exclude from my data set. Any claim contained in the CMS data set is included and there is no other selection criterion on what data should be excluded from the data set. This differs from many clinical studies where the researcher has to choose which members to include and this selection can introduce selection bias whether it is intentional or not. As stated earlier, the claims data for this analysis is Medicare claims data obtained from the Center for Medicare & Medicaid Services (CMS). The claims I used include hospital and physician claims starting at the transplant date and going backwards to the earliest claims available. For the study group I identified all patients who

have received a kidney transplant in the past and looked for specific diagnosis codes, procedure codes, and any other variables that could be important in predicting kidney failure. After identifying all patients that have received a transplant, I compiled my control group which consisted of all other patients in the data that did not receive a kidney transplant. For the group who has not received a transplant I will look at all claims data available regardless of when the claim occurred. What I attempted to determine are the earliest indicators of potential kidney failure which in turn lead to kidney transplantation.

CHAPTER II

LITERATURE REVIEW

There has been a wide range of research done on the topic of what risk factors lead to end stage renal disease and kidney transplantation. The research varies from topics focused on what clinical risk factors are associated with kidney failure to what behaviors may contribute or complicate existing kidney diseases. However, there has not been much research done on whether claims data alone can be used to predict kidney failure, as I am doing for this analysis.

A study done by Hsu (2009) researched 177,570 individuals in a northern California health system who agreed to participate in annual checkups for a ten year period. The study started in 1964 and followed these individuals in the US Renal Data System registry through the year 2000. Hsu found a total of 842 cases of end stage renal disease out of the initial 177,570 participating in the study; which is .47% of the total population. Of these 842 participants who were identified as having end stage renal disease, there were many potential risk factors discovered. These risk factors align with what was found in other studies as well and helps to confirm that these factors can contribute to decreased kidney function. Hsu also mentions some "novel" risk factors such as smoking, which was also included in some of the models he analyzed. Hsu used five different models, each with different risk factors. The final model used in the study was a multivariate model which includes the established risk factors as well as some the novel risk factors. Significant risk factors Hsu discovered were sex, old age, proteinuria, diabetes, low educational attainment,

race, high blood pressure, body mass index, and serum creatinine level. Hsu found that the two most important risk factors are proteinuria and excess weight.

Perry (1995) performed a similar study but only included hypertensive veterans as subjects. The goal of his study was to determine whether or not there is a relationship between high blood pressure and end stage renal disease. This study included 5730 black and 6182 white male veterans identified through the Veterans Hypertension Screening and Treatment Program Clinics. After a 13.9 year follow up, 5337 of the patients died and 245 developed end stage renal disease. Perry used a proportional hazards modeling to fit multivariate survival models in order to determine if there is an effect on end stage renal disease with treatment for high blood pressure. Important risk factors observed in this study were being black or diabetic which could more than double the odds of the patient developing end stage kidney disease. Having a history of urinary tract problems or having high pretreatment SBP are also important risk factors of developing end stage renal disease according to this study.

Diabetes is considered one of the major risk factors associated with end stage renal disease and there are many studies looking at this relationship. Ritz (1999) found that with the increase in type II diabetes there has also been an increase in end stage renal disease; particularly in countries with a western lifestyle. Ritz hypothesized that end stage renal disease was developed due to subjects with hypertension living longer than they had in the past. With the advances in treatment for hypertension it's possible to live longer lives but other complications of hypertension also have more time to develop.

Diabetes is one of the most common risk factors in developing end stage renal disease but it can affect different races in different ways. Cowie (1989) conducted a study looking at the difference between black and white diabetics and how they differ in developing end stage renal disease. Cowie concluded black men were 2.6 times more likely to develop end stage renal disease than their white counterparts. This added variable can further complicate studying the causes of kidney failure especially when demographic information is not available.

In addition to these cohort studies, clinical and demographic data is often used to study end stage renal disease risk factors. Most often both types of data are used as in the study done by Tangri (2011). This study used Cox proportional hazards regression methods to determine significant risk factors of end stage renal disease. The results of the study determined the most accurate model included age, sex, estimated GFR, albuminuria, serum calcium, serum phosphate, serum bicarbonate, and serum ablumium. Tangri concluded that the model created in this study can be used to successfully predict kidney failure in patients with stage 3 to stage 5 chronic kidney disease.

CHAPTER III:

METHODOLOGY

The data I am using comes from the Centers for Medicare & Medicaid Services (CMS). Specifically, the data is Medicare claims data from 2008-2010 which includes member data, inpatient claims, outpatient claims, pharmacy claims, and provider claims. In total, there will be approximately 220 million claims analyzed. I chose to use this data source because it is provided for public use and has no identifying information on the claim so all the claims data remains completely confidential. My main analysis will focus on diagnosis codes and other information provided on a medical claims which makes this data a very reasonable and reliable source for my analysis. In addition, since this data is Medicare data the claims will be coming from an older population and these are the people who will normally be receiving kidney transplants.

The quality of the data is very good; however, there can be some inconsistencies in the data caused primarily by human error. In some cases claims are coded incorrectly by the providers and this data is then passed on to the claims adjudication system. When this happens the member may have incorrect diagnosis or procedure codes listed on their claims which will affect how the member is flagged for specific disease diagnosis. When a claim is coded incorrectly, the error is usually caught by either the insurance company processing the claim or the provider; however, it may take time to reprocess the correct claim so there still may be

errors in the data. Another issue with the quality of the data is that patients can move and switch health plans so the data may not follow the patient to their new health plan. Using CMS data this issue should not be too much of an issue, but it is something consider when analyzing claims data.

The first step in my analysis is to identify all the patients who have received a kidney transplant. To identify those with a kidney transplant I looked for a diagnosis code of V420 and flagged those members as "received a kidney transplant". Then, I looked at all of these member's claims up to the kidney transplant date. I only wanted to look at claims data before the transplant date since I am looking for risk factors leading to a kidney transplant, not factors after a transplant takes place.

I chose to run a binary logistic regression to complete my analysis. I chose this type of analysis for many different reasons. First of all, there is no linear relationship with my independent variables and dependent variable so I was unable to perform an OLS regression. Secondly, my goal in this analysis is to predict the likelihood of a patient in receiving a kidney transplant. The maximum likelihood estimation associated with the binary logistic regression makes analyzing each independent variables influence on the dependent variable relatively easy by looking at each variables corresponding odds ratio. Also, my use of dummy variables makes a binary logistic regression a very good choice. Because diagnosis codes are not continuous variables, I converted all of my diagnosis codes into dummy variables for each specific diagnosis. The initial list of risk variables along with the name of the corresponding dummy variable is listed in the below table (Table 1). For example, in the case of the end stage

renal disease diagnosis of 5856 a dummy variable was created called “End Stage Renal Disease” and the field was marked with a 1 if the patient had this diagnosis and marked with a 0 is there was no history of this diagnosis. This was done in a similar manner for all other diagnosis codes as well as with the other risk factors I initially looked at. In the below table the % indicates a wild card. Some diagnosis codes and prescription drug NDC codes have more than one code indicating the same drug or diagnosis.

Table 1: Risk Factors and Dummy Variable Names

Risk Factor	CPT Code	Risk Factor	NDC
PROTEIN URINE TEST PROCEDURE CODE	84155, 82570, 84156	CALCITROL RX	000930657%%
Risk Factor	**Demographic Variable**	CALCIUM ACETATE RX	000540088%%
AGE 50-59	Age 50-59	FUROSEMIDE RX	0037802%%%%
AGE 40-49	Age 40-49	ALLOPURINOL RX	003780137%%
MALE	Male	INSULIN RX	000882220%%
Risk Factor	**TIN**	LIPITOR RX	00071015%%%
FAIRVIEW	410991680	NORVASC RX	000691540%%
HENNEPIN	411461900	PHOSLO RX	492300640%%
HEALTHSPAN	363261413	RENAGEL RX	584680021%%
KIDNEY SPECIALISTS	411356741	RENAL CAPS RX	602580162%%
Risk Factor	**Therapy Class Code**	**Risk Factor**	**ICD Code**
DIHYDROPYRIDINES THERAPY CLASS RX	242808	END STAGE RENAL DISEASE DIAGNOSIS	5856
HMG-COA REDUCTASE INHIBITORS THERAPY CLASS RX	240608	UNSPECIFIED DISORDER OF KIDNEY AND URETER DIAGNOSIS	5939
ADRENALS THERAPY CLASS RX	680400	CHRONIC KIDNEY DISEASE DIAGNOSIS	585%
BETA-ADRENERGIC BLOCKING AGENTS THERAPY CLASS RX	242400	DIABETES DIAGNOSIS	250%
INSULINS THERAPY CLASS RX	682008	HYPERTENSION DIAGNOSIS	403%
LOOP DIURETICS THERAPY CLASS RX	402808	DIALYSIS COMPLICATIONS	99673
OPIATE AGONISTS THERAPY CLASS RX	280808		
ANGIOTENSIN-CONVERTING ENZYME INHIBITORS THERAPY CLASS RX	243204		

The initial list of diagnosis and procedure codes is quite extensive and would have been too lengthy to include in my final model. In order to minimize the risk factors and make the analysis more feasible, I started by looking at what risk factors were insignificant and could be safely removed from my analysis. My analysis started with a lengthy list of variables, shown below (Table 2), along with their corresponding point estimates and significance test scores derived from my binary logistic regression. There were a variety of variables which I expected to be significant that were actually shown as being insignificant along with point estimates that did not seem logical. As you can see from the below list, the vast majority of the variables are not significant and the ones that I would expect to be significant have a negative point estimate which goes against all previous research on which variables lead to kidney transplantation.

Table 2. Initial Regression Results

Parameter	DF	Estimate	Standard Error	Chi-Square	Pr > ChiSq
END STAGE RENAL DISEASE	1	0.26612	0.15516	2.9417	0.0863
UNSPECIFIED DISORDER OF THE KIDNEY	1	-0.50499	0.1426	12.5405	0.0004
RELEASE_URETHRAL_STR	1	-0.42647	0.20483	4.3349	0.0373
CHRONIC KIDNEY DISEASE	1	-0.10038	0.16433	0.3731	0.5413
CORONARY ATHEROSCLEROSIS	1	-0.10426	0.18971	0.302	0.5826
RENAL DIALYSIS COMPLICATIONS	1	-0.11067	0.16213	0.466	0.4949
DIABETES	1	0.00773	0.18071	0.0018	0.9659

Table 2. cont.

HYPERTENSION CHRONIC KIDNEY DISEASE	1	-0.01991	0.16342	0.0148	0.9031
PROTEIN URINE TEST	1	-0.15487	0.16018	0.9347	0.3336
MALE	1	0.19827	0.13008	2.3232	0.1275
AGE	1	0.05588	0.0127	19.3531	<.0001
TEENS	1	-0.06272	0.50865	0.0152	0.9019
TWENTIES	1	-0.77517	0.54504	2.0227	0.155
THIRTIES	1	-0.0465	0.58715	0.0063	0.9369
FORTIES	1	0.74627	0.66193	1.2711	0.2596
FIFTIES	1	1.12802	0.72863	2.3967	0.1216
SIXTIES	1	1.56352	0.83135	3.537	0.06
SEVENTY PLUS	1	2.04738	0.96325	4.5178	0.0335
CALCITRIOL	1	-0.06948	0.15151	0.2103	0.6465
INSULIN	1	0.31487	0.23441	1.8043	0.1792
RENAL_CAP	1	-0.15797	0.15339	1.0605	0.3031
LIPITOR	1	-0.35738	0.15627	5.2298	0.0222
CALCIUM_ACETATE	1	-0.12243	0.14944	0.6712	0.4126
NORVASC	1	-0.31119	0.1976	2.4802	0.1153
FUROSEMIDE	1	0.09149	0.16412	0.3108	0.5772
RENAGAL	1	0.05533	0.16896	0.1072	0.7433
ALLOPURINOL	1	-0.52829	0.23121	5.2209	0.0223
PHOSLO	1	0.16335	0.16535	0.9761	0.3232
BETA_ADRENERGIC	1	-0.12222	0.1509	0.656	0.418
OPIATE_AGONISTS	1	-0.57826	0.13781	17.6067	<.0001
HMG_COA_REDUCTASE	1	-0.14777	0.15293	0.9337	0.3339
DIHYDROPYRIDINES	1	-0.20104	0.13186	2.3245	0.1274
ANGIOTENSIN_CONVERTI	1	-0.15115	0.12974	1.3573	0.244
INSULIN_THER	1	0.16651	0.22029	0.5714	0.4497
LOOP_DIURETICS	1	-0.05367	0.14544	0.1362	0.7121
ADRENALS	1	-0.20834	0.1244	2.8047	0.094

Since all of my variables are describing a very specific population and because all of them are dummy variables there is a very good chance there is multicollinearity in my initial model. To correct for this I removed many of the variables that were correlated with each other. For instance, the drug Norvasc is used to treat hypertension so if the patient is diagnosed with hypertension chances are they are also taking Norvasc. This issue occurred for all of the prescription drugs I initially included in my model so I decided it would be best to remove all drugs from my regression and simply focus on the disease diagnosis codes. Because I am solely focusing on diagnosis code data, I also removed the age variables and procedure code variables from the model. I did this because I wanted to limit any other variables affecting the outcome of my disease diagnosis variables. I determined that a person's age could be correlated with hypertension and diabetes and I wanted to limit the multicollinearity the best that I could. The below table (Table 3) shows my final model along with point estimates and confidence intervals for all of the included variables in the model. These variables included in the final model were all significant at the 95% level and each appeared to contribute to a patient potentially needing a kidney transplant.

Table 3: Final Model/Model Fit Statistics

Odds Ratio Estimates			
Effect	Point Estimate	95% Wald Confidence Limits	
END STAGE RENAL DISEASE	1.854	1.612	2.133
UNSPECIFIED DISORDER OF THE KIDNEY	1.356	1.137	1.618
CHRONIC KIDNEY DISEASE	1.642	1.438	1.877
CORONARY ATHEROSCLEROSIS	1.23	1.03	1.43
RENAL DIALYSIS COMPLICATIONS	1.12	0.950	1.290
DIABETES	1.29	1.05	1.53
HYPERTENSION CHRONIC KIDNEY DISEASE	1.092	0.966	1.235

Model Fit Statistics			
Criterion	Intercept Only	Intercept and Covariates	
AIC	2665.691	1488.122	
SC	2674.03	1554.835	
-2 Log L	2663.691	1472.122	

Testing Global Null Hypothesis: BETA=0			
Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	1191.569	7	<.0001
Score	4328.2922	7	<.0001
Wald	971.1524	7	<.0001

CHAPTER IV:

RESULTS AND INTERPRETATION

The results of the model shows similar results to what has been found in previous research of what risk factors can lead to kidney failure. Past research has shown that hypertension, diabetes, end stage renal disease, and coronary atherosclerosis are all leading indicators of potential kidney transplantation. Using claims data to analyze these common factors I came to the same conclusion.

The odds ratio calculation is the main factor I used to quantify how strongly my independent variables are associated with my dependent variable. The odds ratio is calculated by dividing the probability of the dependent variable being 1 by 1 minus the probability of the dependent variable being 1.

$$odds = \frac{P}{1 - P}$$

In my analysis each odds ratio is calculated by dividing the probably of the patient having a kidney transplant based on each specific risk factor. By looking at the odds ratio estimates provided with my final output in Table 3 it shows that a person with end stage renal disease is 1.854 times more like to receive a kidney transplant than someone without a claims diagnosis of end stage renal

disease. Logically, this makes sense and is supported by other research and data. When a patient develops end stage renal disease a kidney transplant is likely the only option so I would expect the odds ratio on this estimate to be high. Similarly, diabetes is also a leading cause of kidney transplantation and an odds ratio of 1.29 indicates the patient is 1.29 times more likely to receive a kidney transplant than someone without this diagnosis. Interestingly, the diagnosis of hypertension with chronic kidney disease has a relatively low odds ratio only indicating a patient with this diagnosis as having an increased likelihood of kidney transplantation of 1.092 times that of someone without that diagnosis. This low odds ratio could be due to the diagnosis being very specific and some of the variation could be picked up by the chronic kidney disease diagnosis.

The final model seems to have a very good fit compared to an empty model. As shown by the Model Fit Statistics computed by my SAS program (Table 3) the three criteria used to determine overall fit all have very high Chi-Square estimates and low P values. This would seem to indicate the variables I chose to include in my final model are reasonable and I should not reject my model.

Even though my final model has a limited number of independent variables, it does a relatively good job of predicting kidney transplantation based on the seven risk factors included. Of these seven risk factors, the diagnosis of end stage renal disease has the most impact on predicting if a patient will need a kidney transplant in the future. By looking at all the variables as a whole, a researcher could use the corresponding odds ratios of all of these variables and predict which patients will eventually need a kidney transplant with relative confidence. As stated earlier, using claims data alone could lead to some false positives based on errors in claims data and the

fact that claims data may not tell the whole story. Even with these limitations, my analysis could prove to be very useful for someone interested in factors leading to kidney transplantation.

CHAPTER V:

FUTURE RESEARCH

Overall, claims data paints a good picture of each patient's overall health and has proven to be very useful when looking for risk factors leading to kidney transplant. In terms of data to include in a model I think the data I am lacking most is clinical data. Data such as test results from blood or urine samples, blood pressure, and heart rate would provide even more insight into the patient's health. Although this information would be nice to have, a lot of what is in the claims data can help explain the outcome of some test results. For example, the results of a GFR test would indicate what stage of renal failure a patient is in. In this case using the diagnosis code to show what stage of renal failure a patient is in can be just as useful as the clinical data.

In this analysis I am only looking at the Medicare population for a limited time period of four years. This population only includes older patients so I'm not looking at the entire population as a whole. Most people needing kidney transplants are older so this shouldn't' have a large impact on the results, but it should be noted that I'm not looking at all ages and groups of people. Using claims data older than four years old would also be useful in this analysis to potentially identify kidney transplant recipients earlier. Chronic kidney disease can develop over a long period of time and there could be some diagnoses very early in the patient's care that may be useful in predicting future kidney transplant recipients.

Based on the results of this model it would be interesting to put this method into practice and attempt to predict future kidney transplant recipients in a health plan. The health plan researcher could then follow the patients who were flagged as potentially needing a kidney transplant and see which ones did in fact require a kidney transplant in the future. This could be a very long process since developing end stage renal disease can take many years but it would be a good way to validate the model.

CHAPTER VI:

SUMMARY

Kidney transplantation is a costly and life altering procedure that can potential decrease a patient's quality of life. It is important to identify potential kidney failure as early as possible to help increase positive outcomes for the patient and to help reduce costs associated with end stage renal disease. By identifying a patient early it is possible to be put on a kidney donor waiting list earlier to potentially decrease the time waiting for a kidney while the person is on dialysis. The longer a patient is on dialysis the higher risk they will have of developing complications related to kidney failure. They can also expect a decreased life expectancy after the transplant.

My analysis confirms what prior clinical research has shown except I am using claims data in place of clinical data. Major risk factors cited in prior research include diabetes, hypertension, and end stage renal disease and I also show similar results. Based on these results it may be possible to predict other potential health outcomes using claims data in place of other research methods. This may provide useful information to health insurance companies and others who do not have direct access to clinical data.

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