A Two-Part Model of the Individual Costs of Chronic Kidney Disease

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Abstract

Chronic Kidney Disease (CKD) affects many lives and has a large impact on health systems around the world. To better understand and predict costs for insurance plan members with CKD in the United States, we built a new model of their individual costs. Our model is the first to explicitly model both the CKD stage transition process and the distribution of costs given those stages. Additionally, it incorporates numerous covariates and comorbidities. We applied the models to two large and rich datasets, one commercial insurance and the other Medicare fee-for-service, totaling about 40 million beneficiary months. We found that the XGBoost models best predict both stage transitions and costs. If XGBoost models are unavailable, a multivariate logistic regression model with regularization to predict stage and a logit-gamma model of the costs given the stage best predicted the member's healthcare costs in the next month.

1 Introduction

CKD is a global health issue, but in this article we focus on the United States. In the United States, the Center for Disease Control and Prevention (2019) notes that 37 million people (about 15% of the adult population) are estimated to have CKD. CKD is most common in older populations. Roughly one in ten people globally are affected by CKD, which can be developed at any age.

In the United States, many patients with end-stage renal disease (ESRD) and chronic kidney disease (CKD) are covered by Medicare. Collins et al. (2010) reviewed the 2009 annual data report from the US Renal Data System (USRDS) and found that in 2007, over 100,000 patients started ESRD therapy, spending over $35 billion (roughly $24 billion covered by Medicare). Over 17,500 transplants were performed, and the total CKD-treatment-receiving population reached over 500,000 patients. Roughly 6% of Medicare expenses were attributed to ESRD treatment alone.

The stage of a CKD patient is determined by the patient's glomerular filtration rate (GFR), which measures how quickly blood is filtered through the kidneys. The GFR determines six stages of CKD. Stage 1 is any GFR higher than 90 ml/min. A GFR of 60 to 89 ml/min corresponds to stage 2, 45-59 ml/min to stage 3a, 30-44 ml/min to stage 3b, 15-29 ml/min to stage 4, and less than 15 ml/min to stage 5 (Johnson et al. 2004). Kidney failure (or end stage renal disease, ESRD) are patients in stage 5 who require dialysis or a transplant.

These GFR stages can be combined with three categories of albuminuria to assess a patient's risk. Healthy kidneys prevent albumin (a protein found in the blood) from passing into urine. Albuminuria is the level of albumin in the urine; more albumin is a sign of unhealthy kidneys. Stage A1 corresponds to less than 30 mg of albumin per gram of urine, A2 to 30 to 300 mg/g, and A3 to any higher level (Levey et al. 2015). The combination of a higher GFR stage and higher albuminuria indicate a higher risk level to the kidneys. For the interested reader, Levey & Coresh (2012) provide a general introduction to CKD and related topics.

In 2017, spending on Medicare beneficiaries with CKD was over $84 billion, and members with ESRD spent an additional $36 billion (Centers for Disease Control and Prevention 2021). On average, the higher the patient's CKD stage, the higher the costs, across all medical services. Our analysis of administrative claims datasets shows that for both the Medicare and commercial data, the average costs per member, per month (PMPM) throughout the study period (2016-2018) increase exponentially as stage increases (Tables 1 and 2), highlighting the need for accurate models. These results are similar to those found in other studies (Golestaneh et al. 2017, Saran et al. 2021, Gandjour et al. 2020).

In early stages, CKD progression can be slowed through improvements in diet, exercise, and certain medical interventions (Drawz & Rosenberg 2013, Drawz et al. 2020). As the disease progresses and the kidneys can no longer sufficiently filter the blood, patients may require dialysis (assisted blood filtration). In cases of extreme risk or occurrence of ESRD, a kidney transplant may be necessary. The costs associated with these treatments are often large. The first year of a kidney transplant costs, on average, $442,500 in the US (Bentley & Ortner 2020). To help account for the large impact of CKD on the US health system, we

CKD Stage	Inpatient Claims PMPM ($)	Outpatient Claims PMPM ($)	Professional Claims PMPM ($)	Total Claims PMPM ($)
1	1,600	400	998	2,998
2	2,084	426	1,064	3,574
3	2,707	490	1,253	4,450
4	3,427	514	1,505	5,446
5	3,385	561	1,520	5,466
6 (ESRD)	3,739	3,459	1,737	8,935

Table 1: Average PMPM Medicare claims by CKD stage 2016-2018. Notes: Excludes pharmacy drug costs and is derived from diagnoses present in administrative claims data.

CKD Stage	Inpatient Claims PMPM ($)	Outpatient Claims PMPM ($)	Professional Claims PMPM ($)	Total Claims PMPM ($)
1	980	756	807	2,543
2	1,539	870	869	3,277
3	2,561	1,117	1,129	4,807
4	3,316	1,284	1,377	5,977
5	2,777	1,453	1,322	5,553
6 (ESRD)	5,411	12,043	2,110	19,564

Table 2: Average PMPM Commercial claims by CKD stage 2016-2018. Notes: Excludes pharmacy drug costs and is derived from diagnoses present in administrative claims data.

developed a new model which better predicts the healthcare cost of CKD members by explicitly modeling both the stage and the costs within that stage. Section 2 will describe the current state of the art in CKD modeling around the world and how our models improve stage and cost prediction. Section 3 describes the commercial and Medicare datasets used in our analyses. Section 4 details our model and section 5 provides the results of our analysis. Finally, section 6 presents our conclusions.

2 Literature Review

Kerr et al. (2012) showed that CKD-related costs to the English National Health Service are very large, comprising mostly renal replacement therapy but also excess comorbidities. The literature points to several drivers of these costs. Tangri et al. (2011) found that common lab results such as calcium, albumin, and phosphate levels are good indicators of kidney failure. Along with other demographic information, Damien et al. (2016) and Manns et al. (2019) found comorbidities to be significant drivers for CKD-related costs. Damien et al. (2016) also found treatment type (dialysis, non-dialysis, or transplant) and insurance type (public or private) to have a significant effect on costs. Laliberté et al. (2009) examined patients with hypertension and/or diabetes in a managed-care setting and found that costs spiked after CKD diagnosis.

Chang et al. (2016) performed an observational study that indicated that peritoneal dialysis dominates hemodialysis in cost effectiveness. Khan & Amedia Jr (2008) reviewed the related literature and found that early nephrologist referrals, the use of erythropoiesis-stimulating proteins (ESP), and management of hypertension each have a large impact on outcomes and costs.

Intervention techniques were found to reduce costs. Hopkins et al. (2011) show that multidisciplinary care can reduce costs, mainly by decreasing the length of hospital stays. Similarly, P. M. Chen et al. (2015) found that a multidisciplinary approach improves health outcomes and reduces average costs. Wei et al. (2010) show that multidisciplinary care is associated with higher costs before dialysis, but much lower costs after dialysis. Erickson et al. (2013) show that preemptive prescription of statins is cost-effective for high-risk patients. Manns et al. (2010) found that the cost of a broad one-off screening for CKD was not cost-effective in Canada. In contrast, Kondo et al. (2012) show that in Japan a widespread test was cost-effective.

Several models have been implemented to examine the costs and progression of CKD. Tangri et al. (2011) used a binary prediction model for kidney failure. Generalized linear models have assessed various covariates as well. Honeycutt et al. (2013) used a two-part model to show the specific effects of CKD on costs and its important covariates. They modeled total costs for patients with CKD and those without CKD to compare the effect of CKD on costs. Damien et al. (2016) also uses a generalized linear model to understand the impact of cost drivers.

Markov-style models are useful in this scenario due to the common use of the CKD stages in clinical practice. Hoerger et al. (2010) used microsimulation to look at CKD progression, focusing on costs. In Orlando et al. (2011), a simple Markov model was constructed to simulate progression and provide base cases for costs. simulates progression and provides base cases for costs. This model assumes fixed transition probabilities and fixed effects of intervention on costs. Fricks et al. (2016) used Markov reward modeling to simulate transitions, but the costs per year for each stage are also fixed. They note that after healthy patients, patients with transplants have the best health outcomes; however, the donor pool is insufficient for those with ESRD.

Our model simultaneously improves on the current state of the art in both CKD stage modeling and cost modeling. We use a large number of covariates and a regularization technique to focus on the most important predictors of CKD stage and cost. We also compare several different distributional families, Medicare and commercial populations, as well as explicitly model both the stage transitions and the distribution of costs in each stage.

3 Data

We perform these analyses on two different datasets. Milliman's Consolidated Health Cost Source Database (the commercial dataset) and the Medicare 5% Sample Medicare Standard Analytical Files (the Medicare dataset). We limit both datasets to claims from members with at least one CKD diagnosis from 2016 to 2018. After applying this inclusion criteria, the Medicare dataset contains about 11 million beneficiary months and the commercial dataset contains about 28 million member months. We connect each member's monthly data within each dataset, but cannot connect patients across datasets. Note that there are conditions for a patient with CKD to qualify for Medicare before age 65 (Centers for Medicare and Medicaid Services 2021). For each member month, we have information on age, sex, state, a measure of rurality (IIR 2010, Waldorf & Kim (2018)), inpatient, outpatient, and professional costs, and a series of indicators for CKD stage and the presence of about 50 other comorbidities, which were drawn from claims data. The costs are all-cause healthcare spending, not just the CKD-related costs. Using total costs allows us to account for comorbidities directly and enables practitioners to more easily apply our models to their data. The summary statistics of all the indicators used in our models are provided in Table 3. The ICD-10 codes that trigger indicators of comorbidities are available in Appendix B. With the exception of gross hematuria and the two urinary tract infection (UTI) flags, comorbidities are considered chronic; and therefore, members have the indicator and every subsequent month following its first occurrence. All data has been processed through the Milliman Health Cost Guidelines Grouper, which uses continuous stay logic to keep together inpatient claims where intermediate billing records may be generated (for example an inpatient stay that extends across the end of one month into the beginning of the next). For other services, they are recorded in the month indicated in each record's starting date (often the first of the month, or once per week). The rurality indicator is based on member location. Our data cannot differentiate between stages 3a and 3b, so we combine them into stage 3. For ease in defining our model, we will call ESRD stage 6. We also define stage 0 as members who do not yet have a CKD diagnosis but will in the future. In summary, our data encompasses seven stages: 0 (no CKD), 1, 2, 3 (both 3a and 3b), 4, 5 and 6 (ESRD).

	Commercial	Medicare
Total beneficiary months	27,645,493	10,870,922
Continuous Covariates: Mean (sd)		
IRR 2010	0.33 (0.11)	0.35 (0.13)
Age	59.92 (14.15)	75.92 (11.37)
Inpatient claims	867.48 (21,913.51)	1,079.82 (6,471.09)

Outpatient claims	904.21 (7,046.38)	475.27 (1,673.71)
Professional claims	559.30 (2,281.30)	696.41 (1,630.95)
Categorical Covariates: Count (%)		
CKD stage 0 (no CKD yet)	10,060,507 (36.4)	3,501,047 (32.2)
CKD stage 1	1,197,109 (4.3)	173,249 (1.6)
CKD stage 2	3,280,333 (11.9)	765,838 (7)
CKD stage 3	9,837,864 (35.6)	4,489,667 (41.3)
CKD stage 4	1,451,143 (5.2)	883,228 (8.1)
CKD stage 5	220,030 (0.8)	102,743 (0.9)
CKD stage 6 (ESRD)	1,598,507 (5.8)	955,150 (8.8)
Acute myocardial infarction	816,151 (03.0)	613,334 (05.6)
Aspiration and specified bacterial pneumonias and other severe lung infections	377,514 (01.4)	346,112 (03.2)
Asthma	2,956,670 (10.7)	1,913,269 (17.6)
Atrial and Ventricular Septal Defects, Patent Ductus Arteriosus, and Other Congenital Heart/Circulatory Disorders	208,634 (00.8)	131,715 (01.2)
Back Pain	4,545,147 (16.4)	2,645,135 (24.3)
Breast (age > 50) and prostate cancer, benign/uncertain brain tumors, and other cancers and tumors	1,644,239 (05.9)	1,140,431 (10.5)
Cardiomegaly	2,158,610 (07.8)	1,686,058 (15.5)
Chronic obstructive pulmonary disease, including bronchiectasis	2,621,373 (09.5)	2,623,010 (24.1)
Colorectal, breast (Age < 50), kidney, and other cancers	1,194,058 (04.3)	708,144 (06.5)
Congenital renal cyst	147,167 (00.5)	78,210 (00.7)
Congestive heart failure	3,934,178 (14.2)	3,313,255 (30.5)
Diabetes with chronic complications	8,491,807 (30.7)	4,168,533 (38.3)
Diabetes without complication	9,644,788 (34.9)	4,908,413 (45.2)
Diet	881,294 (03.2)	329,187 (03.0)
Gross hematuria	60,418 (00.2)	37,894 (00.3)
Heart infection/inflammation except rheumatic	415,396 (01.5)	256,521 (02.4)
Hemodialysis	1,002,348 (03.6)	716,230 (06.6)
Hepatic cysts	35,746 (00.1)	9,963 (00.1)
High blood pressure not diagnosed as hypertension	913,072 (03.3)	392,343 (03.6)
Hyperlipidemia	15,175,366 (54.9)	7,448,121 (68.5)
Hypertension	19,281,458 (69.7)	9,036,831 (83.1)
Hypoplastic left heart syndrome and other severe congenital heart disorders	7,072 (00.0)	1,194 (00.0)
Ischemic or unspecified stroke	900,171 (03.3)	881,535 (08.1)
Kidney transplant	789,791 (02.9)	230,309 (02.1)
Lung, brain, and other severe cancers, including pediatric acute lymphoid leukemia	592,515 (02.1)	364,227 (03.4)
Major congenital heart/circulatory disorders	195,853 (00.7)	120,427 (01.1)

Metastatic cancer	511,958 (01.9)	256,884 (02.4)
Nicotine dependence	5,083,096 (18.4)	3,316,243 (30.5)
Non-Hodgkin's lymphomas and other cancers and tumors	403,712 (01.5)	239,980 (02.2)
Proteinuria	3,259,233 (11.8)	967,955 (08.9)
Renal anemia	2,441,513 (08.8)	1,682,580 (15.5)
Sex = M (%)	15,684,760 (56.7)	5,245,898 (48.3)
Specified heart arrhythmias	3,301,685 (11.9)	2,930,344 (27.0)
Thyroid cancer, melanoma, neurofibromatosis, and other cancers and tumors	430,456 (01.6)	239,045 (02.2)
Unstable angina and other acute ischemic heart disease	787,089 (02.8)	619,325 (05.7)
Urinary tract infection with hematuria	36,481 (00.1)	25,071 (00.2)
Urinary tract infection without hematuria	611,394 (02.2)	540,293 (05.0)
Weight: BMI - 19.9 or less	202,621 (00.7)	194,772 (01.8)
Weight: BMI - 20 to 24.9	811,211 (02.9)	577,837 (05.3)
Weight: BMI - 25 to 29.9	2,001,557 (07.2)	1,029,930 (09.5)
Weight: BMI - 30 to 34.9	2,402,540 (08.7)	1,092,267 (10.0)
Weight: BMI - 35 to 39.9	1,737,144 (06.3)	730,401 (06.7)
Weight: BMI - 40 or greater	1,888,576 (06.8)	663,713 (06.1)
Weight, Newborns: <500 Grams	186 (00.0)	0 (00.0)
Weight, Newborns: 500-749 Grams	1,293 (00.0)	34 (00.0)
Weight, Newborns: 750-999 Grams	1,471 (00.0)	2 (00.0)
Weight, Newborns: 1000-1499 Grams	1,750 (00.0)	46 (00.0)
Weight, Newborns: 1500-1999 Grams	2,511 (00.0)	35 (00.0)
Weight, Newborns: 2000-2499 Grams	2,982 (00.0)	229 (00.0)
Weight, Newborns: Other Low Birthweight issues	9,298 (00.0)	268 (00.0)
Weight, Pediatric: <5th Percentile	6,081 (00.0)	430 (00.0)
Weight, Pediatric: 5% - 95%	43,461 (00.2)	1,212 (00.0)
Weight, Pediatric: >95th Percentile	17,535 (00.1)	535 (00.0)

Table 3: Exploratory Data Description

4 Model

Our model has two parts, both explicitly modeled. The first part models the CKD stage and the second part models the monthly cost given the CKD stage.

4.1 Stage Model

Our stage model uses the covariate information from the current month, especially the current CKD stage, to predict the CKD stage for the following month. We also assume that the members cannot reverse their

CKD progression (National Institutes of Health 2021). There are some other months which imply movement to lower stages, we assume that those are coding or measurement errors. There are other months with no stage-related claim, we assume that they still have CKD. Specifically, we model the odds of a CKD patient remaining in their current state or progressing to any worse state.

We compare two types of models—multivariate logistic regression and extreme gradient boosting ("XG-Boost") (Chen & Guestrin 2016, Chen, He, Benesty, Khotilovich, Tang, Cho et al. 2015)—to predict the transition probabilities. Because we have many potential covariates, we simplify our model by using regularization in the logistic regression through the lasso penalty (Tibshirani 1996). The lasso penalty automatically shrinks some coefficients to zero and also effectively constrains the other variables.

We set up our two different training and test sets temporally. The first uses all the 2016 data as the training set and the 2017 data as the test set, imagining we are currently in December 2016 and trying to predict CKD stages for next year. The second uses the 2016-2017 data as the training data and the 2018 data as the test data.

To find appropriate values of the logistic regression hyperparameters (in this case, the lasso penalty λ), we perform five-fold cross validation on the training data. Our hyperparameter estimation technique for the XGBoost model is described in Appendix A.

4.2 Cost Model

The cost model uses covariate information from the current month and next month's CKD stage to predict the member's full (not just CKD-related) healthcare costs for next month. We chose to use next month's stage rather than use the current month's stage so we could simply multiply the probabilities from the stage model by the distribution of costs in the cost model to get the overall cost prediction for the member. Also, next month's stage has a more direct impact on next month's costs than the current month's stage. We fit three different cost models: (1) a logit-gamma model, (2) a Tweedie model, and (3) an XGBoost model. The gamma model allows only positive values, so we first run an additional logistic regression model to predict whether the member had any costs for that specific month and then fit the gamma model on only the members with positive costs. We use a log link to enable better coefficient interpretation than the canonical (inverse) link. The Tweedie and XGBoost models can handle both zero and positive values.

5 Results

For both the stage model and the cost model, we discuss both the model selection results (i.e., which model best predicts) and the covariate inference (which covariates are most influential to costs and stage progression).

5.1 Stage Model

The stage model explicitly models the odds of progression of the member through the CKD stages.

5.1.1 Model Selection

In addition to the XGBoost model, we compared three different multinomial logistic regression models: one with no regularization, one with a lasso penalty equal to the minimum as selected by the cross validation (min), and a third model with the lasso penalty creating the simplest model within one standard error of the minimum λ (1 s.e.). To compare the models, we calculated the categorical cross-entropy (the negative log of the probability of the correct class) in the test set. The smaller the cross-entropy, the better the model fits. The results of the tests are summarized in Table 4.

The XGBoost model outperforms the logistic model in all subsets except one. XGBoost models are generally more difficult to interpret than the logistic models but predict stage transitions more accurately. If you must use the logistic models, a model with regularization is almost always better (90%) than the model without regularization. For the Medicare data, the 1 s.e. penalty is better for stages 1, 3, and 4 while the minimum penalty is better in stages 2 and 5. The optimal model in the commercial data varies with no regularization being optimal for stage 1 with prediction year 2018 and stage 2 with predictive year 2017. The min penalty is optimal for stage 3 (both predictive years) and for stage 4 with predictive year 2017. The 1 s.e. penalty is optimal for all others. In both situations where the model without regularization is better, the multi min model performance is very close, showing that generally the regularized model is preferred if a logistic model is required.

5.1.2 Covariate Inference using the Multinomial Model with Optimal Regularization

Figure 1 plots the preliminary (before accounting for any covariates) odds of transitioning to various stages for someone currently in stage 3. In all the plots, the colors are simply to improve visualization. For a member currently in stage 3, Figure 1 shows that the most likely outcome is that the member will stay in

Dataset	Stage	Prediction Year	Cross-entropy multi	multi min	multi 1 s.e.	XGBoost
Commercial	1	2017	29,633	29,633	29,533	**29,472**
Commercial	1	2018	26,195	26,200	26,372	**25,860**
Commercial	2	2017	78,986	78,995	79,553	**78,108**
Commercial	2	2018	74,439	74,430	74,166	**72,840**
Commercial	3	2017	137,285	137,201	137,665	**131,353**
Commercial	3	2018	125,789	125,770	125,915	**119,264**
Commercial	4	2017	52,612	52,588	52,687	**51,359**
Commercial	4	2018	46,816	46,794	46,593	**45,160**
Commercial	5	2017	19,067	18,929	17,193	**16,243**
Commercial	5	2018	16,026	15,955	15,218	**14,433**
Medicare	1	2017	8,372	8,053	7,289	**7,277**
Medicare	1	2018	7,435	7,257	6,733	**6,658**
Medicare	2	2017	28,298	**28,229**	28,603	28,379
Medicare	2	2018	25,691	25,658	25,696	**25,590**
Medicare	3	2017	76,988	76,943	76,376	**75,346**
Medicare	3	2018	111,191	110,890	87,736	**66,559**
Medicare	4	2017	25,823	25,423	24,432	**23,914**
Medicare	4	2018	22,533	22,498	22,011	**21,552**
Medicare	5	2017	5,925	5,912	5,943	**5,802**
Medicare	5	2018	5,436	5,433	5,533	**5,237**

Table 4: Stage Model Comparison by Cross-Entropy, Minimum Values in Bold

stage 3. If the member does move, they will most likely move to stage 4. They are less likely to jump to stage 6, and least likely to jump to stage 5 in the next month. Similar plots for all stages and both datasets are available in Appendix C. The biggest difference between the preliminary odds of the two patient cohorts is that the members in the commercial dataset are much less likely to jump directly to stage 6 from stage 3. A similar pattern is seen across the other stages. In all cases though, the most likely outcome by a significant margin is that the member will stay in the same stage from one month to the next. Figure 2 shows the model coefficients for the Medicare data in stage 3 at the optimal value of λ (in this case 1 s.e.). Plots for all stages are also available in Appendix C. Any covariate not in the plot was removed from the model by the lasso penalization. Patients receiving hemodialysis are very likely to be in stage 6 next month (it is likely they are already there but have not been diagnosed or coded yet). Some other covariates like renal anemia and proteinuria make it likely that they will move to stage 4, but not to stage 6. Others (gross hematuria and UTI with hematuria) appear to show that the member is much more likely to move to stage 5 than expected, but less likely to move to stage 4. All of these associations are correlations and not necessarily causal. Many could be driven by small sample sizes (see Table 3). The majority of these relationships are similar in the commercial data and across stages.

5.2 Cost Model

The cost model predicts the total healthcare costs of a member during a certain month, given the CKD stage in that month

5.2.1 Model Selection

For the cost models, we compared the logit-gamma and the Tweedie models each with three different levels of regularization (none, min, and 1 s.e.), with the XGBoost model. To compare them, we predicted the costs for each member and then computed the median absolute error. In about half of the cases (13 out of 24), the XGBoost model performed the best. In most other cases, the unregularized logit-gamma model performed the best. The regularized logit-gamma min model matched the unregularized model in many cases, meaning the optimal regularization was no regularization. The complete results are in Table 5.

5.2.2 Covariate Inference

In the logit-gamma models, essentially all the values are non-zero; however, some of the smallest values are removed to make the plot easier to read. The logit model (Figure 3) only models the probability that the costs for that month are non-zero, so the values at the top (urinary tract infection, kidney transplant, gross hematuria, and metastatic cancer) are all conditions that make it more likely that a member will have costs in the following month. There are not many covariates that significantly reduce the likelihood of a claim, which makes sense because in general the fewer conditions a member has, the less likely they are to incur medical costs.

While the logit model predicts the probability of non-zero costs, the gamma model predicts the total cost, given that it is non-zero. As Figure 4 shows, the indicators associated with the highest costs in the following month are cancer, UTI, and gross hematuria. Newborn birthweight is an interesting indicator. Medicare covers all people with ESRD, even newborns (Kirchhoff 2018). Newborns (of any birth weight) with ESRD are likely to have very high costs. Rurality (IRR2010) has the most negative impact on cost. Members who live in more rural areas are predicted to have significantly lower costs than those in more urban settings.

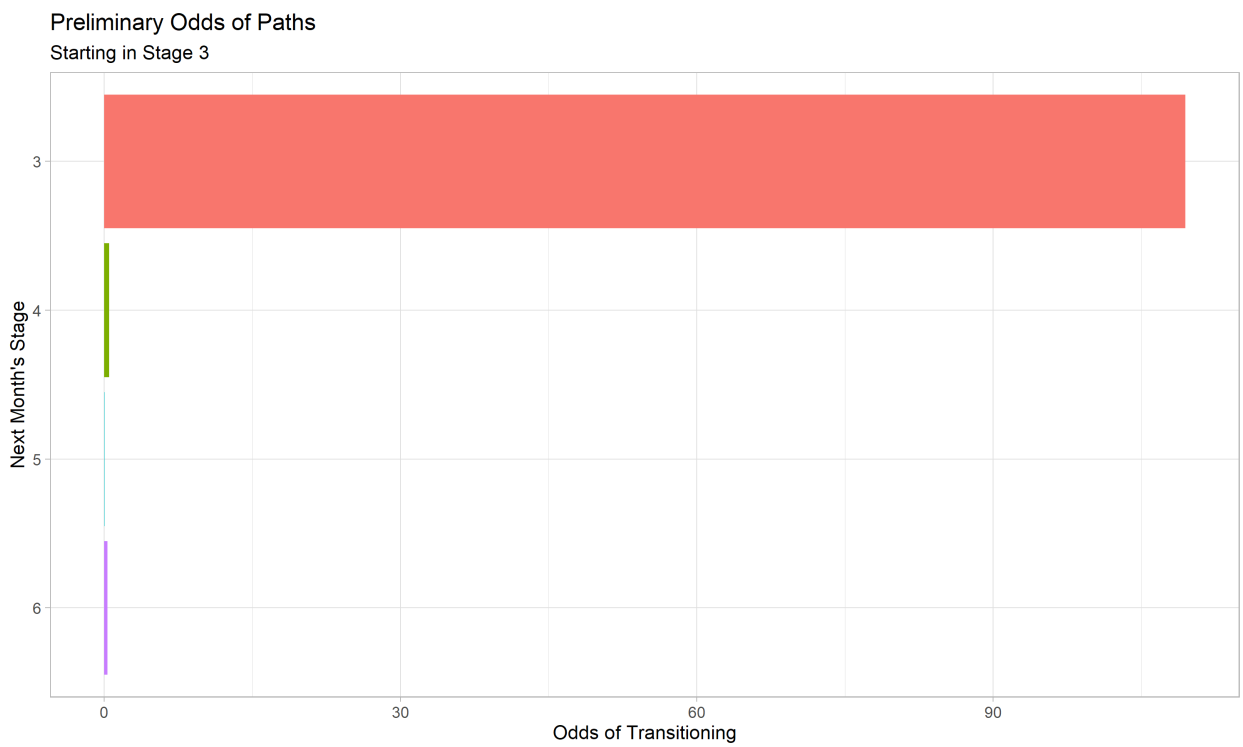

Figure 1: Stage Model Intercepts for the Medicare data for a member currently in Stage 3

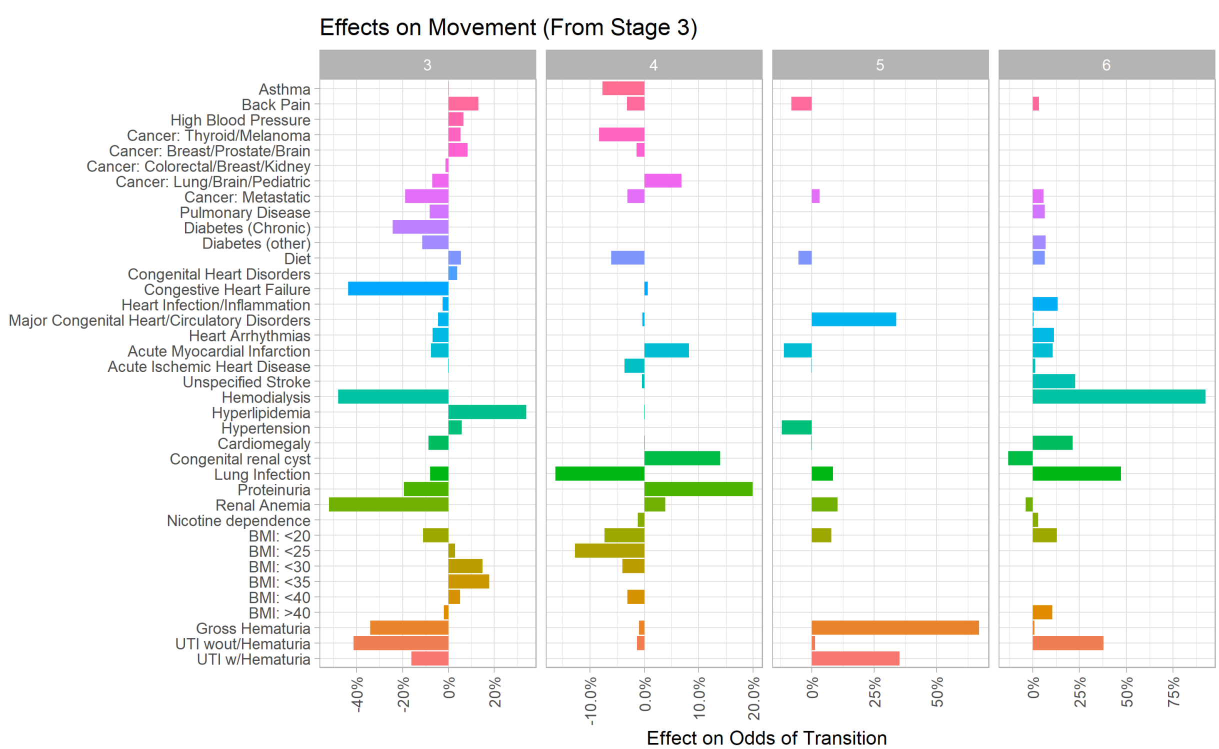

Figure 2: Stage Model Coefficients for the Medicare data in Stage 3

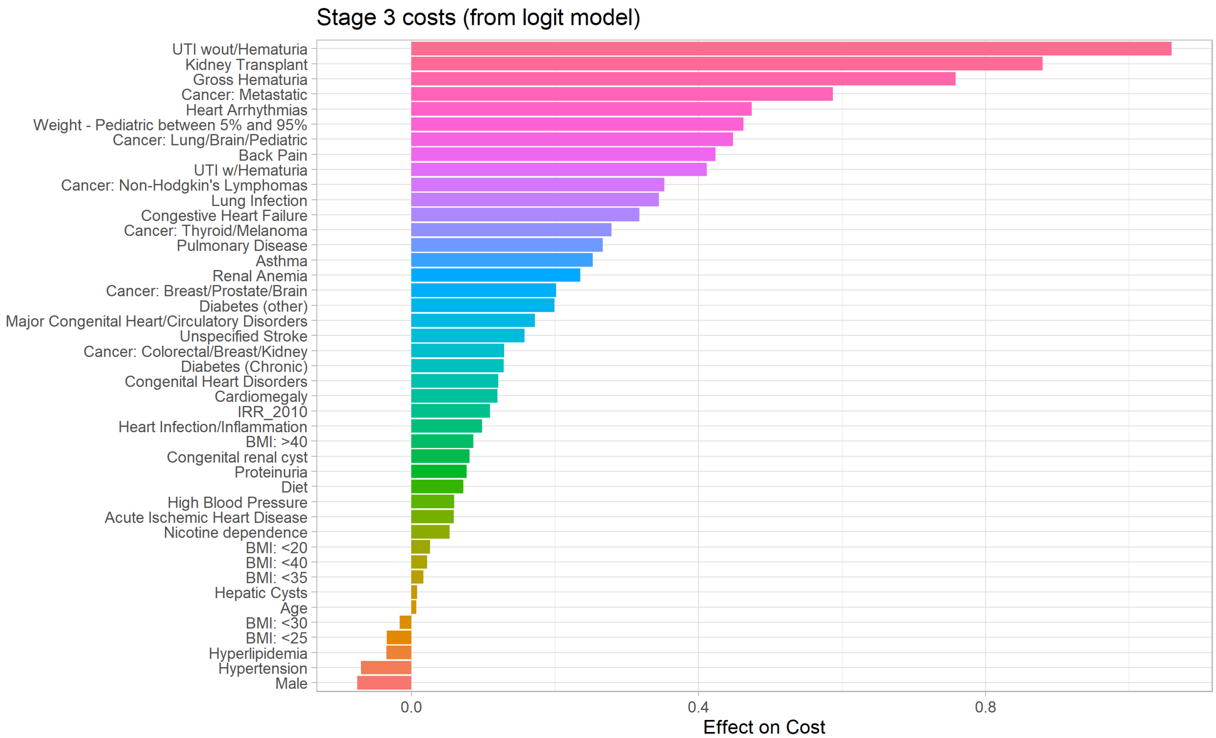

Figure 3: Cost Model Coefficients for the Logistic Regression Model for Medicare data in Stage 3

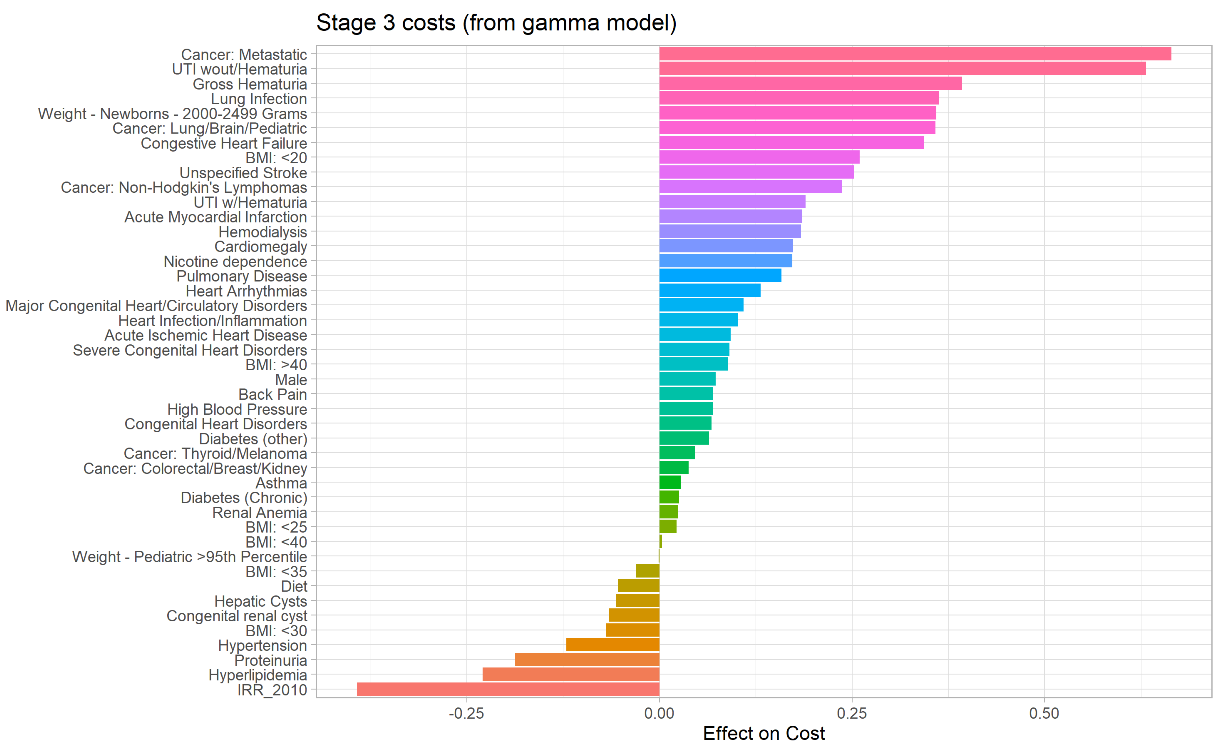

Figure 4: Cost Model Coefficients for the Gamma Model for Medicare data in Stage 3

			Median Absolute Error						
		Prediction	Gamma			Tweedie			XGBoost
Dataset	Stage	Year	None	Min	1se	None	Min	1se	n/a
Commercial	1	2017	823	823	852	1,362	1,362	1,969	**737**
Commercial	1	2018	796	796	834	1,413	1,413	1,982	**638**
Commercial	2	2017	897	897	914	1,483	1,483	2,144	**864**
Commercial	2	2018	855	855	868	1,526	1,526	2,155	**762**
Commercial	3	2017	**1,327**	1,327	1,335	2,028	2,028	2,799	1,359
Commercial	3	2018	**1,297**	1,297	1,309	2,098	2,098	2,803	1,302
Commercial	4	2017	2,173	2,173	2,203	3,027	3,027	3,884	**2,025**
Commercial	4	2018	2,163	2,163	2,196	3,158	3,158	3,888	**1,897**
Commercial	5	2017	**2,448**	2,448	2,505	3,246	3,246	4,222	2,522
Commercial	5	2018	2,403	2,403	2,440	3,354	3,354	4,233	**2,155**
Commercial	6	2017	8,460	8,460	8,626	10,092	10,092	13,181	**7,498**
Commercial	6	2018	8,065	8,065	8,248	10,067	10,067	13,295	**5,216**
Medicare	1	2017	**965**	966	994	1,263	1,263	1,903	1,028
Medicare	1	2018	972	972	983	1,371	1,371	1,916	**846**
Medicare	2	2017	**1,098**	1,098	1,113	1,443	1,443	1,807	1,240
Medicare	2	2018	**1,079**	1,079	1,092	1,538	1,538	1,996	1,104
Medicare	3	2017	**1,389**	1,389	1,393	1,762	1,762	1,962	1,693
Medicare	3	2018	**1,387**	1,387	1,390	1,884	1,884	2,013	1,417
Medicare	4	2017	**2,177**	2,177	2,180	2,597	2,597	2,766	2,569
Medicare	4	2018	2,228	2,228	2,249	2,799	2,799	2,939	**2,121**
Medicare	5	2017	2,447	**2,445**	2,486	2,909	2,909	3,702	3,016
Medicare	5	2018	2,506	2,506	2,570	3,129	3,129	3,714	**2,482**
Medicare	6	2017	**4,075**	4,075	4,129	4,453	4,453	5,035	4,820
Medicare	6	2018	4,239	4,239	4,262	4,809	4,809	5,249	**3,735**

Table 5: Comparison of Healthcare Cost Models, minimum error in bold

6 Conclusion

CKD impacts lives and health care systems around the world. To help those invested in preparing for and mitigating those impacts in the United States, we developed a new process that explicitly models both the stage progression and the costs of members with CKD. Applying our models to rich datasets of commercial and Medicare members, we found that XGBoost models perform the best in both the stage and the cost predictions. If XGBoost models are unavailable, multivariate logistic regression models with regularization best predict the stage progression and logit-gamma models best predict the monthly healthcare costs of members with CKD. Because of the unique characteristics of the health care system in the United States, care should be taken before applying these models to other health systems.

These models can help those who need to predict and help manage costs from chronic kidney disease to be more efficient and effective.

7 Limitations

Because of the unique characteristics of the health care system in the United States, care should be taken before applying these models to other health systems. Additionally, other periods of study may yield different results. Also, we used diagnosis codes from claims data and did not use electronic health records to back them up. Finally, the results of some indicators may be unreliable due to small sample sizes.

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A XGBoost hyperparameter settings

For both the cost and stage models, we optimized four different hyperparameters (Chen, He, Benesty, Khotilovich, Tang, Cho et al. 2015), each with their ranges in brackets.

- nrounds [100, 500] - the number of trees in each model (each one built sequentially)
- max_depth [1, 10] - maximum number of splits in each tree
- eta [0.1, 0.5] - Step size shrinkage, used to prevent overfitting
- lambda [1, 10] - L2 regularization, also to prevent overfitting

We randomly selected 200 sets of the hyperparameters listed above and compared them using four-fold cross-validation on the training set.

B ICD-10 Codes by Indicator Flag

Category Description	ICD-10 Codes
CKD Stage 1	N181
CKD Stage 2	N182
CKD Stage 3	N183
CKD Stage 4	N184
CKD Stage 5	N185
CKD Stage 6 (ESRD)	N186
Acute Myocardial Infarction	I2101, I2102, I2109, I2111, I2119, I2121, I2129, I213, I214, I219, I21A1, I21A9, I220, I221, I222, I228, I229, I234, I235, I511, I512
Aspiration and Specified Bacterial Pneumonias and Other Severe Lung Infections	A065, A481, A5004, B380, B381, B382, B390, B391, B392, B400, B401, B402, B410, B664, B671, J150, J151, J1520, J15211, J15212, J1529, J155, J156, J158, J690, J691, J698, J850, J851, J852, J853, J860, J869, P230, P231, P232, P233, P234, P235, P236, P238, P239, P2401, P2411, P2421, P2431, P2481
Asthma	J4520, J4521, J4522, J4530, J4531, J4532, J4540, J4541, J4542, J4550, J4551, J4552, J45901, J45902, J45909, J45990, J45991, J45998, J410, J411, J418, J42, J440, J441
Atrial and Ventricular Septal Defects, Patent Ductus Arteriosus, and Other Congenital Heart/Circulatory Disorders	Q206, Q209, Q210, Q211, Q214, Q218, Q219, Q221, Q222, Q223, Q249, Q250, Q265, Q266, Q270, Q271, Q272, Q2730, Q2731, Q2732, Q2733, Q2734, Q2739, Q274, Q278, Q279, Q280, Q281, Q288, Q289, Q893
Back Pain	M545

Breast (Age 50+) and Prostate Cancer, Benign/Uncertain Brain Tumors, and Other Cancers and Tumors	C4A0, C4A10, C4A11, C4A111, C4A112, C4A12, C4A121, C4A122, C4A20, C4A21, C4A22, C4A30, C4A31, C4A39, C4A4, C4A51, C4A52, C4A59, C4A60, C4A61, C4A62, C4A70, C4A71, C4A72, C4A8, C4A9, C510, C511, C512, C518, C519, C52, C530, C531, C538, C539, C540, C541, C542, C543, C548, C549, C55, C577, C578, C579, C61, C661, C662, C669, C670, C671, C672, C673, C674, C675, C676, C677, C678, C679, C680, C681, C688, C689, C6900, C6901, C6902, C6910, C6911, C6912, C6920, C6921, C6922, C6930, C6931, C6932, C6940, C6941, C6942, C6950, C6951, C6952, C6960, C6961, C6962, C6980, C6981, C6982, C6990, C6991, C6992, C760, C761, C762, C763, C7640, C7641, C7642, C7650, C7651, C7652, C768, C7A00, C7A010, C7A011, C7A012, C7A019, C7A020, C7A021, C7A022, C7A023, C7A024, C7A025, C7A026, C7A029, C7A090, C7A091, C7A092, C7A093, C7A094, C7A095, C7A096, C7A098, C7A1, C7A8, C802, C8100, C8101, C8102, C8103, C8104, C8105, C8106, C8107, C8108, C8109, C8110, C8111, C8112, C8113, C8114, C8115, C8116, C8117, C8118, C8119, C8120, C8121, C8122, C8123, C8124, C8125, C8126, C8127, C8128, C8129, C8130, C8131, C8132, C8133, C8134, C8135, C8136, C8137, C8138, C8139, C8140, C8141, C8142, C8143, C8144, C8145, C8146, C8147, C8148, C8149, C8170, C8171, C8172, C8173, C8174, C8175, C8176, C8177, C8178, C8179, C8190, C8191, C8192, C8193, C8194, C8195, C8196, C8197, C8198, C8199, D1802, D320, D321, D329, D330, D331, D332, D333, D334, D337, D339, D352, D353, D354, D420, D421, D429, D430, D431, D432, D433, D434, D438, D439, D443, D444, D445, D446, D447, D496, Q851, Q858, Q859, C50011, C50012, C50019, C50021, C50022, C50029, C50111, C50112, C50119, C50121, C50122, C50129, C50211, C50212, C50219, C50221, C50222, C50229, C50311, C50312, C50319, C50321, C50322, C50329, C50411, C50412, C50419, C50421, C50422, C50429, C50511, C50512, C50519, C50521, C50522, C50529, C50611, C50612, C50619, C50621, C50622, C50629, C50811, C50812, C50819, C50821, C50822, C50829, C50911, C50912, C50919, C50921, C50922, C50929
Cardiomegaly	I517
Chronic Obstructive Pulmonary Disease, Including Bronchiectasis	J410, J411, J418, J42, J430, J431, J432, J438, J439, J440, J441, J449, J470, J471, J479, J982, J983
Colorectal, Breast (Age $<$ 50), Kidney, and Other Cancers	C01, C020, C021, C022, C023, C024, C028, C029, C030, C031, C039, C040, C041, C048, C049, C050, C051, C052, C058, C059, C060, C061, C062, C0680, C0689, C069, C07, C080, C081, C089, C090, C091, C098, C099, C100, C101, C102, C103, C104, C108, C109, C110, C111, C112, C113, C118, C119, C12, C130, C131, C132, C138, C139, C140, C142, C148, C180, C181, C182, C183, C184, C185, C186, C187, C188, C189, C19, C20, C210, C211, C212, C218, C260, C261, C269, C300, C301, C310, C311, C312, C313, C318, C319, C320, C321, C322, C323, C328, C329, C37, C381, C382, C383, C388, C390, C399, C50011, C50012, C50019, C50021, C50022, C50029, C50111, C50112, C50119, C50121, C50122, C50129, C50211, C50212, C50219, C50221, C50222, C50229, C50311, C50312, C50319, C50321, C50322, C50329, C50411, C50412, C50419, C50421, C50422, C50429, C50511, C50512, C50519, C50521, C50522, C50529, C50611, C50612, C50619, C50621, C50622, C50629, C50811, C50812, C50819, C50821, C50822, C50829, C50911, C50912, C50919, C50921, C50922, C50929, C561, C562, C569, C5700, C5701, C5702, C5710, C5711, C5712, C5720, C5721, C5722, C573, C574, C58, C641, C642, C649, C651, C652, C659
Congenital renal cyst	Q6100, Q6101, Q6102
Congestive Heart Failure	A3681, B3324, I0981, I110, I130, I132, I2601, I2602, I2609, I270, I271, I2720, I2721, I2722, I2723, I2724, I2729, I2781, I2783, I2789, I279, I280, I281, I288, I289, I420, I421, I422, I423, I424, I425, I426, I427, I428, I429, I43, I501, I5020, I5021, I5022, I5023, I5030, I5031, I5032, I5033, I5040, I5041, I5042, I5043, I50810, I50811, I50812, I50813, I50814, I5082, I5083, I5084, I5089, I509, I514, I515

Diabetes with Chronic Complications	E0821, E0822, E0829, E08311, E08319, E083211, E083212, E083213, E083219, E083291, E083292, E083293, E083299, E083311, E083312, E083313, E083319, E083391, E083392, E083393, E083399, E083411, E083412, E083413, E083419, E083491, E083492, E083493, E083499, E083511, E083512, E083513, E083519, E083521, E083522, E083523, E083529, E083531, E083532, E083533, E083539, E083541, E083542, E083543, E083549, E083551, E083552, E083553, E083559, E083591, E083592, E083593, E083599, E0836, E0837X1, E0837X2, E0837X3, E0837X9, E0839, E0840, E0841, E0842, E0843, E0844, E0849, E0851, E0852, E0859, E08610, E08618, E08620, E08621, E08622, E08628, E08630, E08638, E08649, E0865, E0869, E088, E0921, E0922, E0929, E09311, E09319, E093211, E093212, E093213, E093219, E093291, E093292, E093293, E093299, E093311, E093312, E093313, E093319, E093391, E093392, E093393, E093399, E093411, E093412, E093413, E093419, E093491, E093492, E093493, E093499, E093511, E093512, E093513, E093519, E093521, E093522, E093523, E093529, E093531, E093532, E093533, E093539, E093541, E093542, E093543, E093549, E093551, E093552, E093553, E093559, E093591, E093592, E093593, E093599, E0936, E0937X1, E0937X2, E0937X3, E0937X9, E0939, E0940, E0941, E0942, E0943, E0944, E0949, E0951, E0952, E0959, E09610, E09618, E09620, E09621, E09622, E09628, E09630, E09638, E09649, E0965, E0969, E098, E1021, E1022, E1029, E10311, E10319, E103211, E103212, E103213, E103219, E103291, E103292, E103293, E103299, E103311, E103312, E103313, E103319, E103391, E103392, E103393, E103399, E103411, E103412, E103413, E103419, E103491, E103492, E103493, E103499, E103511, E103512, E103513, E103519, E103521, E103522, E103523, E103529, E103531, E103532, E103533, E103539, E103541, E103542, E103543, E103549, E103551, E103552, E103553, E103559, E103591, E103592, E103593, E103599, E1036, E1037X1, E1037X2, E1037X3, E1037X9, E1039, E1040, E1041, E1042, E1043, E1044, E1049, E1051, E1052, E1059, E10610, E10618, E10620, E10621, E10622, E10628, E10630, E10638, E10649, E1065, E1069, E108, E1121, E1122, E1129, E11311, E11319, E113211, E113212, E113213, E113219, E113291, E113292, E113293, E113299, E113311, E113312, E113313, E113319, E113391, E113392, E113393, E113399, E113411, E113412, E113413, E113419, E113491, E113492, E113493, E113499, E113511, E113512, E113513, E113519, E113521, E113522, E113523, E113529, E113531, E113532, E113533, E113539, E113541, E113542, E113543, E113549, E113551, E113552, E113553, E113559, E113591, E113592, E113593, E113599, E1136, E1137X1, E1137X2, E1137X3, E1137X9, E1139, E1140, E1141, E1142, E1143, E1144, E1149, E1151, E1152, E1159, E11610, E11618, E11620, E11621, E11622, E11628, E11630, E11638, E11649, E1165, E1169, E118, E1321, E1322, E1329, E13311, E13319, E133211, E133212, E133213, E133219, E133291, E133292, E133293, E133299, E133311, E133312, E133313, E133319, E133391, E133392, E133393, E133399, E133411, E133412, E133413, E133419, E133491, E133492, E133493, E133499, E133511, E133512, E133513, E133519, E133521, E133522, E133523, E133529, E133531, E133532, E133533, E133539, E133541, E133542, E133543, E133549, E133551, E133552, E133553, E133559, E133591, E133592, E133593, E133599, E1336, E1337X1, E1337X2, E1337X3, E1337X9, E1339, E1340, E1341, E1342, E1343, E1344, E1349, E1351, E1352, E1359, E13610, E13618, E13620, E13621, E13622, E13628, E13630, E13638, E13649, E1365, E1369, E138
Diabetes without Complication	E089, E099, E109, E119, E139, Z794
Diet	Z713, Z724
Gross Hematuria	R310
Heart Infection/Inflammation, Except Rheumatic	A0102, A3282, A381, A3950, A3951, A3952, A3953, A5054, A5200, A5201, A5202, A5203, A5206, A5209, A5483, B2682, B3320, B3321, B3322, B3323, B376, B5881, D8685, I300, I301, I308, I309, I310, I311, I312, I313, I314, I318, I319, I32, I330, I339, I400, I401, I408, I409, I41
Hemodialysis	Z992
Hepatic Cysts	Q446

High Blood Pressure, not diagnosed as Hypertension	R030
Hyperlipidemia	E782, E783, E784, E7841, E7849, E785
Hypertension	I10
Hypoplastic Left Heart Syndrome and Other Severe Congenital Heart Disorders	Q204, Q224, Q226, Q228, Q229, Q234
Ischemic or Unspecified Stroke	I6300, I63011, I63012, I63013, I63019, I6302, I63031, I63032, I63033, I63039, I6309, I6310, I63111, I63112, I63113, I63119, I6312, I63131, I63132, I63133, I63139, I6319, I6320, I63211, I63212, I63213, I63219, I6322, I63231, I63232, I63233, I63239, I6329, I6330, I63311, I63312, I63313, I63319, I63321, I63322, I63323, I63329, I63331, I63332, I63333, I63339, I63341, I63342, I63343, I63349, I6339, I6340, I63411, I63412, I63413, I63419, I63421, I63422, I63423, I63429, I63431, I63432, I63433, I63439, I63441, I63442, I63443, I63449, I6349, I6350, I63511, I63512, I63513, I63519, I63521, I63522, I63523, I63529, I63531, I63532, I63533, I63539, I63541, I63542, I63543, I63549, I6359, I636, I638, I6381, I6389, I639
Kidney Transplant	Z940
Lung, Brain, and Other Severe Cancers, Including Pediatric Acute Lymphoid Leukemia	C153, C154, C155, C158, C159, C160, C161, C162, C163, C164, C165, C166, C168, C169, C170, C171, C172, C173, C178, C179, C220, C221, C222, C223, C224, C227, C228, C229, C23, C240, C241, C248, C249, C250, C251, C252, C253, C254, C257, C258, C259, C33, C3400, C3401, C3402, C3410, C3411, C3412, C342, C3430, C3431, C3432, C3480, C3481, C3482, C3490, C3491, C3492, C384, C450, C451, C452, C457, C459, C480, C481, C482, C488, C700, C701, C709, C710, C711, C712, C713, C714, C715, C716, C717, C718, C719, C720, C721, C7220, C7221, C7222, C7230, C7231, C7232, C7240, C7241, C7242, C7250, C7259, C729, C7400, C7401, C7402, C7410, C7411, C7412, C7490, C7491, C7492, C751, C752, C753, C9000, C9001, C9002, C9010, C9011, C9012, C9020, C9021, C9022, C9210, C9211, C9212, C9220, C9221, C9222, C9230, C9231, C9232, C9290, C9291, C9292, C92Z0, C92Z1, C92Z2, C9310, C9311, C9312, C9330, C9331, C9332, C9390, C9391, C9392, C93Z0, C93Z1, C93Z2, C9430, C9431, C9432, C9480, C9481, C9482, C9100, C9101, C9102, C9500, C9501, C9502
Major Congenital Heart/Circulatory Disorders	P2930, P2938, Q200, Q201, Q202, Q203, Q205, Q208, Q212, Q213, Q220, Q225, Q230, Q231, Q232, Q233, Q238, Q239, Q240, Q241, Q242, Q243, Q244, Q245, Q246, Q248, Q251, Q2521, Q2529, Q253, Q2540, Q2541, Q2542, Q2543, Q2544, Q2545, Q2546, Q2547, Q2548, Q2549, Q255, Q256, Q2571, Q2572, Q2579, Q258, Q259, Q260, Q261, Q262, Q263, Q264, Q268, Q269
Metastatic Cancer	C770, C771, C772, C773, C774, C775, C778, C779, C7800, C7801, C7802, C781, C782, C7830, C7839, C784, C785, C786, C787, C7880, C7889, C7900, C7901, C7902, C7910, C7911, C7919, C792, C7931, C7932, C7940, C7949, C7951, C7952, C7960, C7961, C7962, C7970, C7971, C7972, C7981, C7982, C7989, C799, C7B00, C7B01, C7B02, C7B03, C7B04, C7B09, C7B1, C7B8, C800, C9100, C9101, C9102, C9200, C9201, C9202, C9240, C9241, C9242, C9250, C9251, C9252, C9260, C9261, C9262, C92A0, C92A1, C92A2, C9300, C9301, C9302, C9400, C9401, C9402, C9420, C9421, C9422, C9440, C9441, C9442, C9500, C9501, C9502, E883
Nicotine dependence	F17200, F17201, F17203, F17208, F17209, F17210, F17211, F17213, F17218, F17219, F17220, F17221, F17223, F17228, F17229, F17290, F17291, F17293, F17298, F17299, T65211A, T65211D, T65211S, T65212A, T65212D, T65212S, T65213A, T65213D, T65213S, T65214A, T65214D, T65214S, T65221A, T65221D, T65221S, T65222A, T65222D, T65222S, T65223A, T65223D, T65223S, T65224A, T65224D, T65224S, T65291A, T65291D, T65291S, T65292A, T65292D, T65292S, T65293A, T65293D, T65293S, T65294A, T65294D, T65294S, Z122, Z716, Z720, Z87891

Non-Hodgkin's Lymphomas and Other Cancers and Tumors	C380, C4000, C4001, C4002, C4010, C4011, C4012, C4020, C4021, C4022, C4030, C4031, C4032, C4080, C4081, C4082, C4090, C4091, C4092, C410, C411, C412, C413, C414, C419, C460, C461, C462, C463, C464, C4650, C4651, C4652, C467, C469, C470, C4710, C4711, C4712, C4720, C4721, C4722, C473, C474, C475, C476, C478, C479, C490, C4910, C4911, C4912, C4920, C4921, C4922, C493, C494, C495, C496, C498, C499, C49A0, C49A1, C49A2, C49A3, C49A4, C49A5, C49A9, C8200, C8201, C8202, C8203, C8204, C8205, C8206, C8207, C8208, C8209, C8210, C8211, C8212, C8213, C8214, C8215, C8216, C8217, C8218, C8219, C8220, C8221, C8222, C8223, C8224, C8225, C8226, C8227, C8228, C8229, C8230, C8231, C8232, C8233, C8234, C8235, C8236, C8237, C8238, C8239, C8240, C8241, C8242, C8243, C8244, C8245, C8246, C8247, C8248, C8249, C8250, C8251, C8252, C8253, C8254, C8255, C8256, C8257, C8258, C8259, C8260, C8261, C8262, C8263, C8264, C8265, C8266, C8267, C8268, C8269, C8280, C8281, C8282, C8283, C8284, C8285, C8286, C8287, C8288, C8289, C8290, C8291, C8292, C8293, C8294, C8295, C8296, C8297, C8298, C8299, C8300, C8301, C8302, C8303, C8304, C8305, C8306, C8307, C8308, C8309, C8310, C8311, C8312, C8313, C8314, C8315, C8316, C8317, C8318, C8319, C8330, C8331, C8332, C8333, C8334, C8335, C8336, C8337, C8338, C8339, C8350, C8351, C8352, C8353, C8354, C8355, C8356, C8357, C8358, C8359, C8370, C8371, C8372, C8373, C8374, C8375, C8376, C8377, C8378, C8379, C8380, C8381, C8382, C8383, C8384, C8385, C8386, C8387, C8388, C8389, C8390, C8391, C8392, C8393, C8394, C8395, C8396, C8397, C8398, C8399, C8400, C8401, C8402, C8403, C8404, C8405, C8406, C8407, C8408, C8409, C8410, C8411, C8412, C8413, C8414, C8415, C8416, C8417, C8418, C8419, C8440, C8441, C8442, C8443, C8444, C8445, C8446, C8447, C8448, C8449, C8460, C8461, C8462, C8463, C8464, C8465, C8466, C8467, C8468, C8469, C8470, C8471, C8472, C8473, C8474, C8475, C8476, C8477, C8478, C8479, C8490, C8491, C8492, C8493, C8494, C8495, C8496, C8497, C8498, C8499, C84A0, C84A1, C84A2, C84A3, C84A4, C84A5, C84A6, C84A7, C84A8, C84A9, C84Z0, C84Z1, C84Z2, C84Z3, C84Z4, C84Z5, C84Z6, C84Z7, C84Z8, C84Z9, C8510, C8511, C8512, C8513, C8514, C8515, C8516, C8517, C8518, C8519, C8520, C8521, C8522, C8523, C8524, C8525, C8526, C8527, C8528, C8529, C8580, C8581, C8582, C8583, C8584, C8585, C8586, C8587, C8588, C8589, C8590, C8591, C8592, C8593, C8594, C8595, C8596, C8597, C8598, C8599, C860, C861, C862, C863, C864, C865, C866, C880, C882, C883, C884, C888, C889, C9030, C9031, C9032, C9110, C9111, C9112, C9130, C9131, C9132, C9140, C9141, C9142, C9150, C9151, C9152, C9160, C9161, C9162, C9190, C9191, C9192, C91A0, C91A1, C91A2, C91Z0, C91Z1, C91Z2, C9510, C9511, C9512, C9590, C9591, C9592, C960, C9620, C9621, C9622, C9629, C964, C965, C966, C969, C96A, C96Z, D151, C7400, C7401, C7402, C7410, C7411, C7412, C7490, C7491, C7492
Proteinuria	R809, R800, R801, R802, R803, R808
Renal Anemia	D631
Specified Heart Arrhythmias	I442, I470, I471, I472, I479, I480, I481, I482, I483, I484, I4891, I4892, I492, I495
Thyroid Cancer, Melanoma, Neurofibromatosis, and Other Cancers and Tumors	C430, C4310, C4311, C43111, C43112, C4312, C43121, C43122, C4320, C4321, C4322, C4330, C4331, C4339, C434, C4351, C4352, C4359, C4360, C4361, C4362, C4370, C4371, C4372, C438, C439, C600, C601, C602, C608, C609, C6200, C6201, C6202, C6210, C6211, C6212, C6290, C6291, C6292, C6300, C6301, C6302, C6310, C6311, C6312, C632, C637, C638, C639, C73, C750, C754, C755, C758, C759, C801, D030, D0310, D0311, D03111, D03112, D0312, D03121, D03122, D0320, D0321, D0322, D0330, D0339, D034, D0351, D0352, D0359, D0360, D0361, D0362, D0370, D0371, D0372, D038, D039, E340, Q8500, Q8501, Q8502, Q8503, Q8509
Unstable Angina and Other Acute Ischemic Heart Disease	I200, I230, I231, I232, I233, I236, I237, I238, I240, I241, I248, I249, I25110, I25700, I25710, I25720, I25730, I25750, I25760, I25790
Urinary Tract Infection - with Hematuria	N3001, N3011, N3021, N3031, N3041, N3081, N3091

Urinary Tract Infection - without Hematuria	N3000, N3010, N3020, N3030, N3040, N3080, N3090, N341, N342, A5401, A5601, A5903, B3741, D8684, N10, A0225, N110, N111, N760, N761, N390
Weight - BMI - 19.9 or less	Z681
Weight - BMI - 20 to 24.9	Z6820, Z6821, Z6822, Z6823, Z6824
Weight - BMI - 25 to 29.9	Z6825, Z6826, Z6827, Z6828, Z6829
Weight - BMI - 30 to 34.9	Z6830, Z6831, Z6832, Z6833, Z6834
Weight - BMI - 35 to 39.9	Z6835, Z6836, Z6837, Z6838, Z6839
Weight - BMI - 40 or greater	Z6841, Z6842, Z6843, Z6844, Z6845
Weight - Newborns - <500 Grams	P0501, P0511, P0701
Weight - Newborns - 1000-1499 Grams	P0504, P0505, P0514, P0515, P0714, P0715, P0720, P0726, P0731
Weight - Newborns - 1500-1999 Grams	P0506, P0507, P0516, P0517, P0716, P0717, P0732, P0733, P0734, P0735
Weight - Newborns - 2000-2499 Grams	P0508, P0518, P0718, P0736, P0737, Z3861, Z3862, Z3863, Z3864, Z3865, Z3866, Z3868, Z3869, Z387, Z388, Q894
Weight - Newborns - 500-749 Grams	P0502, P0512, P0702, P0721, P0722, P0723
Weight - Newborns - 750-999 Grams	P0503, P0513, P0703, P0724, P0725
Weight - Newborns - Other Low Birthweight issues	P0500, P0509, P0510, P0519, P052, P059, P0700, P0710, P0730, P0738, P0739, Z3830, Z3831, Z384, Z385
Weight - Pediatric <5th Percentile	Z6851
Weight - Pediatric >95th Percentile	Z6854
Weight - Pediatric between 5% and 95%	Z6852, Z6853

Table A1: List of corresponding ICD-10 Codes by Indicator

C Complete Stage Model Results

C.1 Commercial - Multinomial Logistic Model

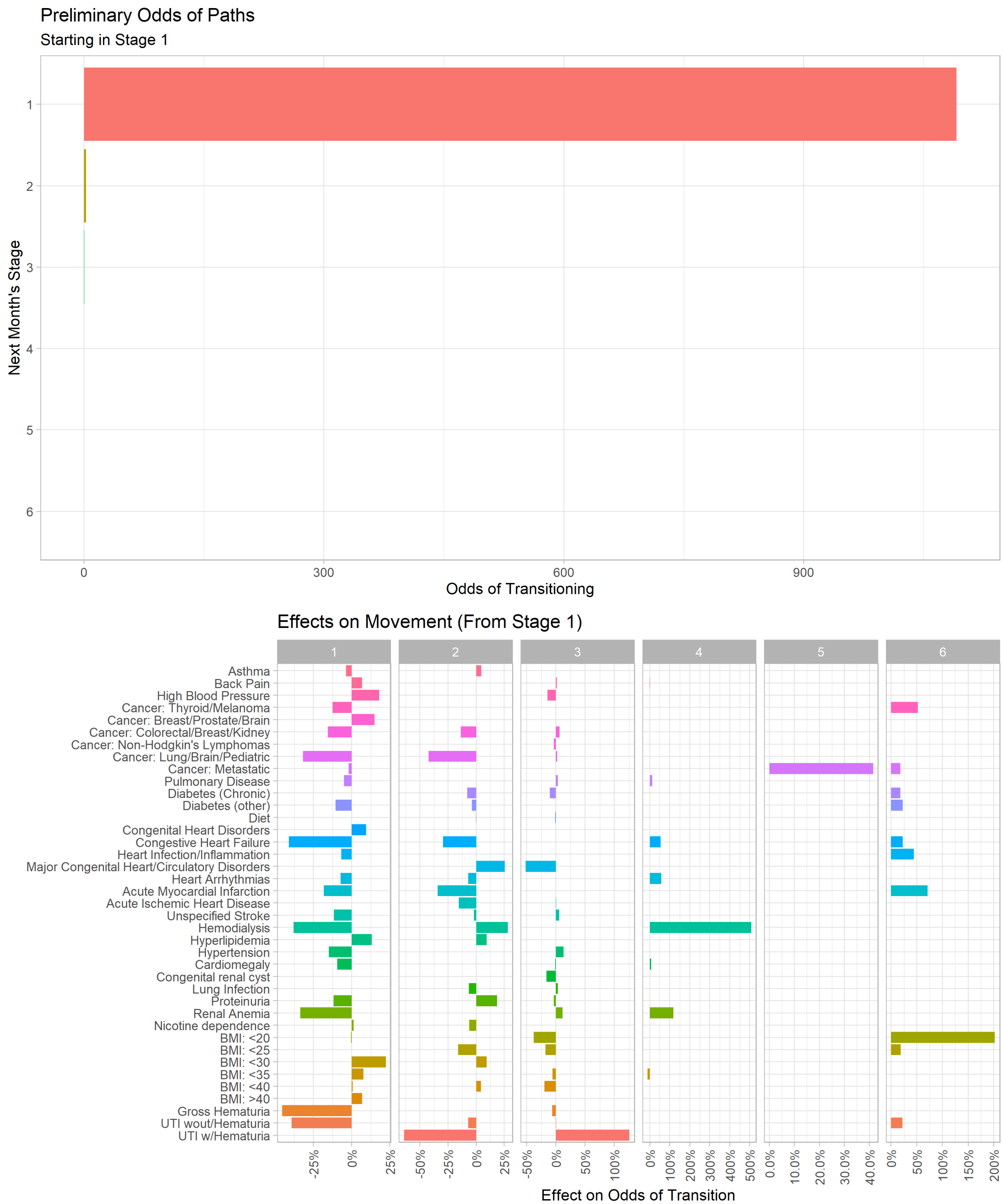


Figure A1: Commercial Stage Transition Model Starting in Stage 1

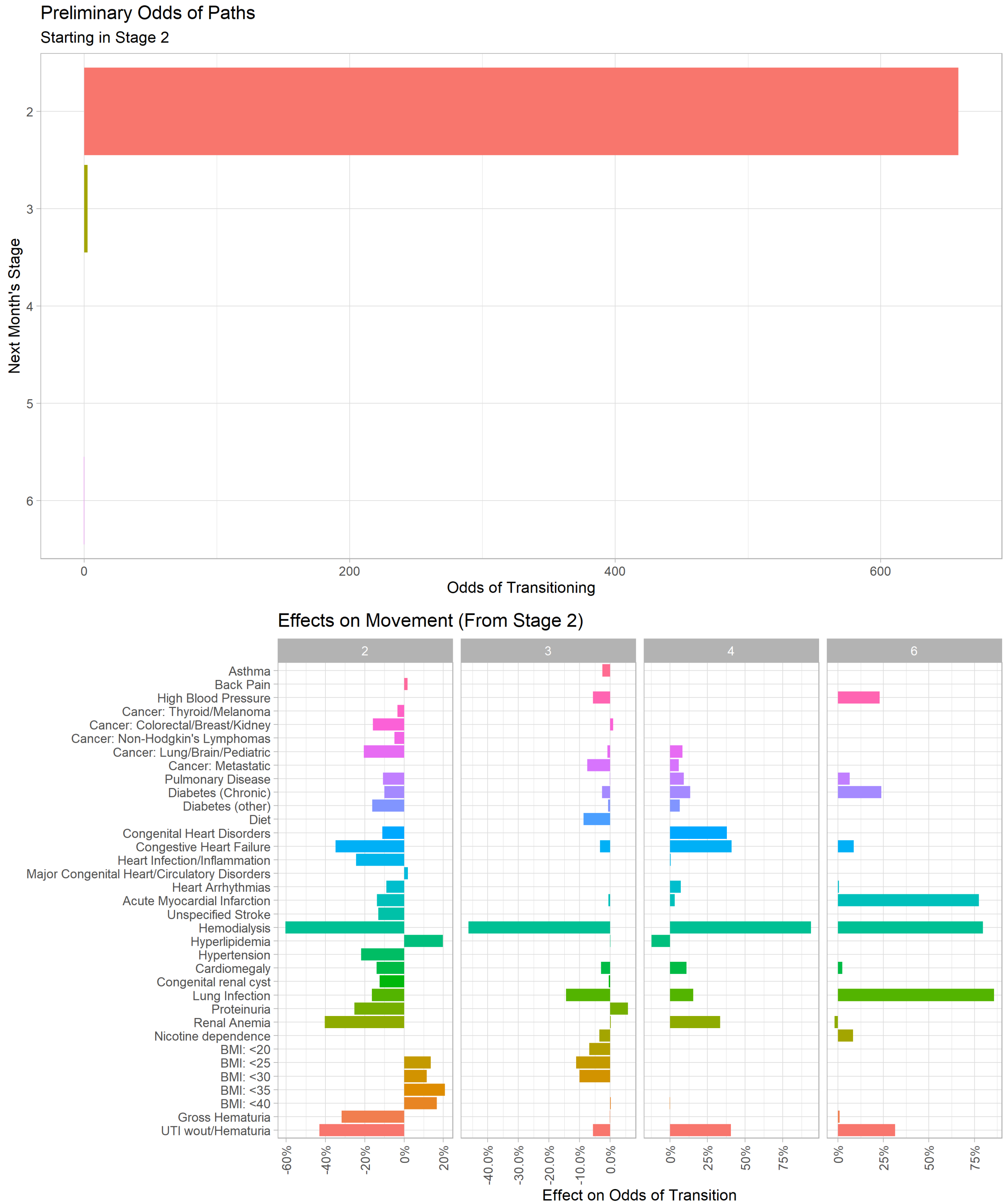


Figure A2: Commercial Stage Transition Model Starting in Stage 2

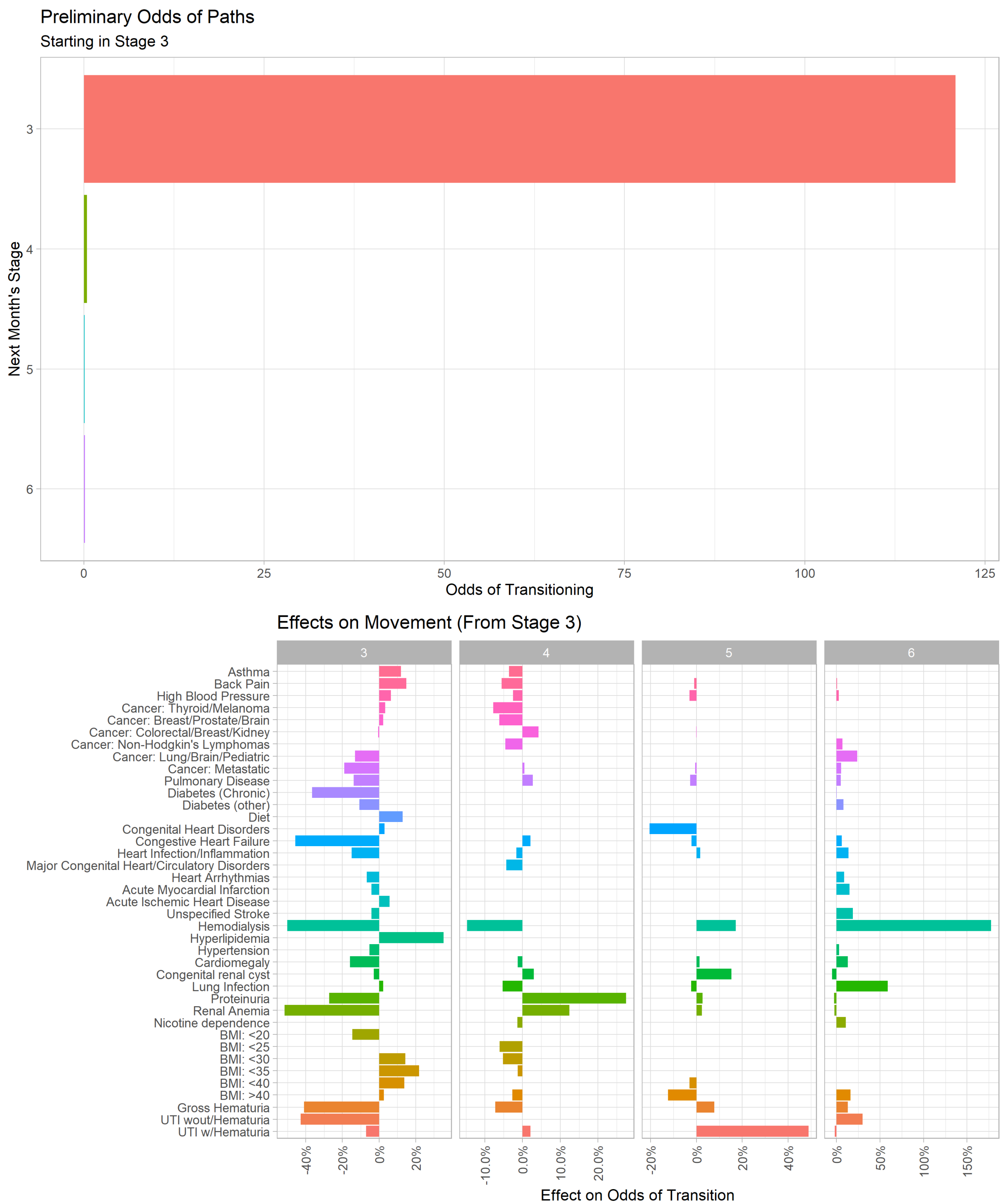


Figure A3: Commercial Stage Transition Model Starting in Stage 3

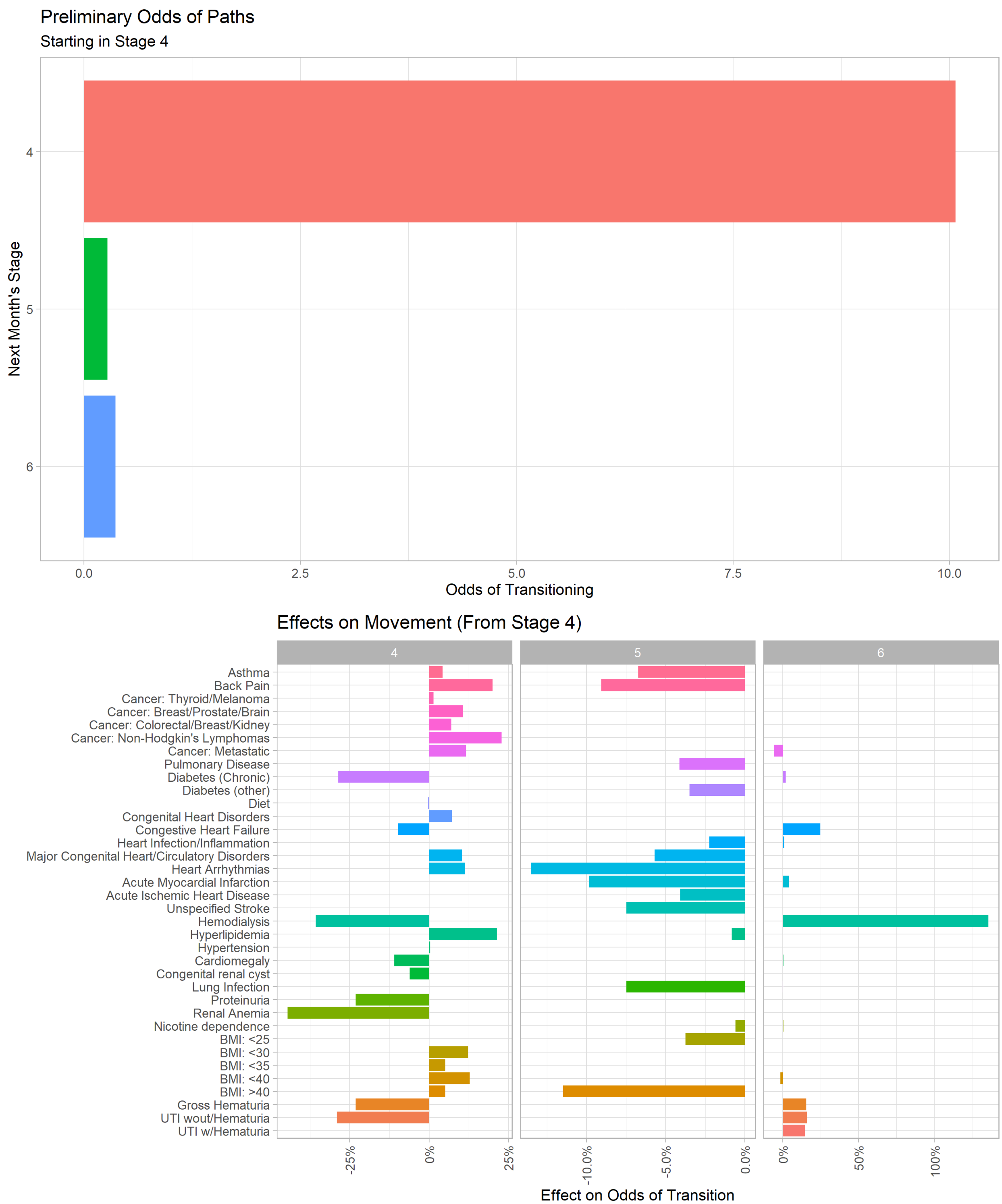


Figure A4: Commercial Stage Transition Model Starting in Stage 4

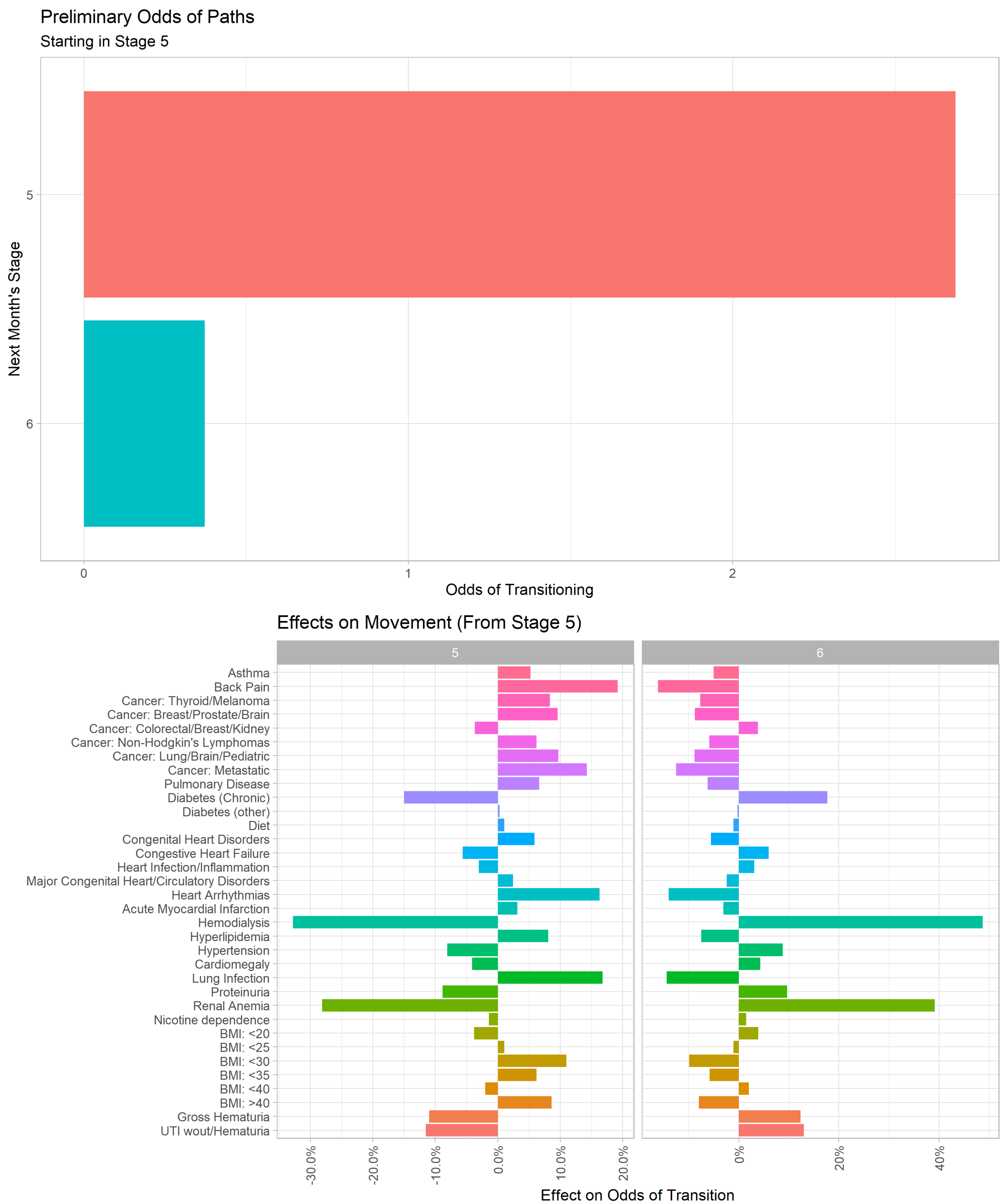


Figure A5: Commercial Stage Transition Model Starting in Stage 5

C.2 Medicare - Multinomial Logistic Model

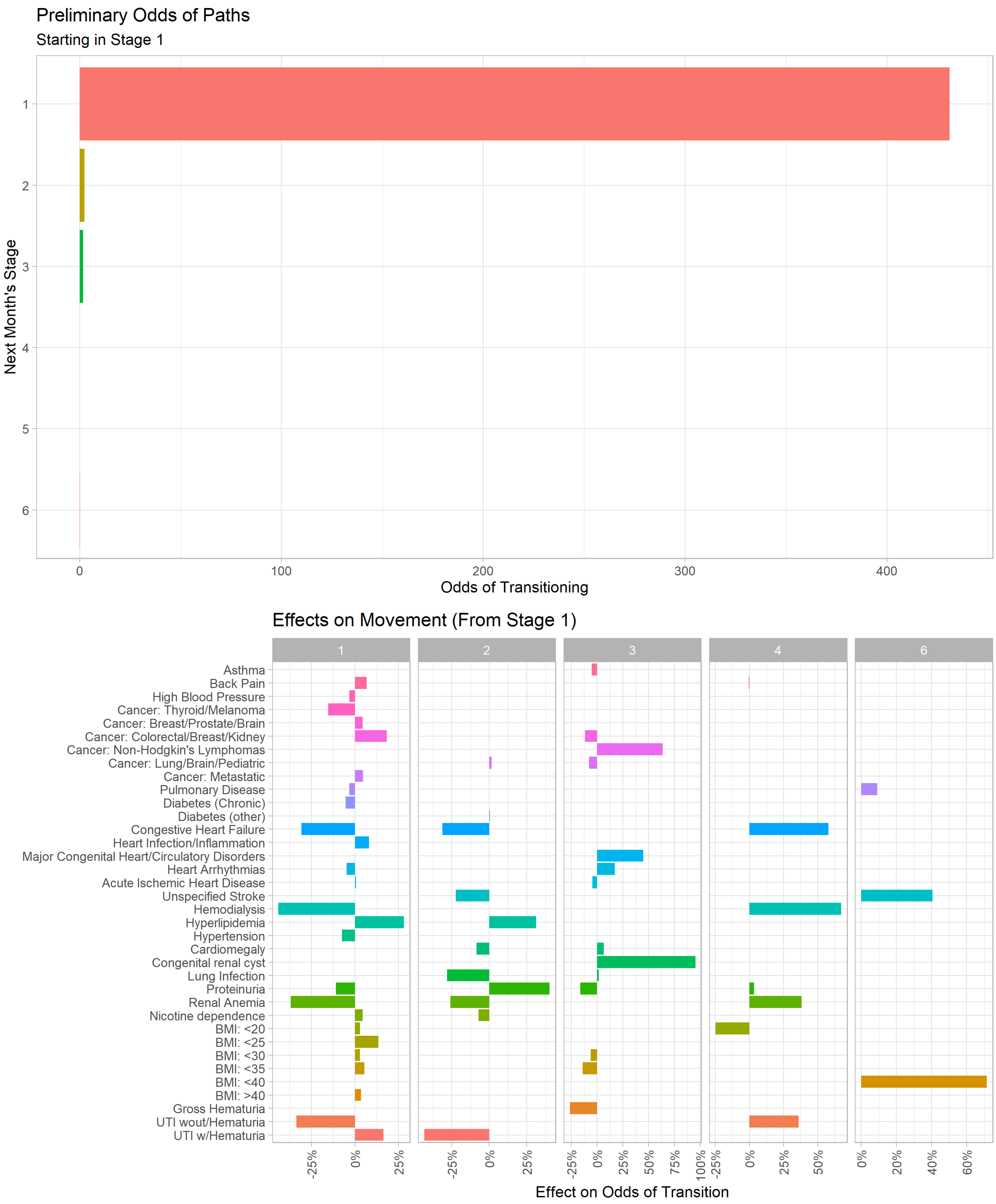


Figure A6: Medicare Stage Transition Model Starting in Stage 1

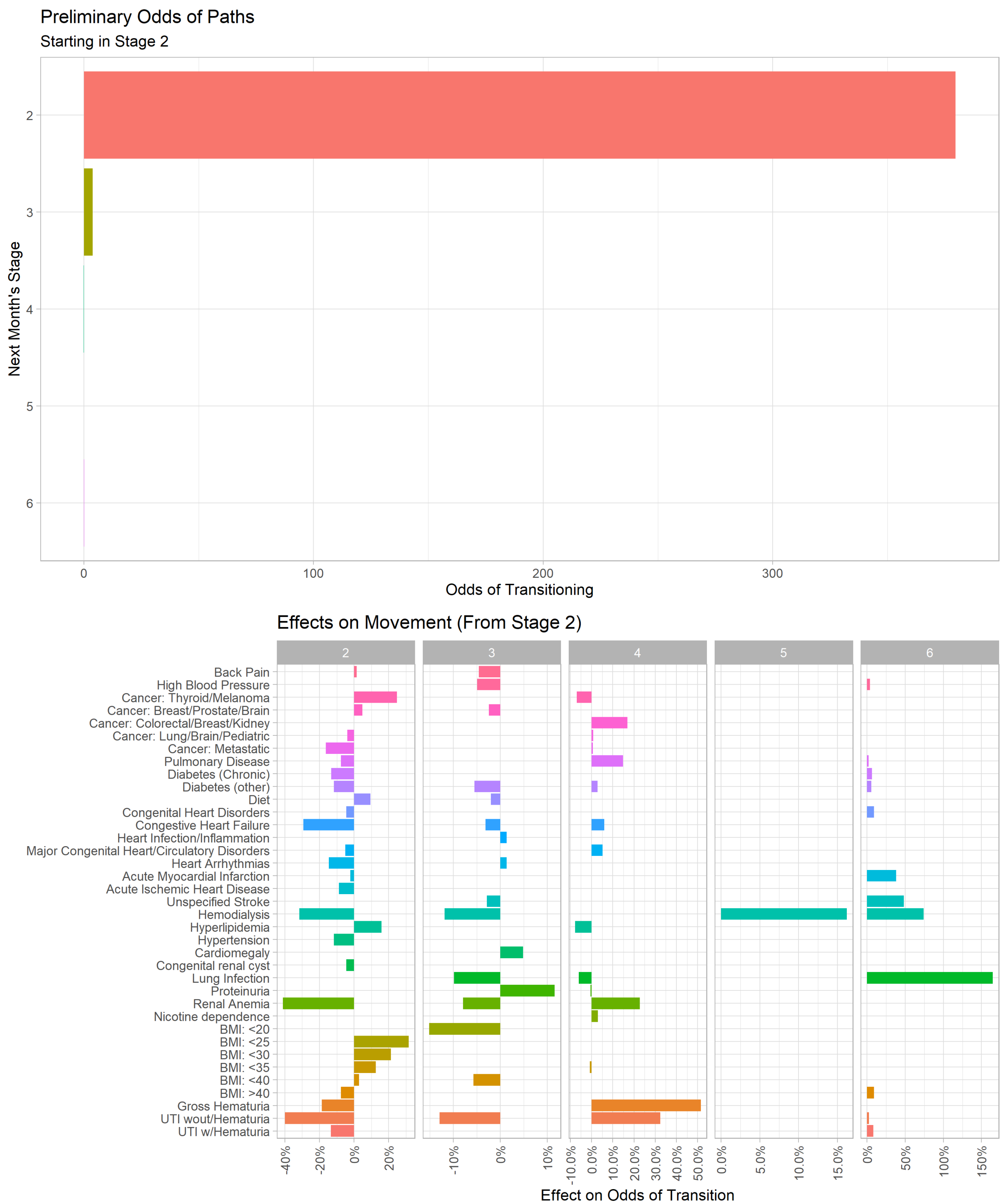
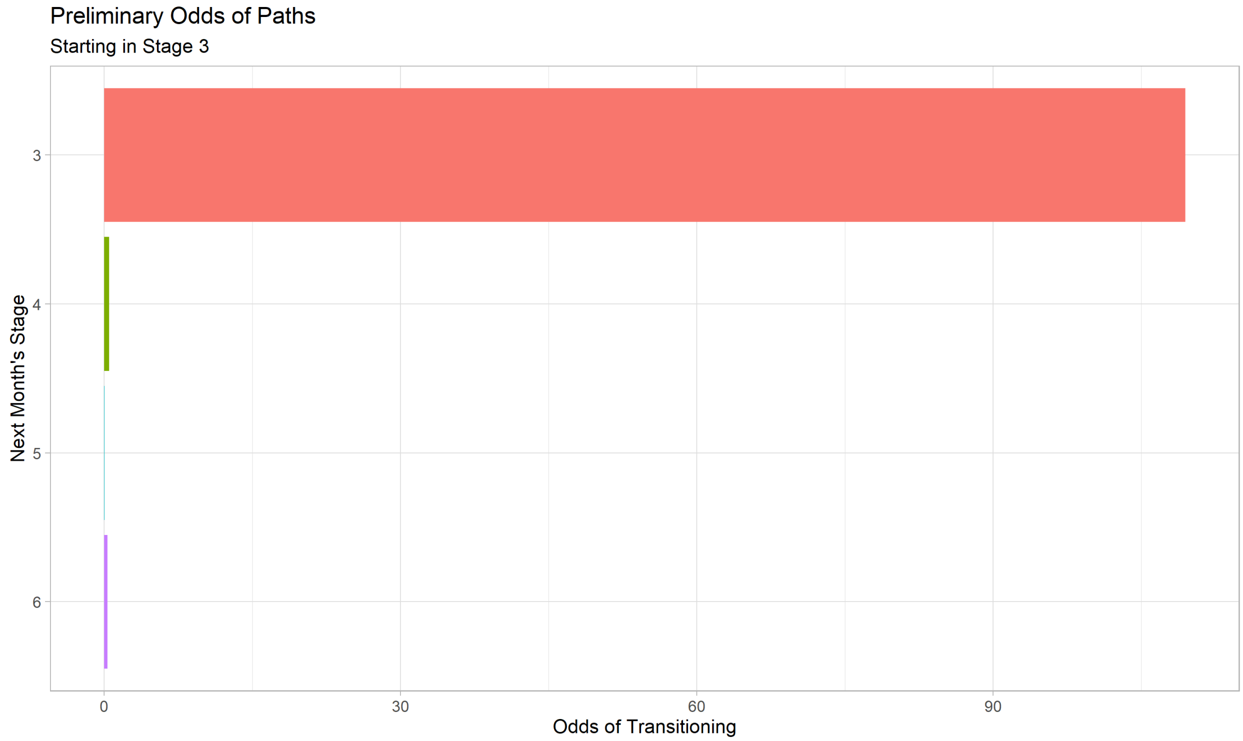


Figure A7: Medicare Stage Transition Model Starting in Stage 2



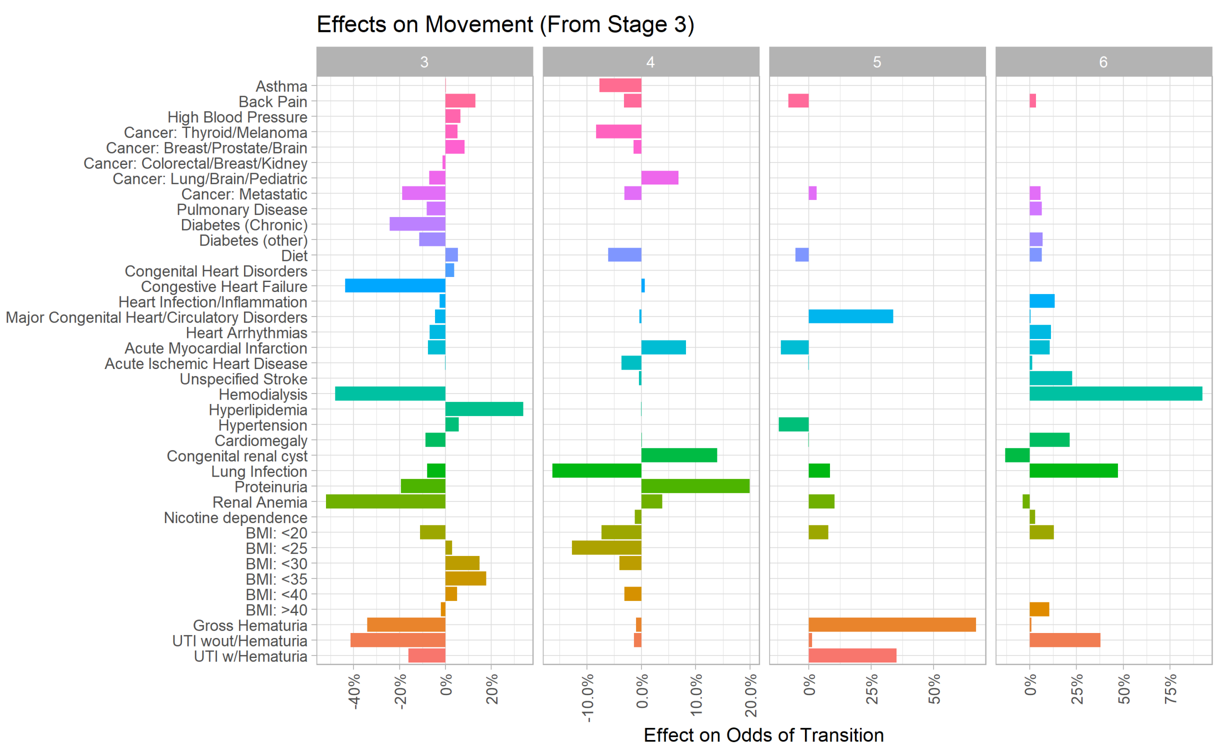


Figure A8: Medicare Stage Transition Model Starting in Stage 3

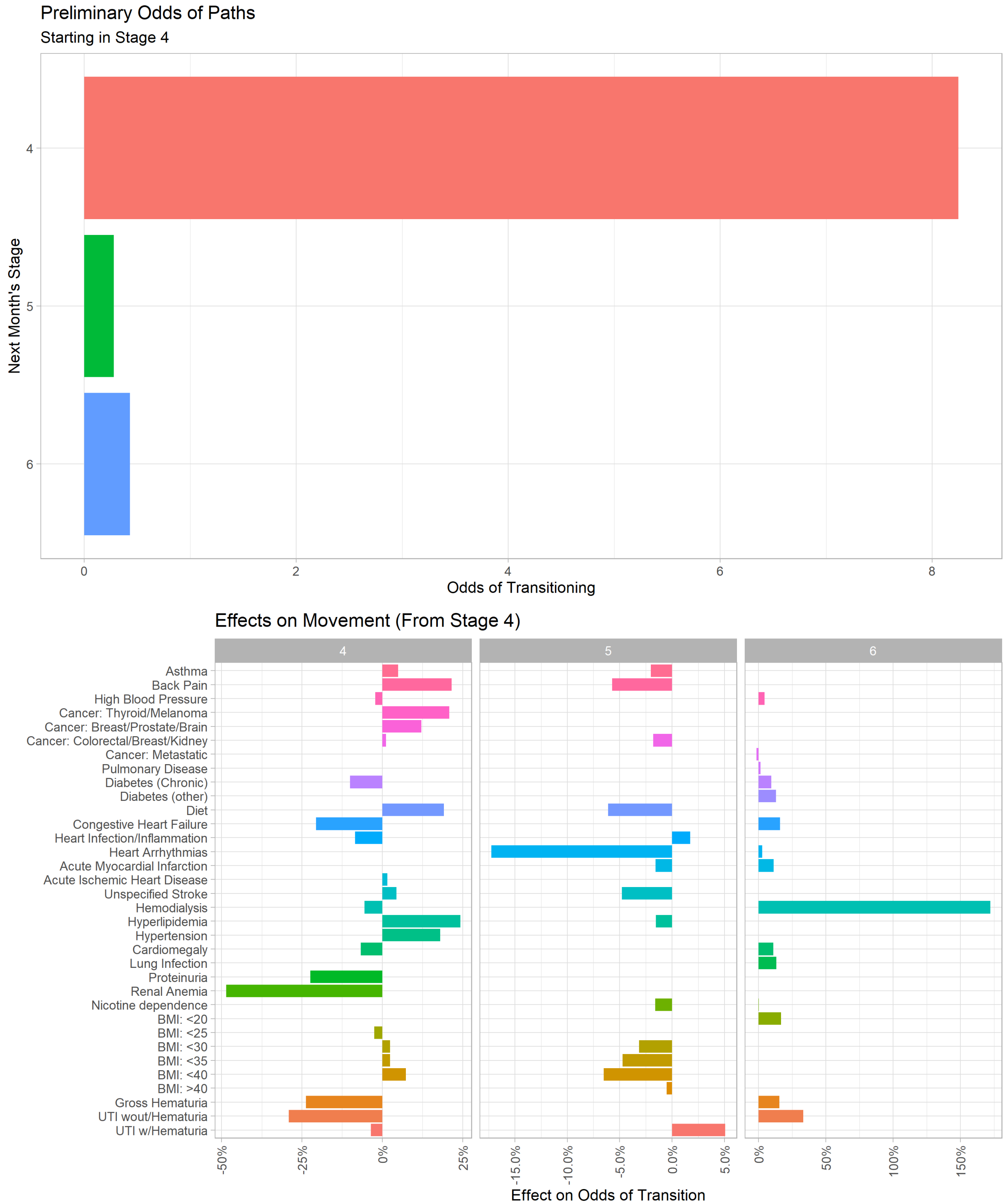


Figure A9: Medicare Stage Transition Model Starting in Stage 4

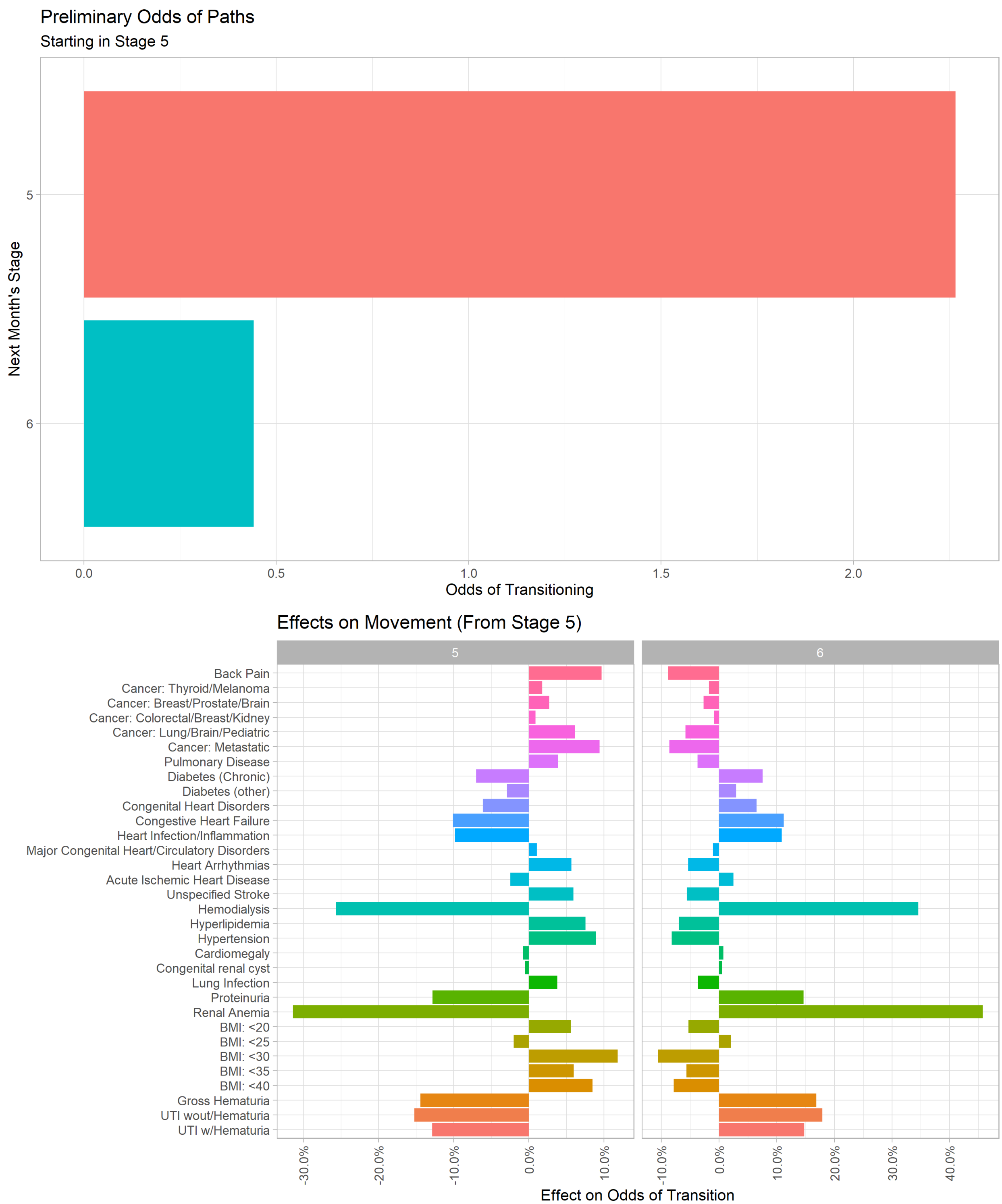


Figure A10: Medicare Stage Transition Model Starting in Stage 5

D Complete Cost Model Results

D.1 Commercial

D.1.1 Logistic Regression (zero/non-zero)

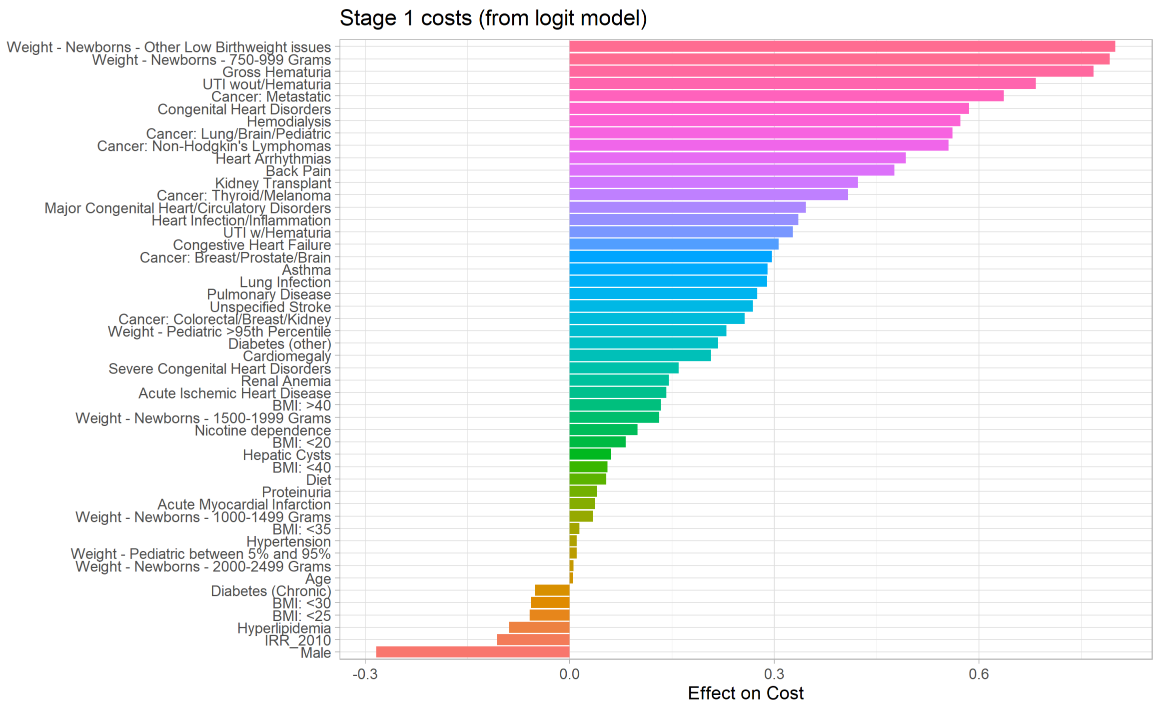


Figure A11: Commercial Logistic Regression Cost Model for Stage 1

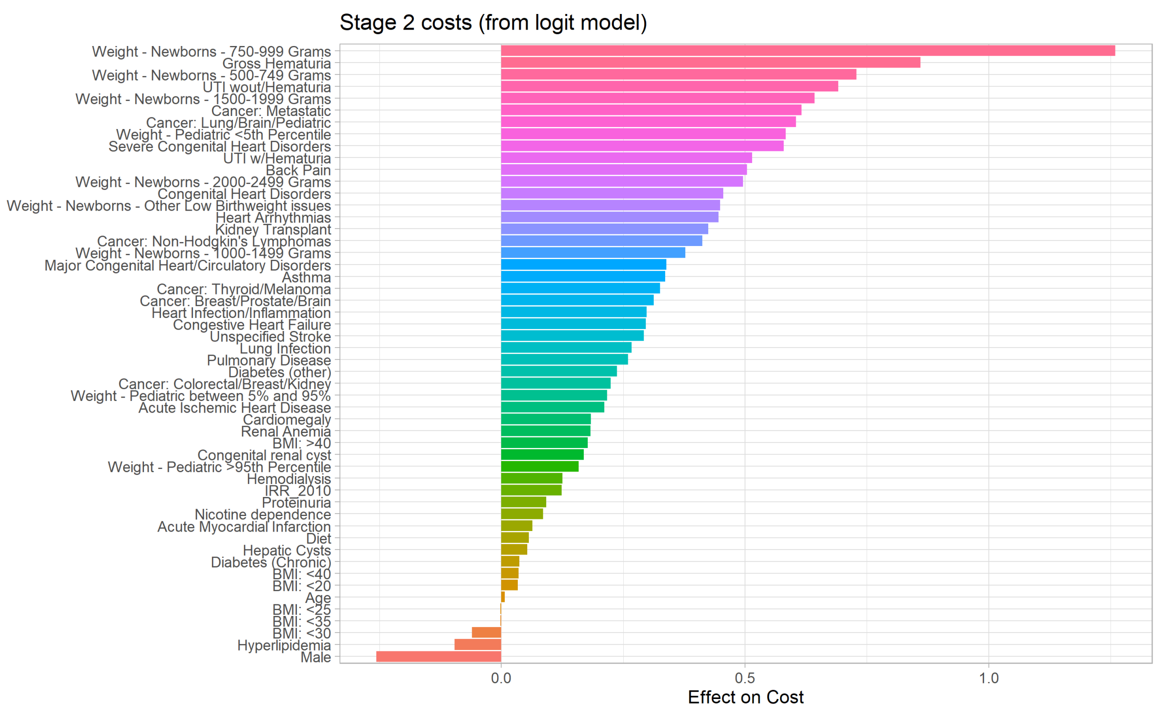


Figure A12: Commercial Logistic Regression Cost Model for Stage 2

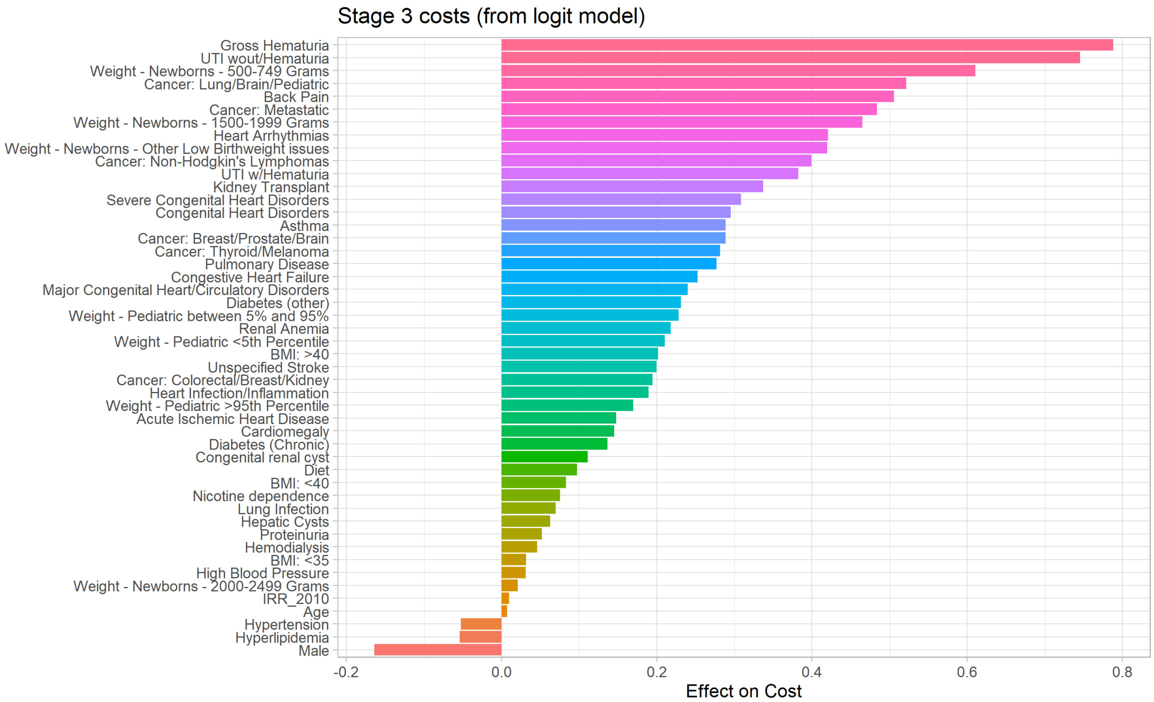


Figure A13: Commercial Logistic Regression Cost Model for Stage 3

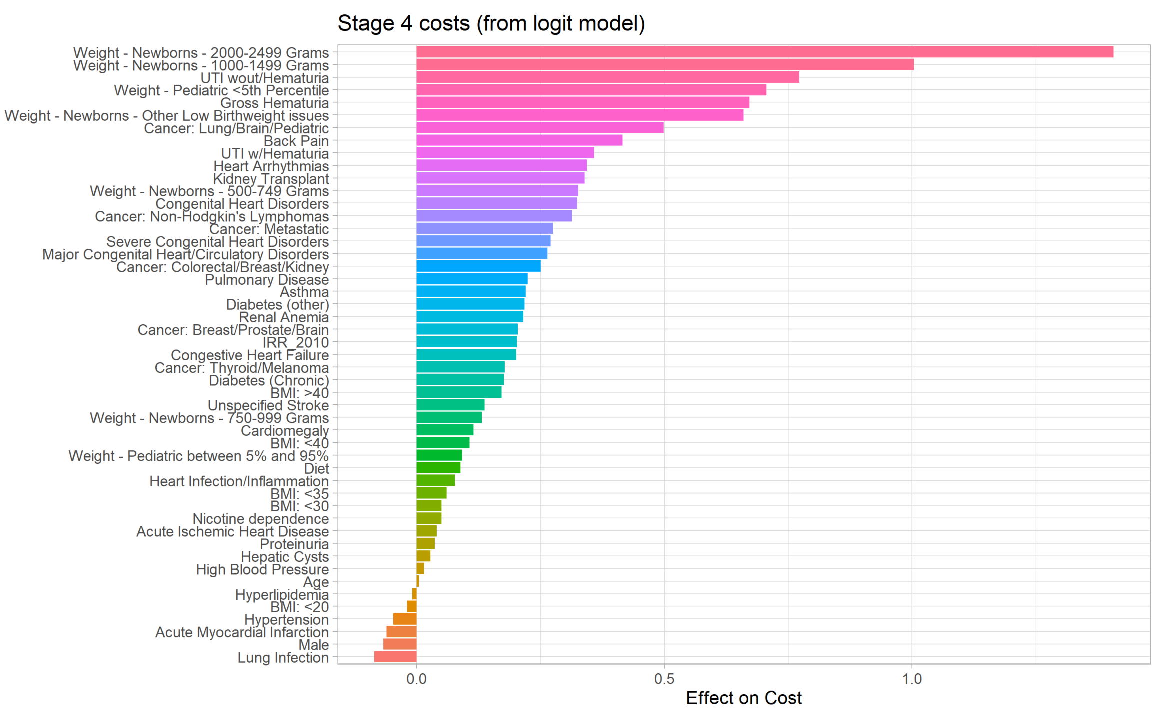


Figure A14: Commercial Logistic Regression Cost Model for Stage 4

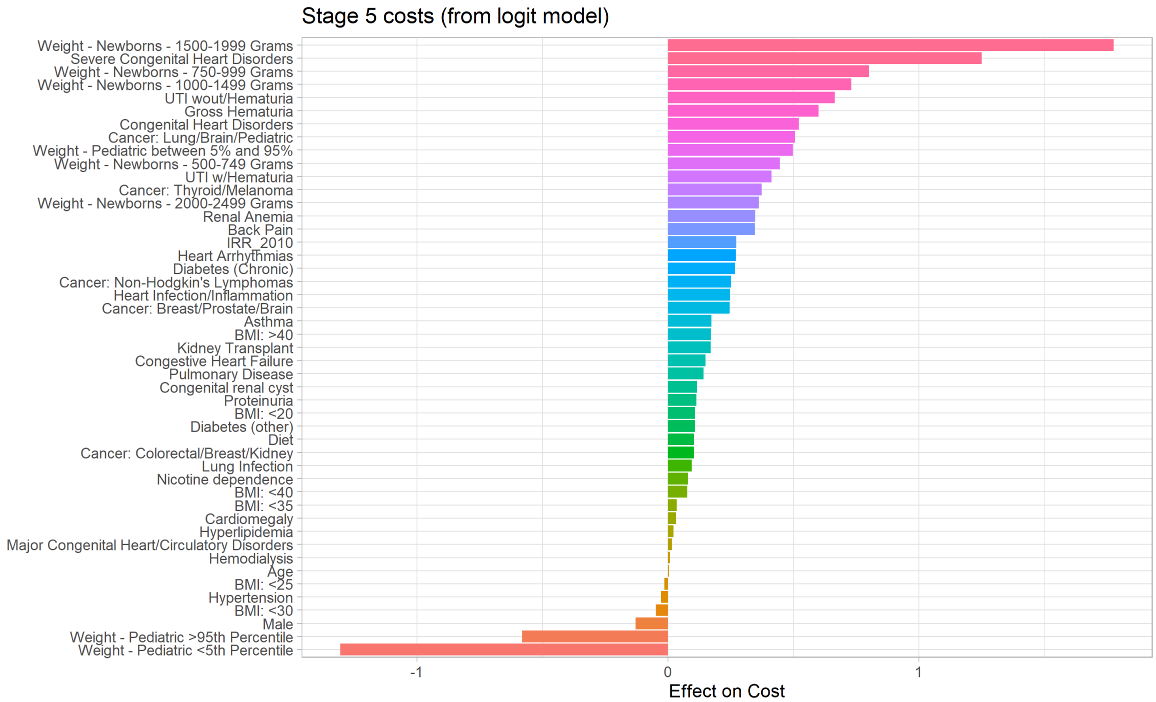


Figure A15: Commercial Logistic Regression Cost Model for Stage 5

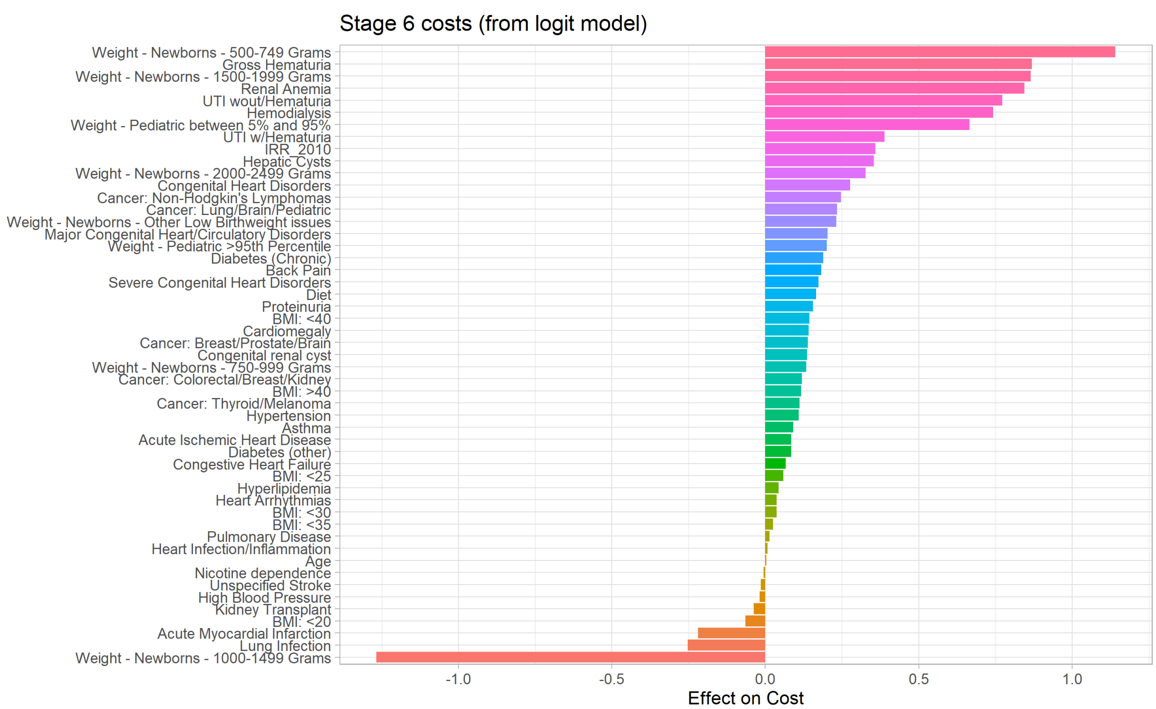


Figure A16: Commercial Logistic Regression Cost Model for Stage 6

D.1.2 Gamma Regression

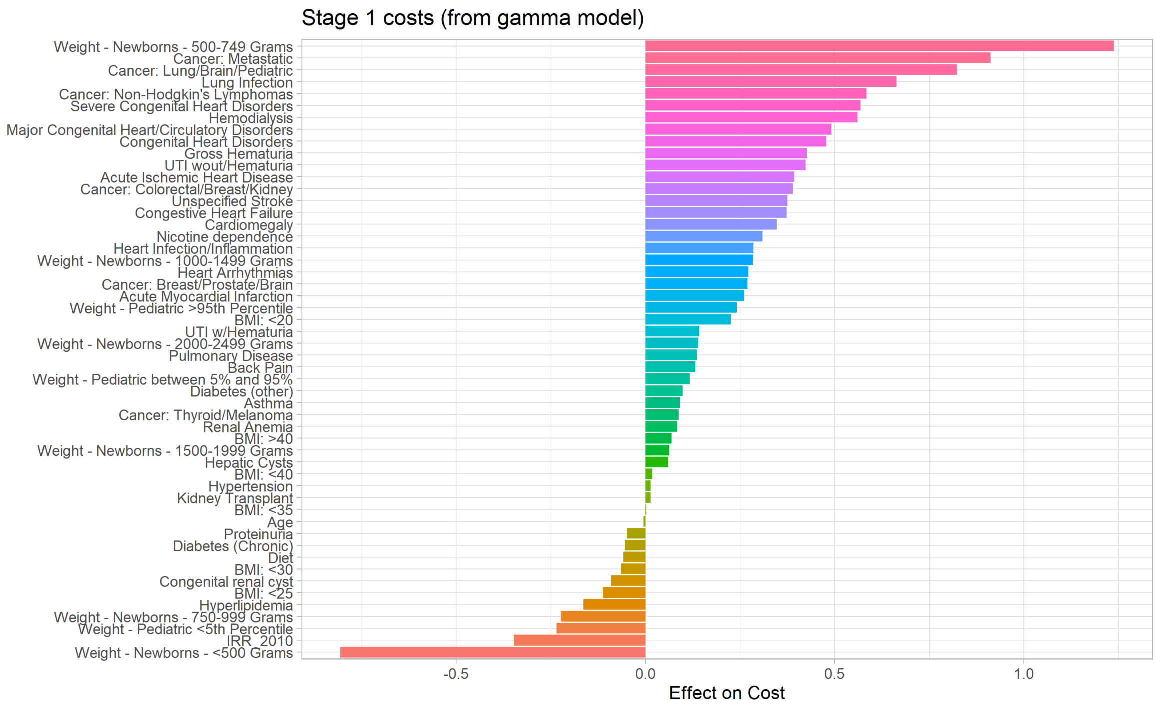


Figure A17: Commercial Gamma Regression Cost Model for Stage 1

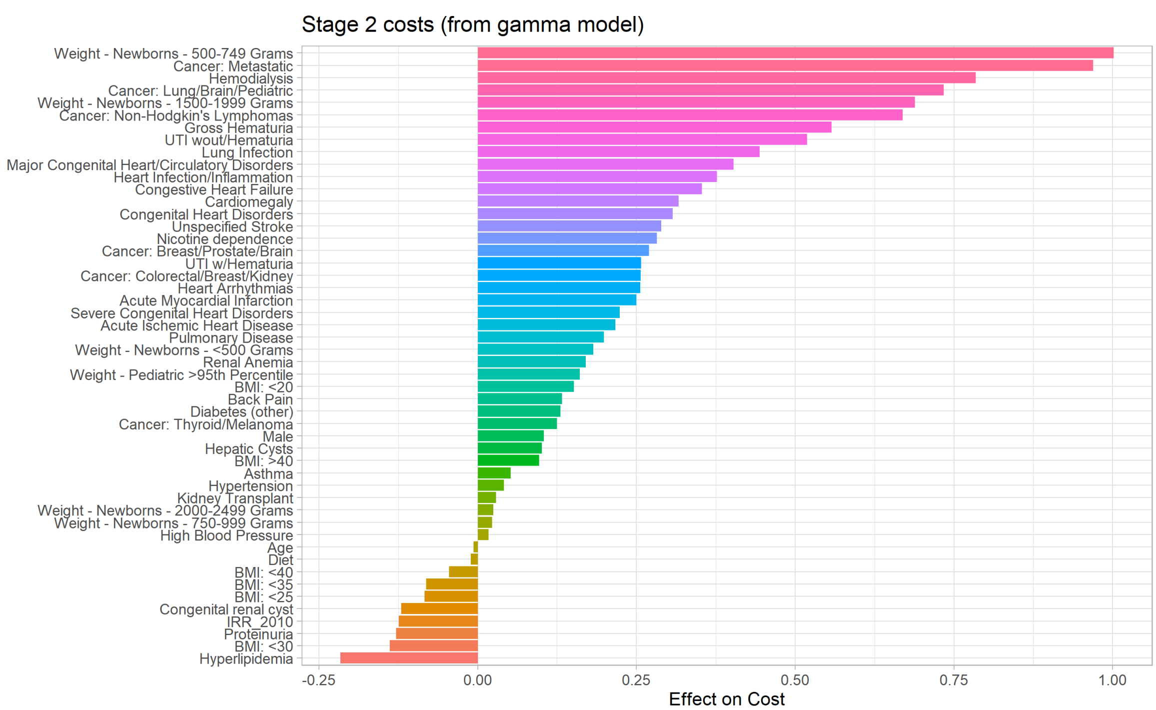


Figure A18: Commercial Gamma Regression Cost Model for Stage 2

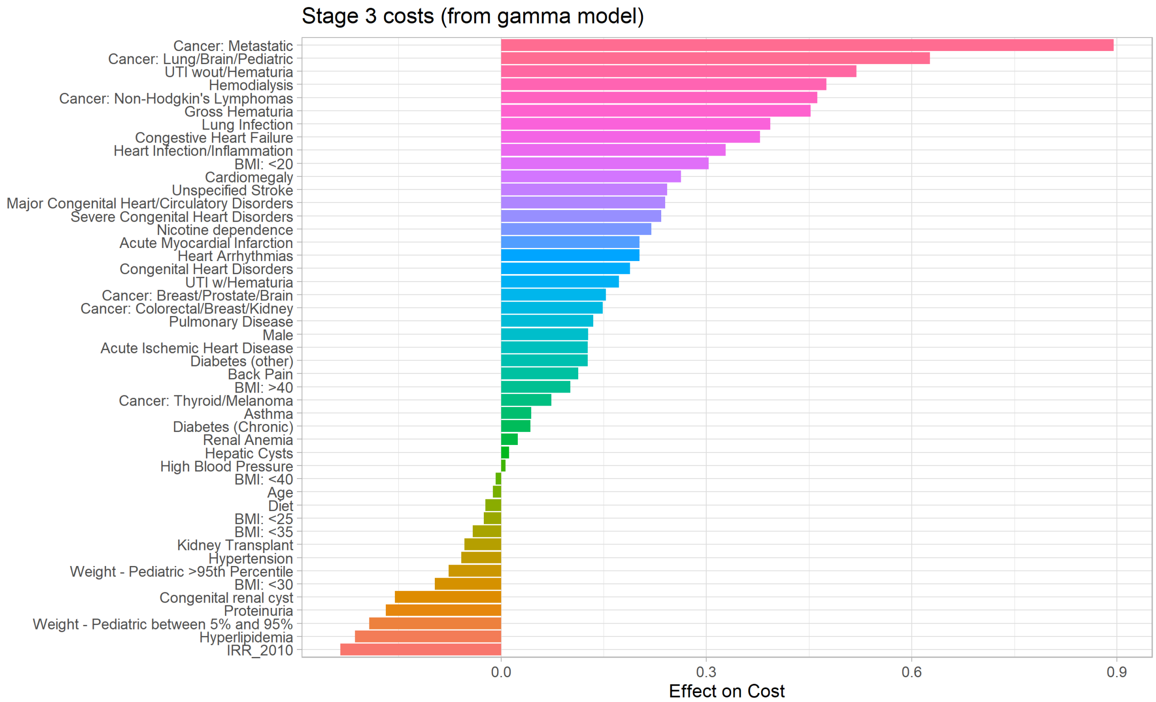


Figure A19: Commercial Gamma Regression Cost Model for Stage 3

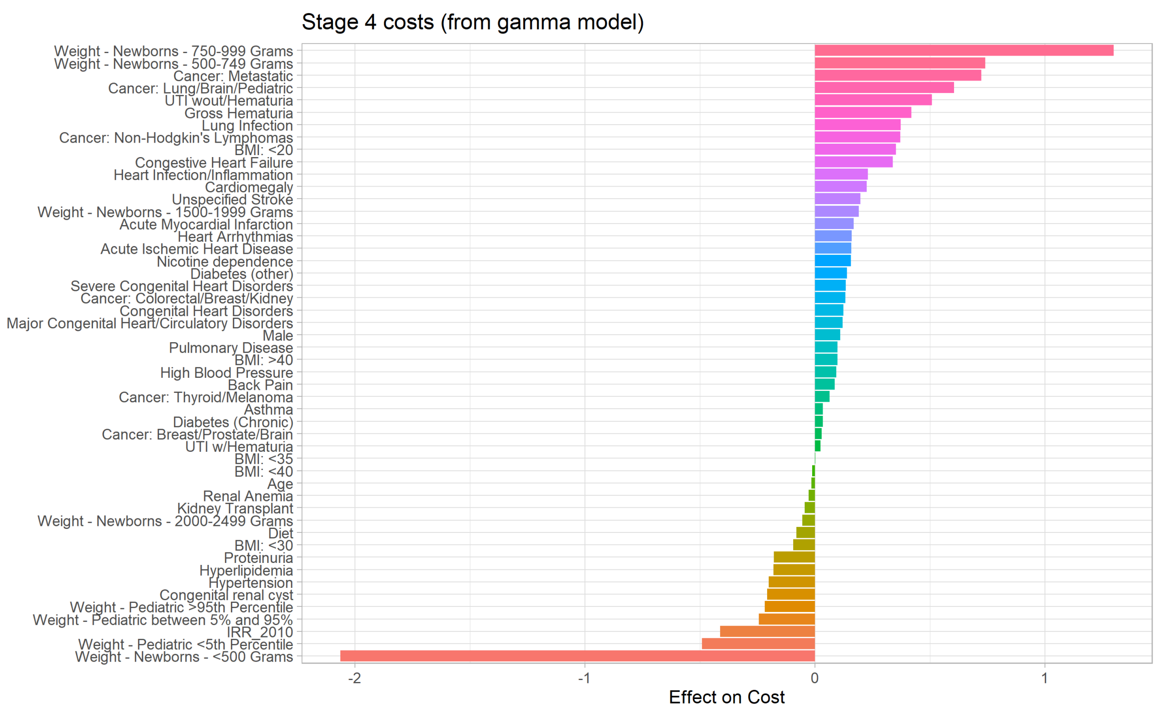


Figure A20: Commercial Gamma Regression Cost Model for Stage 4

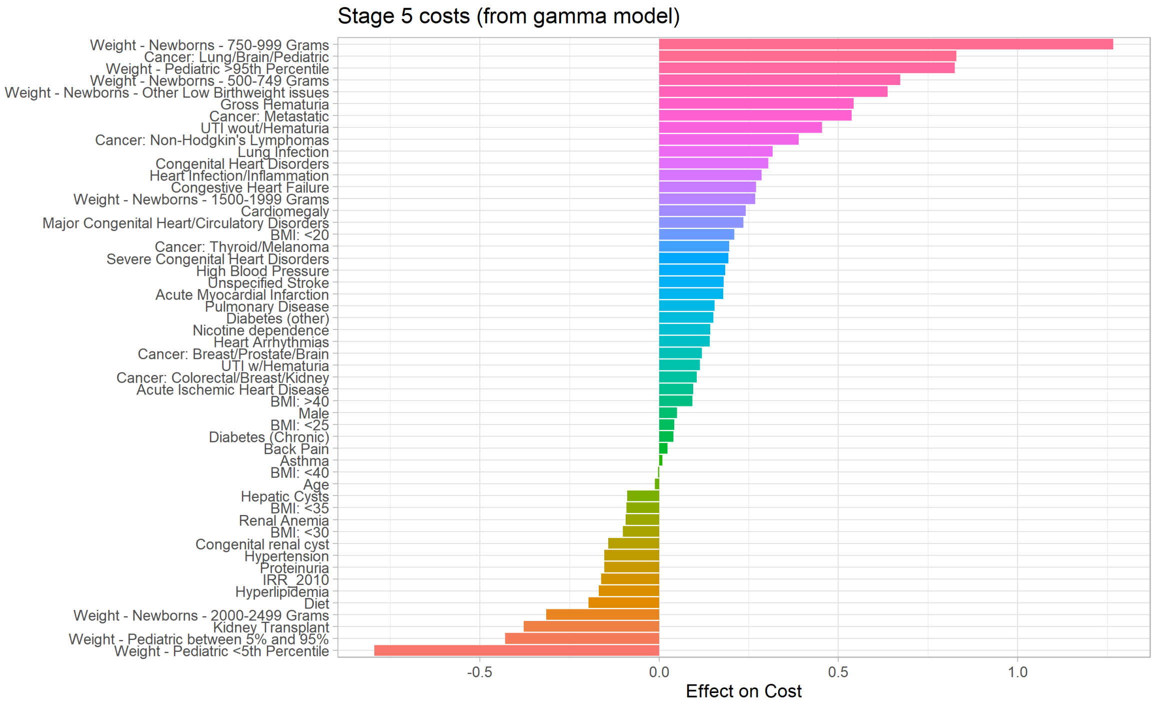


Figure A21: Commercial Gamma Regression Cost Model for Stage 5

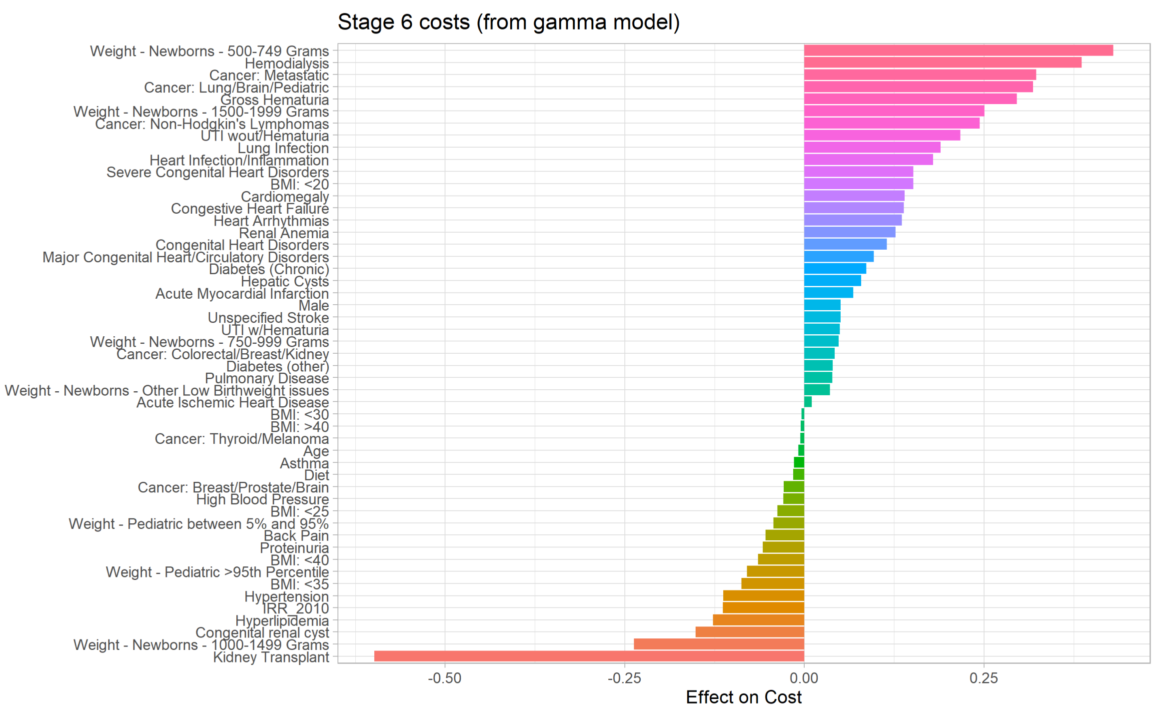


Figure A22: Commercial Gamma Regression Cost Model for Stage 6

D.1.3 Tweedie Regression

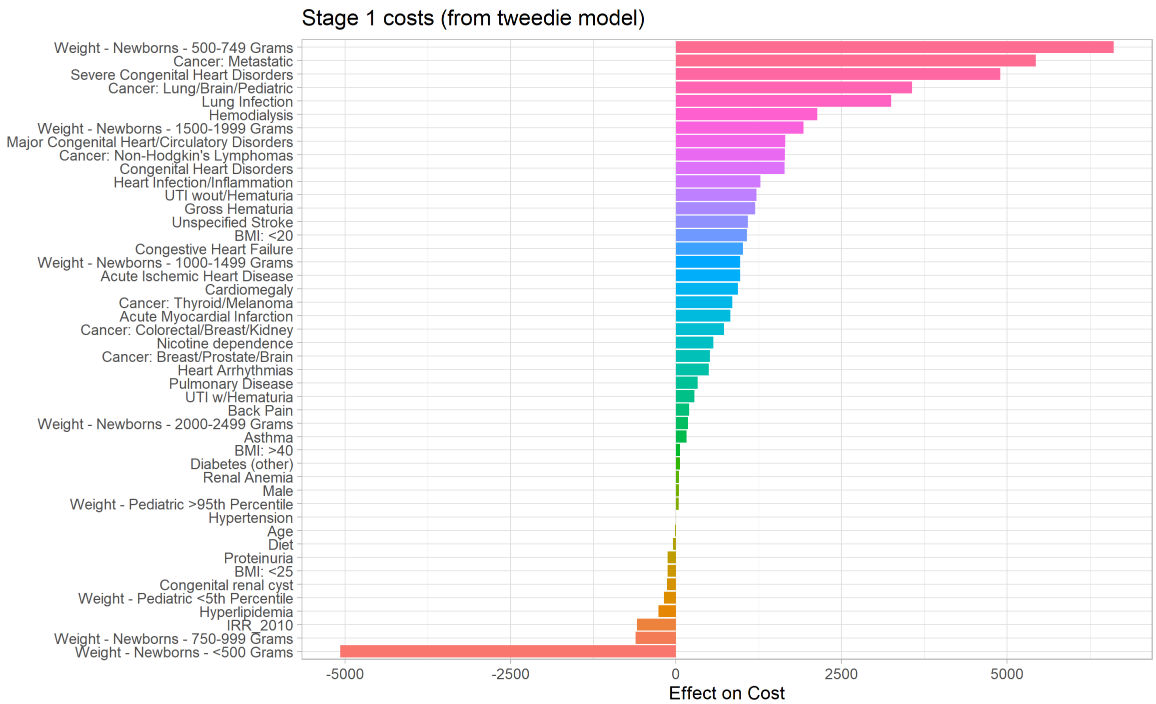


Figure A23: Commercial Tweedie Regression Cost Model for Stage 1

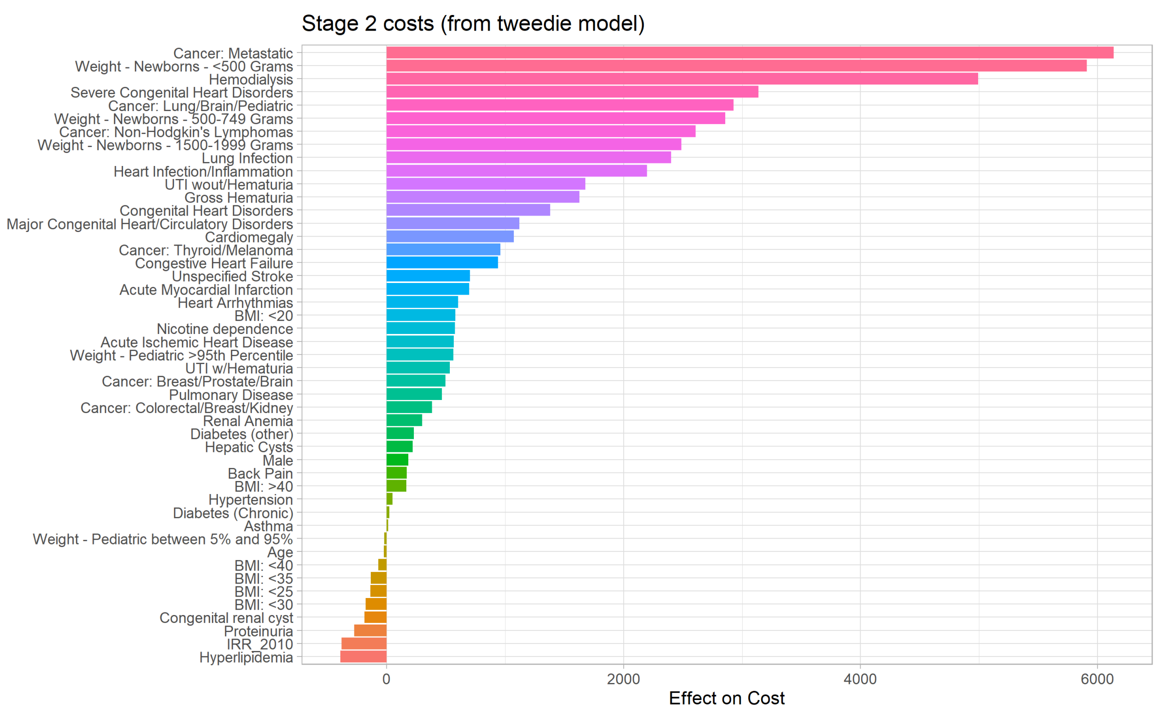


Figure A24: Commercial Tweedie Regression Cost Model for Stage 2

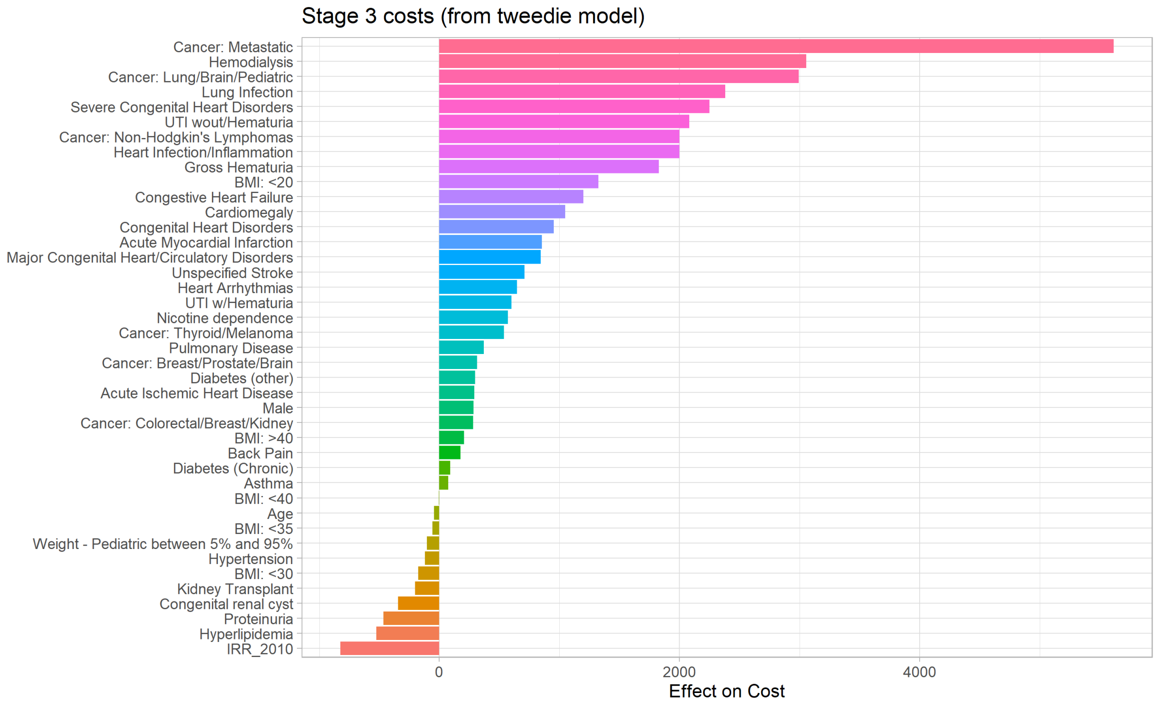


Figure A25: Commercial Tweedie Regression Cost Model for Stage 3

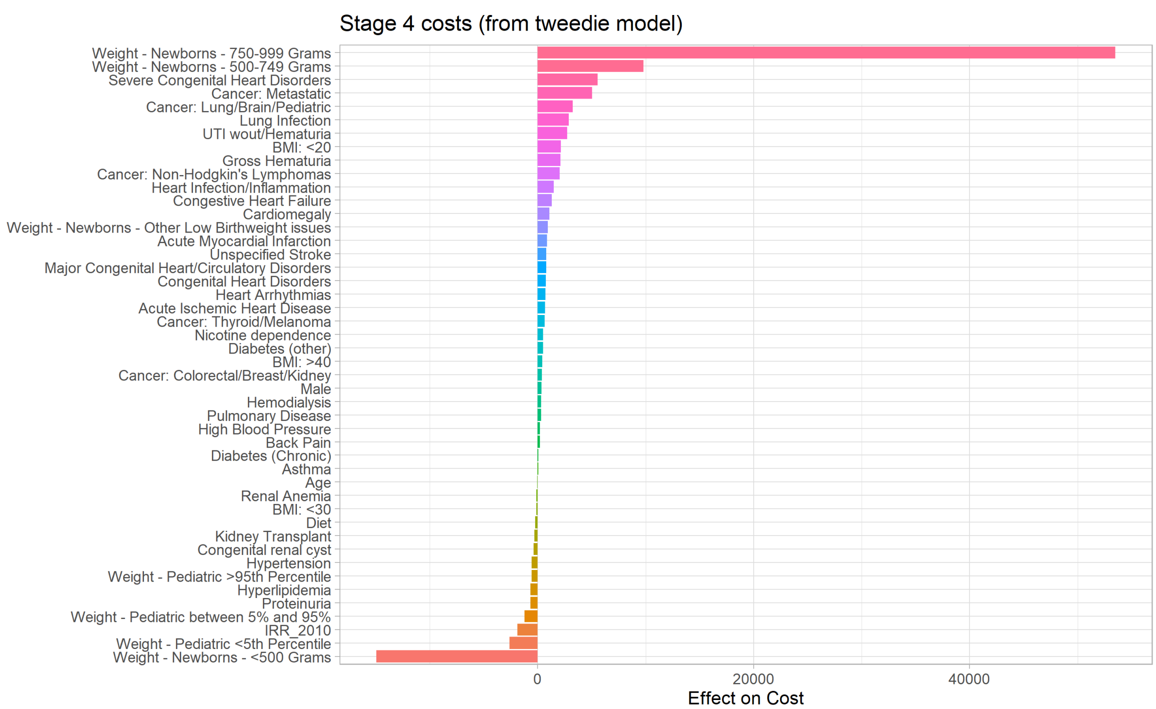


Figure A26: Commercial Tweedie Regression Cost Model for Stage 4

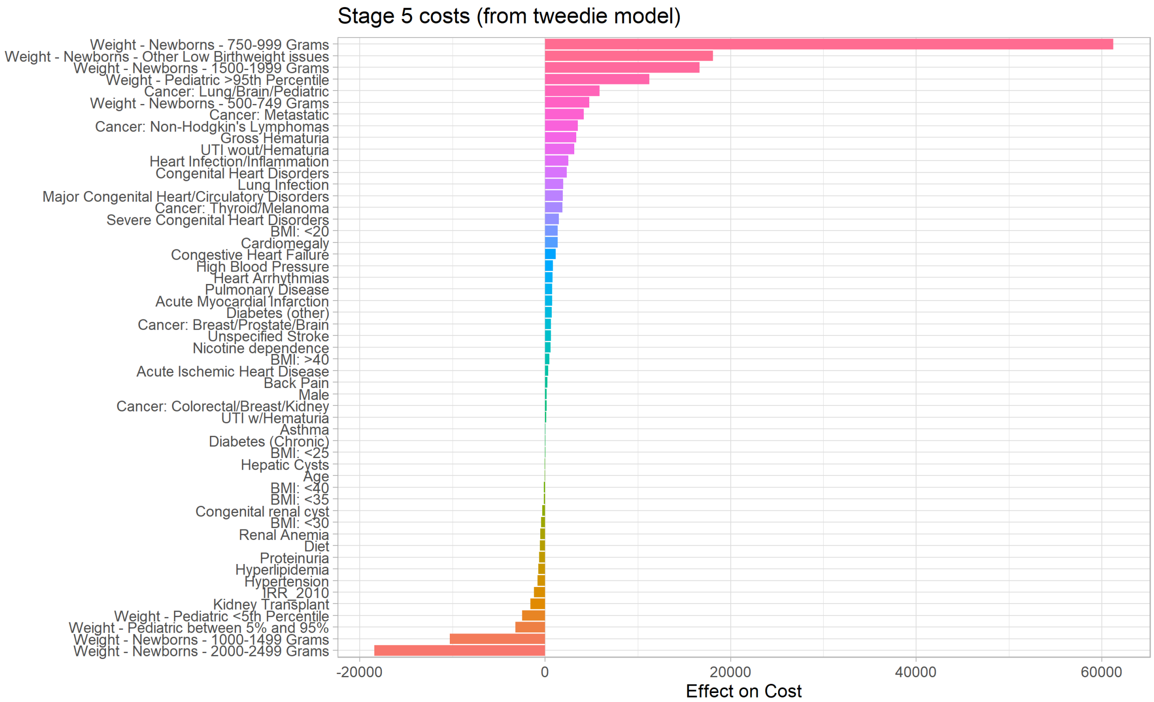


Figure A27: Commercial Tweedie Regression Cost Model for Stage 5

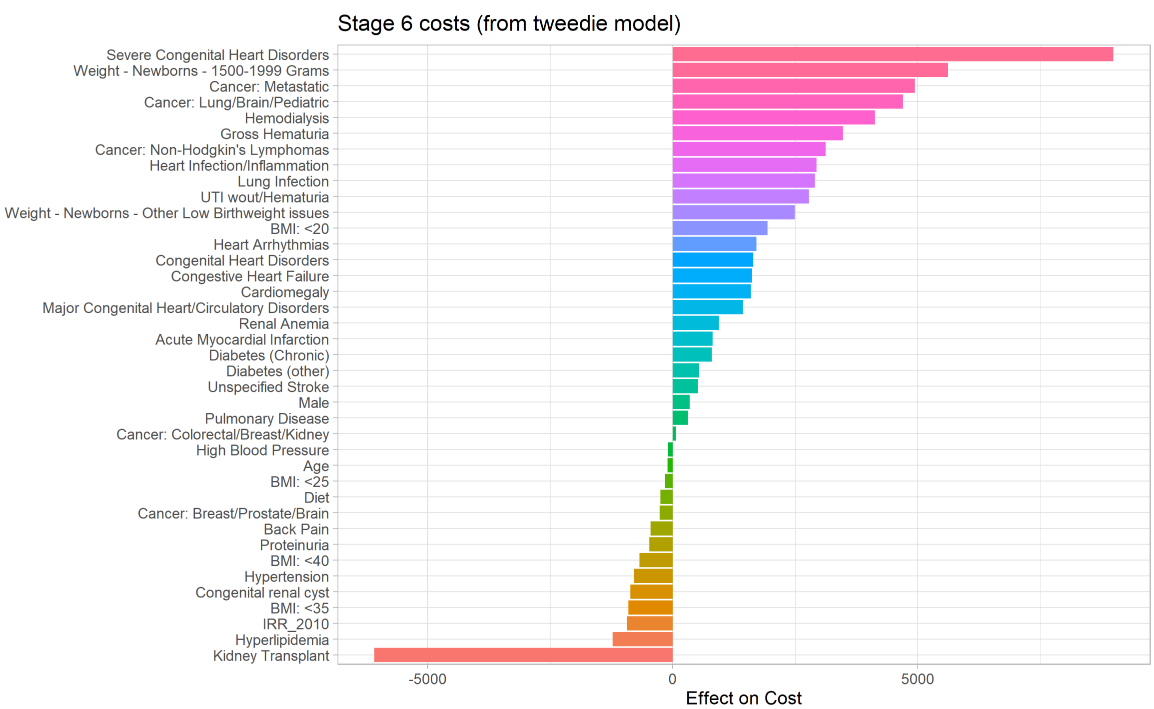


Figure A28: Commercial Tweedie Regression Cost Model for Stage 6

D.2 Medicare

D.2.1 Logistic Regression (zero/non-zero)

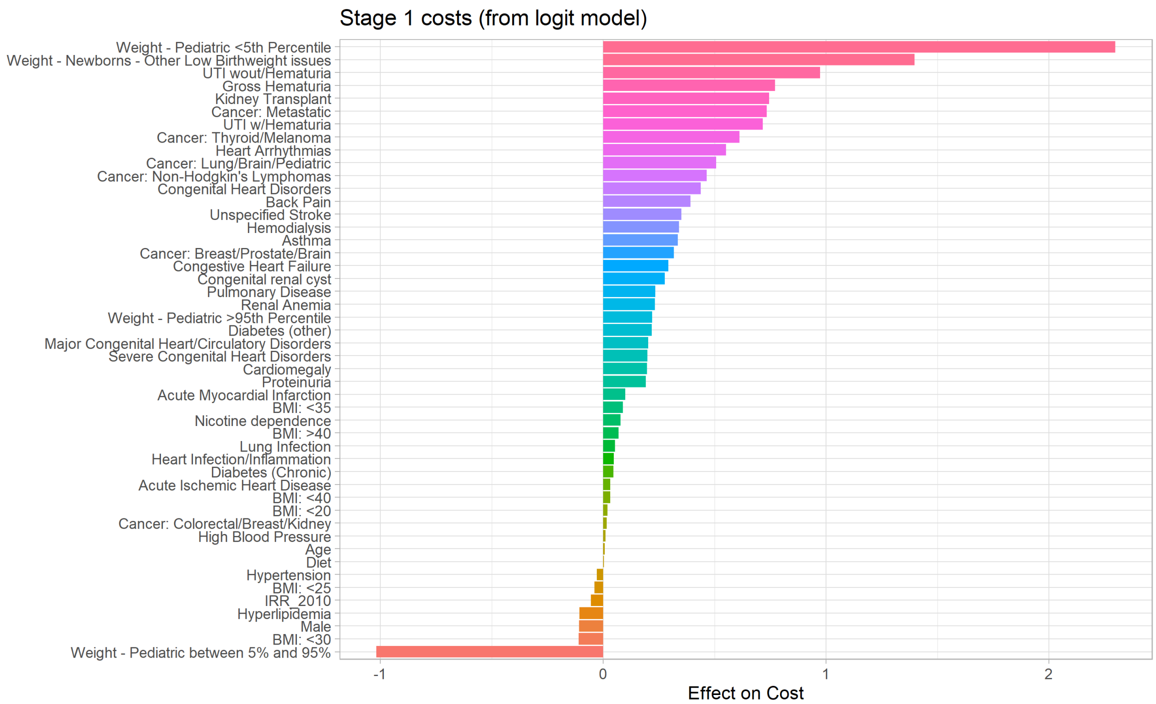


Figure A29: Medicare Logistic Regression Cost Model for Stage 1

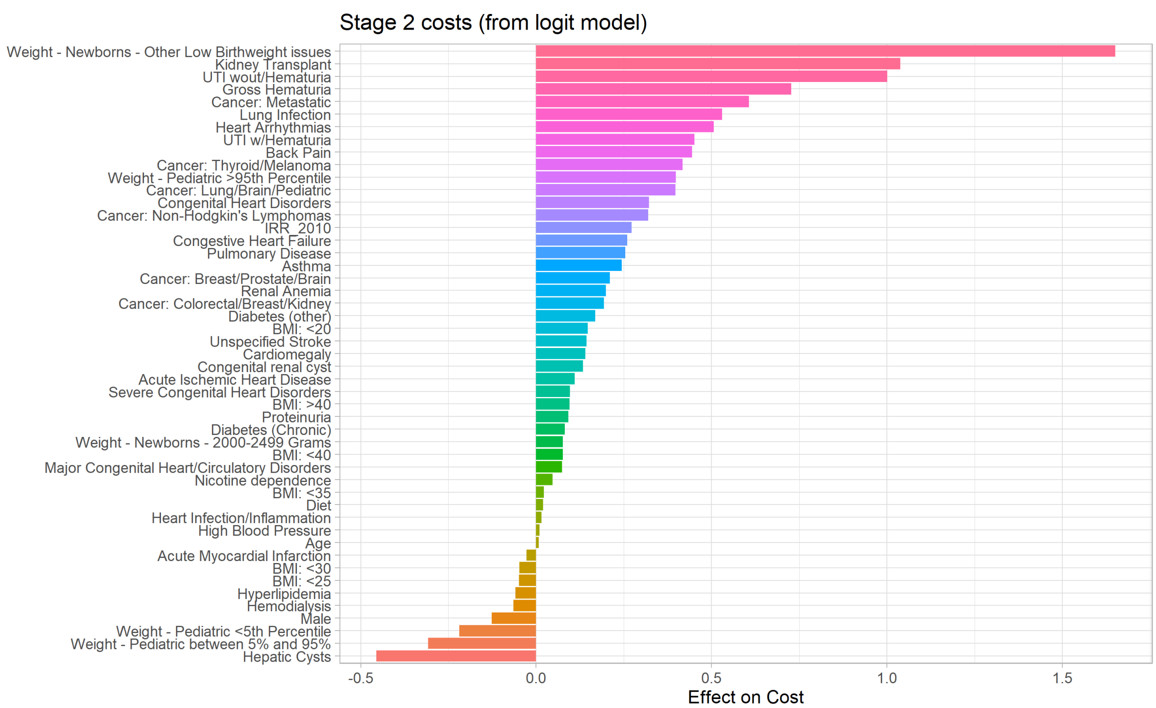


Figure A30: Medicare Logistic Regression Cost Model for Stage 2

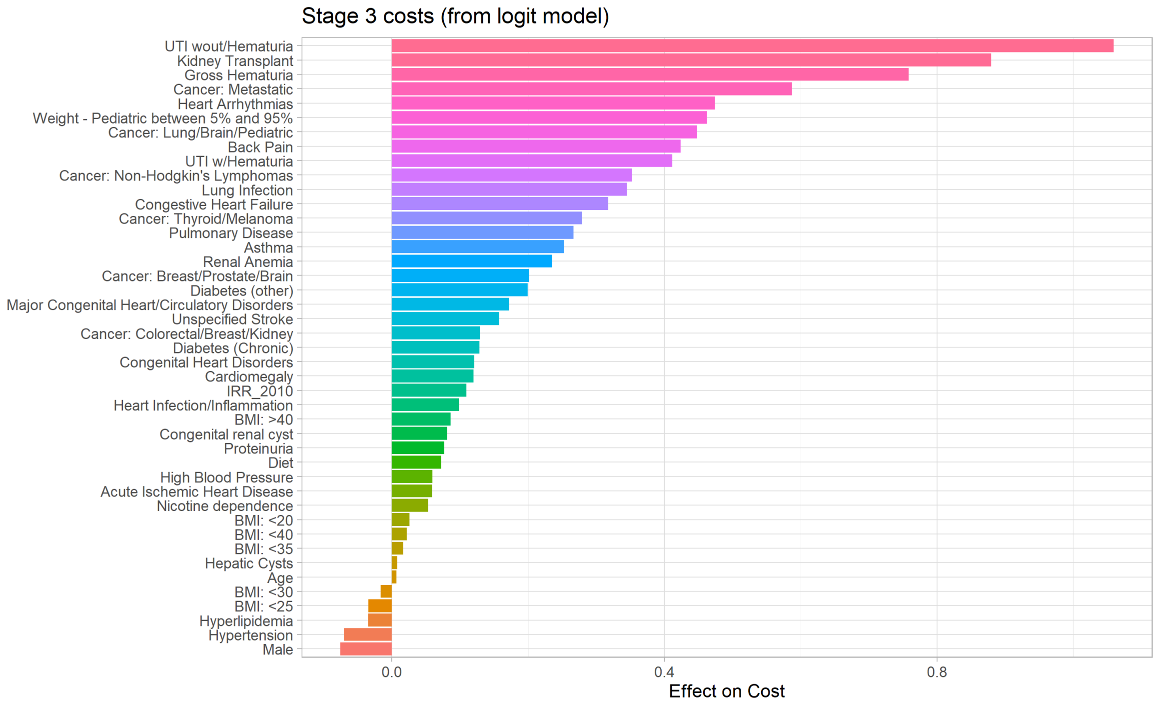


Figure A31: Medicare Logistic Regression Cost Model for Stage 3

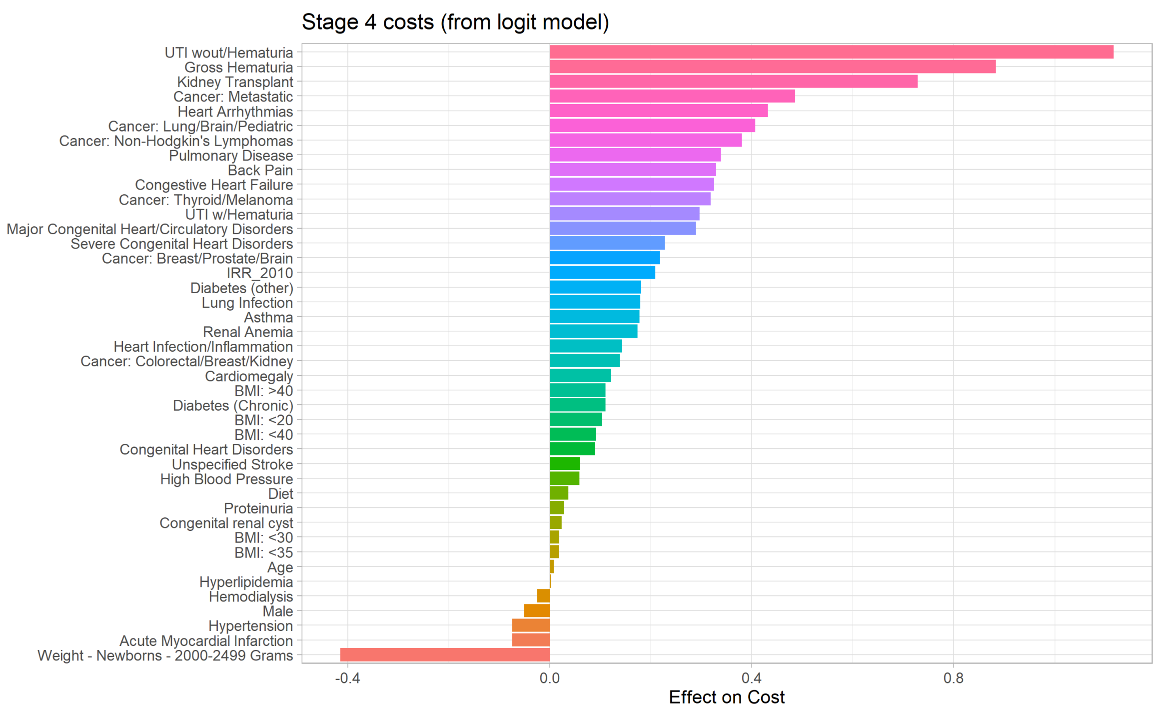


Figure A32: Medicare Logistic Regression Cost Model for Stage 4

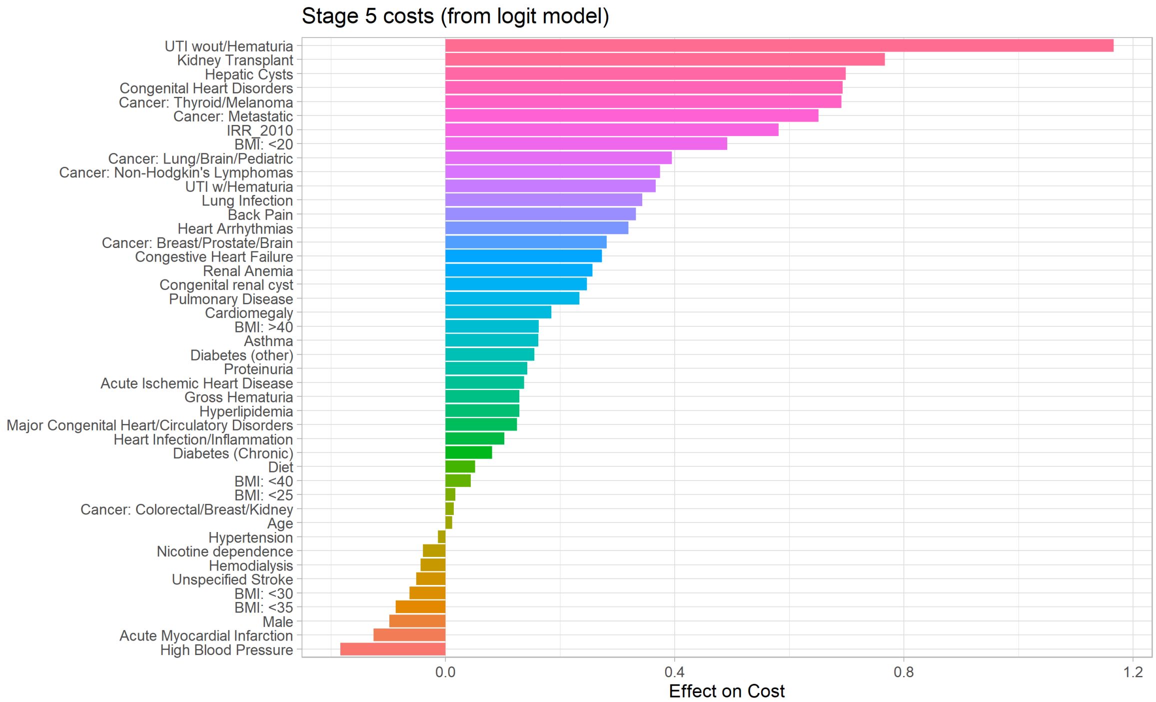


Figure A33: Medicare Logistic Regression Cost Model for Stage 5

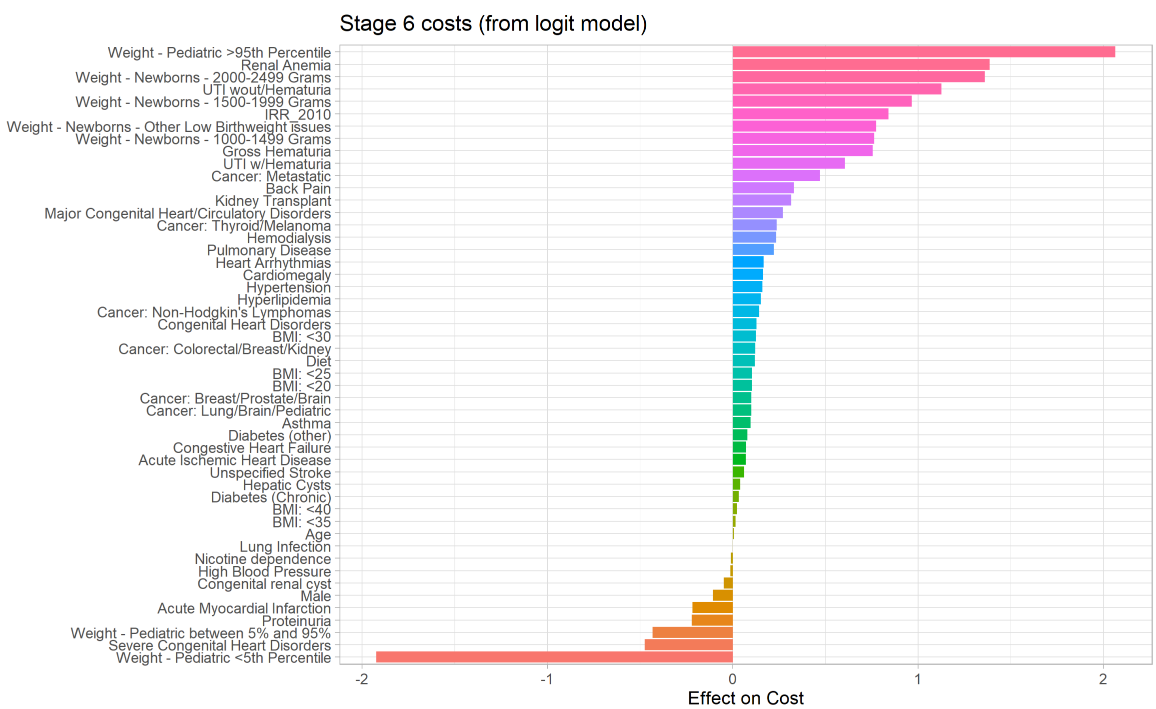


Figure A34: Medicare Logistic Regression Cost Model for Stage 6

D.2.2 Gamma Regression

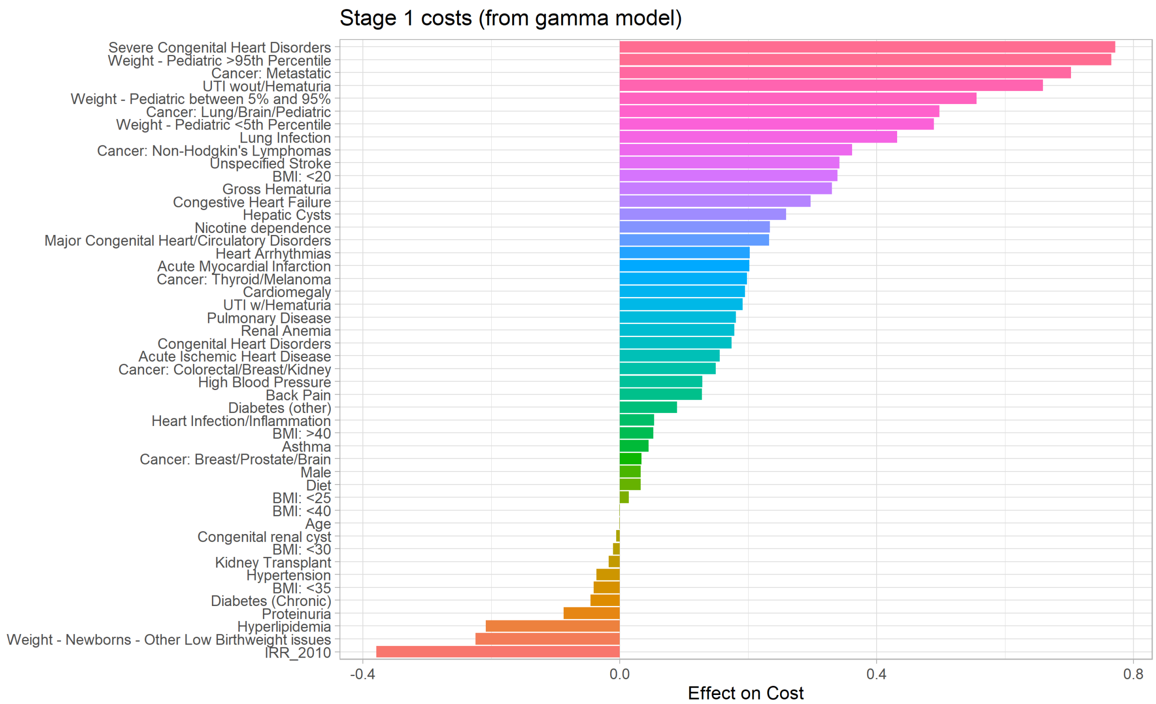


Figure A35: Medicare Gamma Regression Cost Model for Stage 1

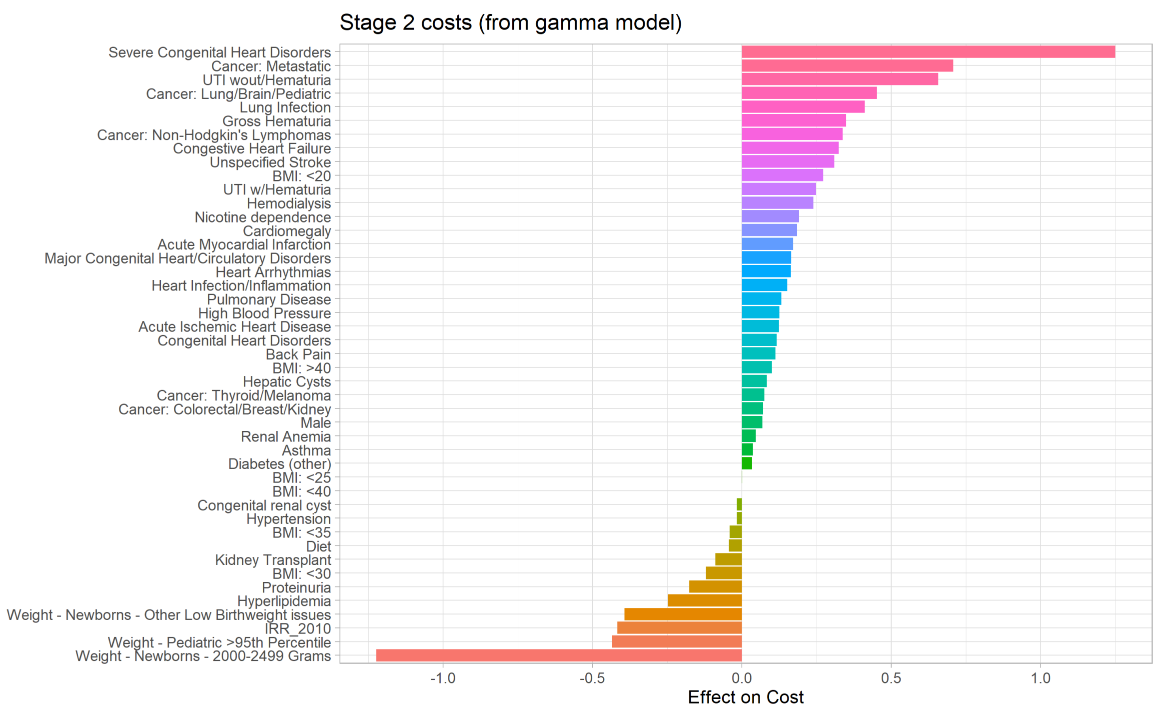


Figure A36: Medicare Gamma Regression Cost Model for Stage 2

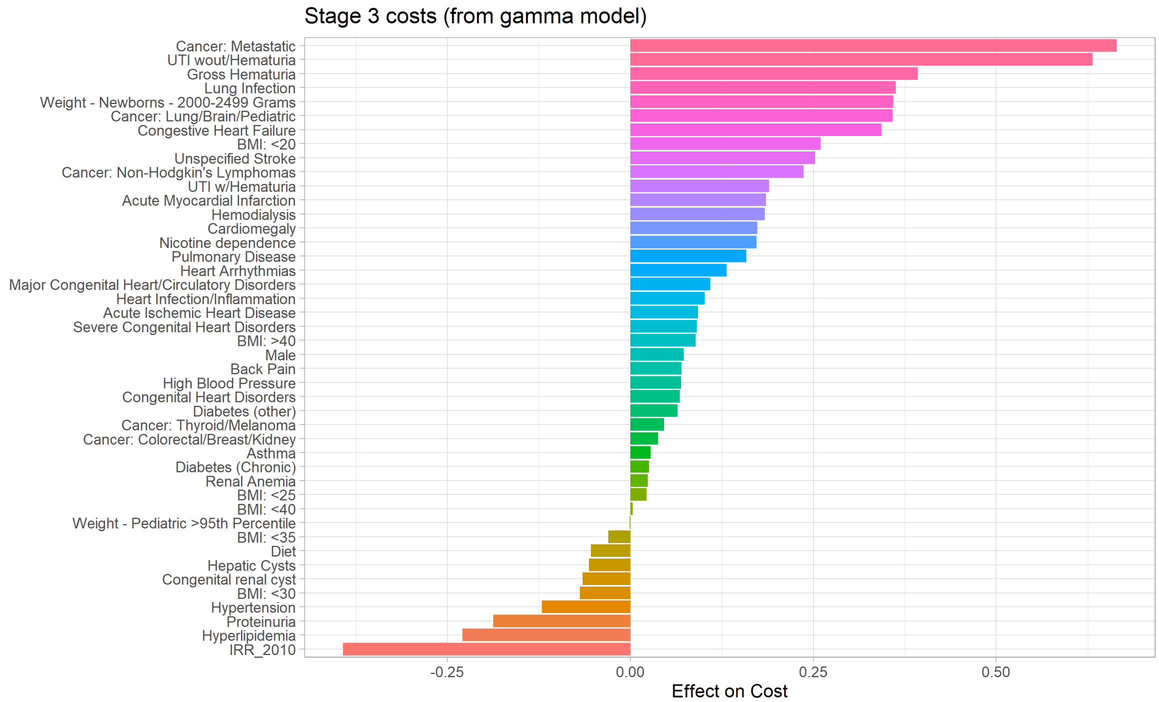


Figure A37: Medicare Gamma Regression Cost Model for Stage 3

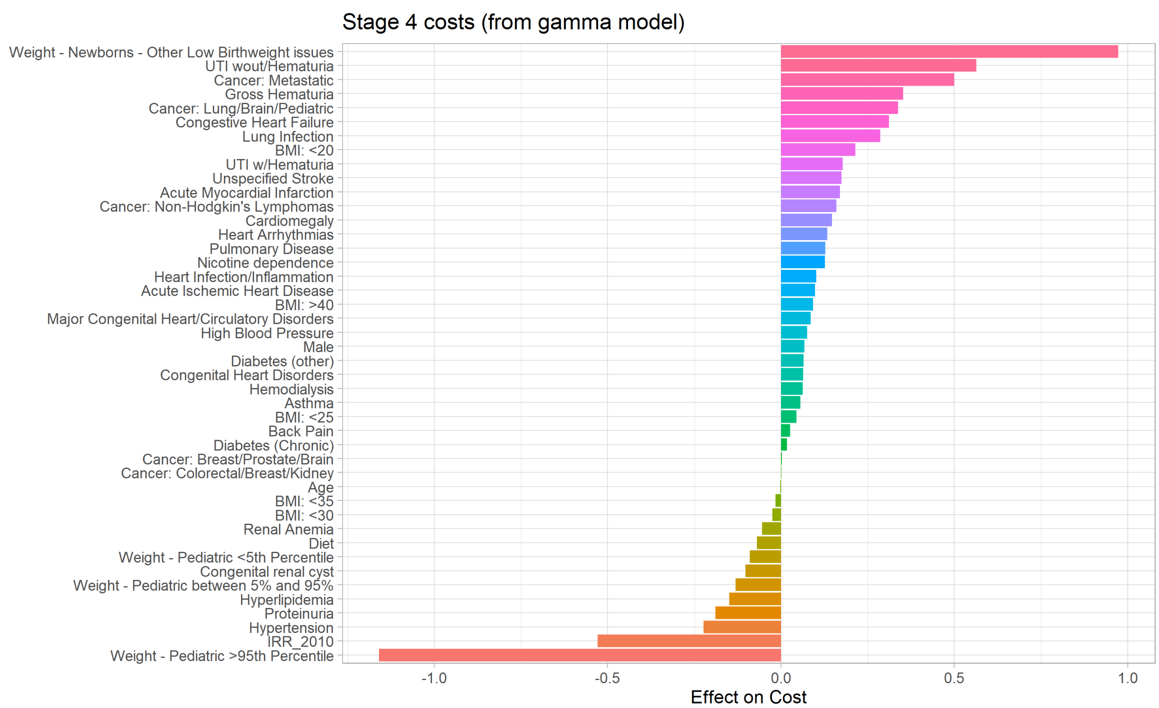


Figure A38: Medicare Gamma Regression Cost Model for Stage 4

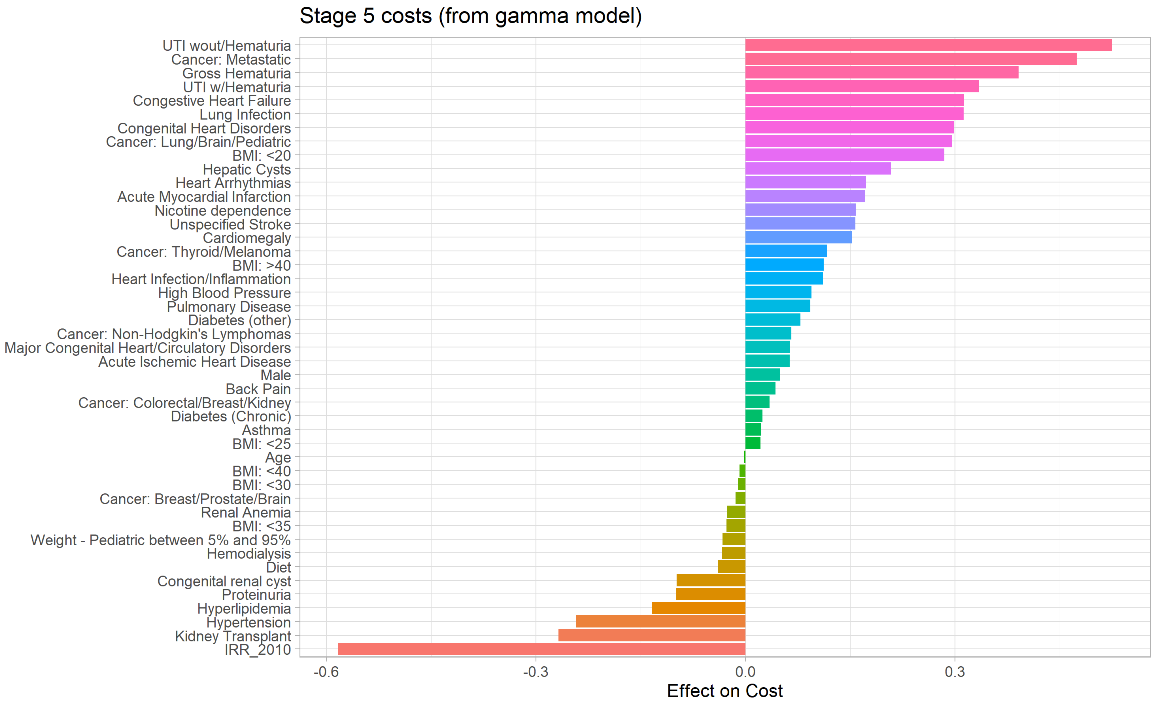


Figure A39: Medicare Gamma Regression Cost Model for Stage 5

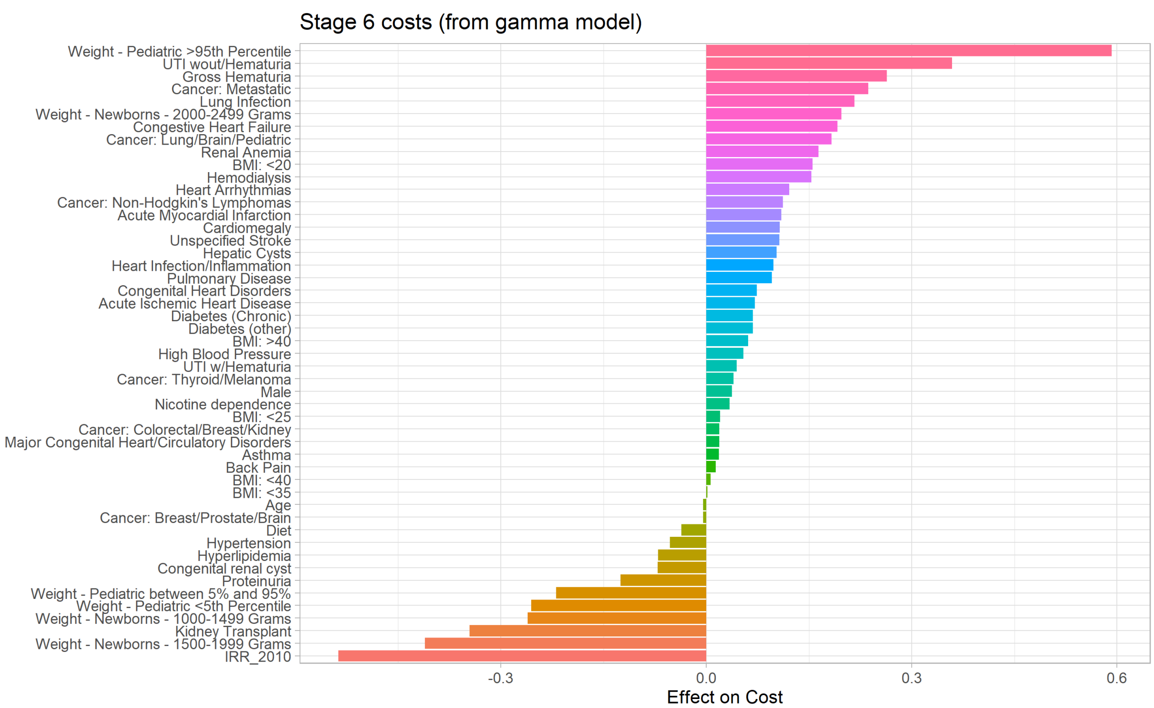


Figure A40: Medicare Gamma Regression Cost Model for Stage 6

D.2.3 Tweedie Regression

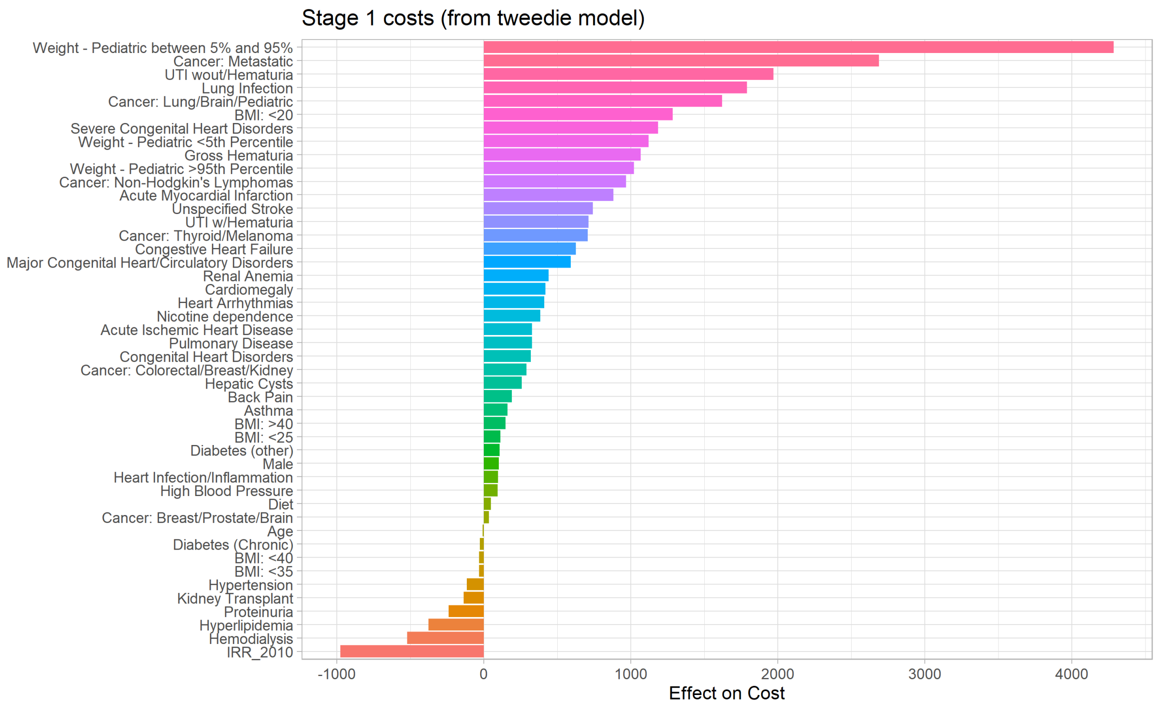


Figure A41: Medicare Tweedie Regression Cost Model for Stage 1

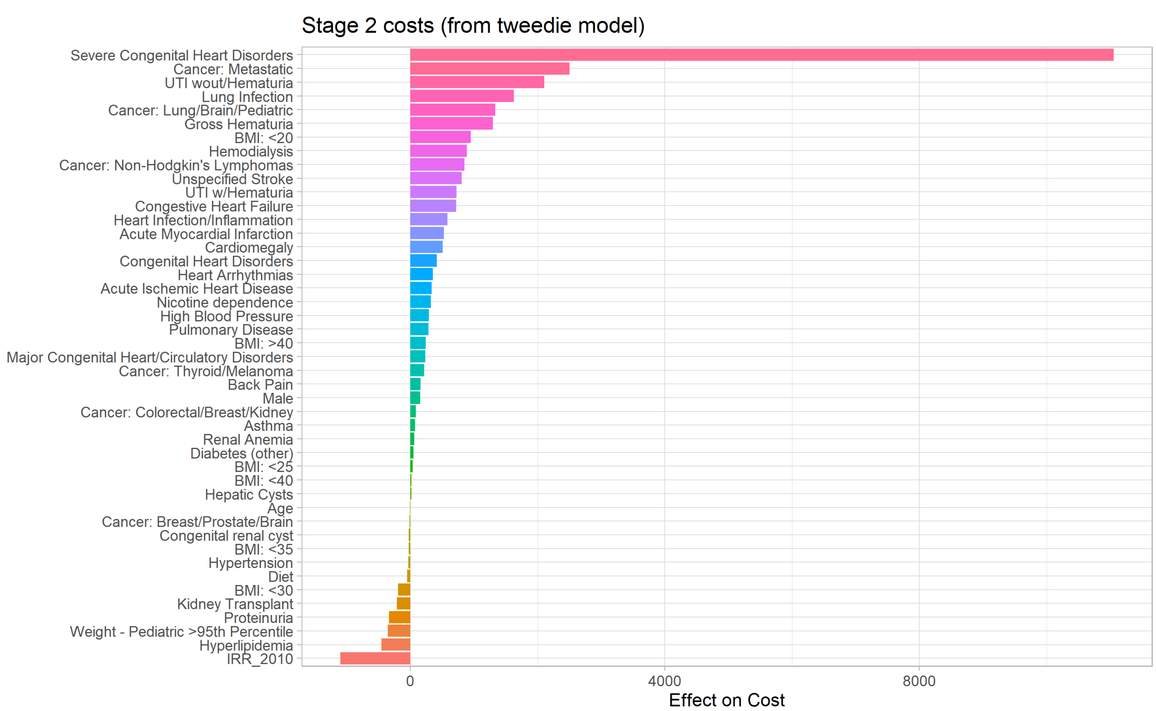


Figure A42: Medicare Tweedie Regression Cost Model for Stage 2

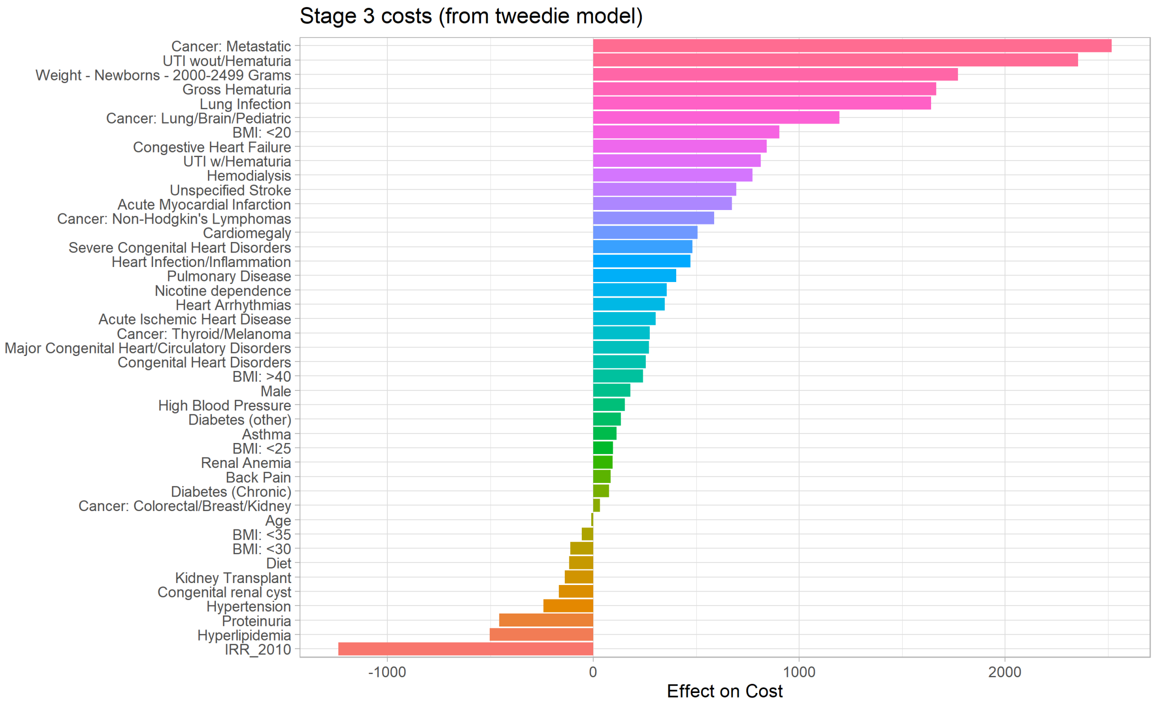


Figure A43: Medicare Tweedie Regression Cost Model for Stage 3

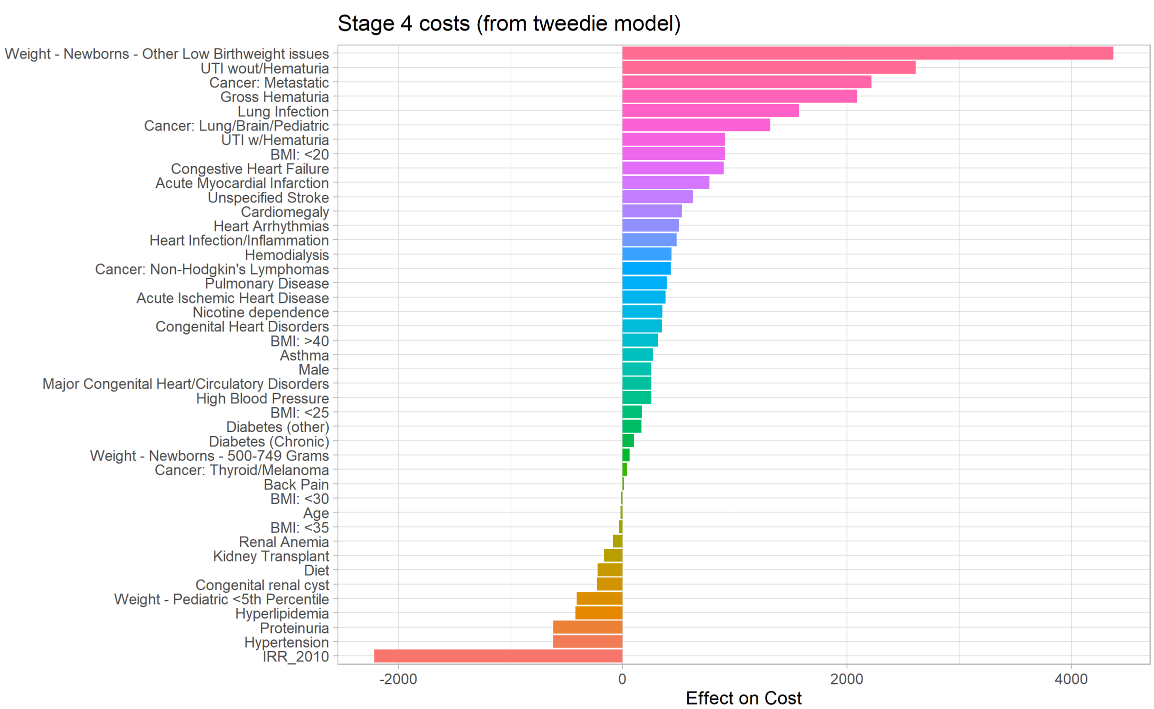


Figure A44: Medicare Tweedie Regression Cost Model for Stage 4

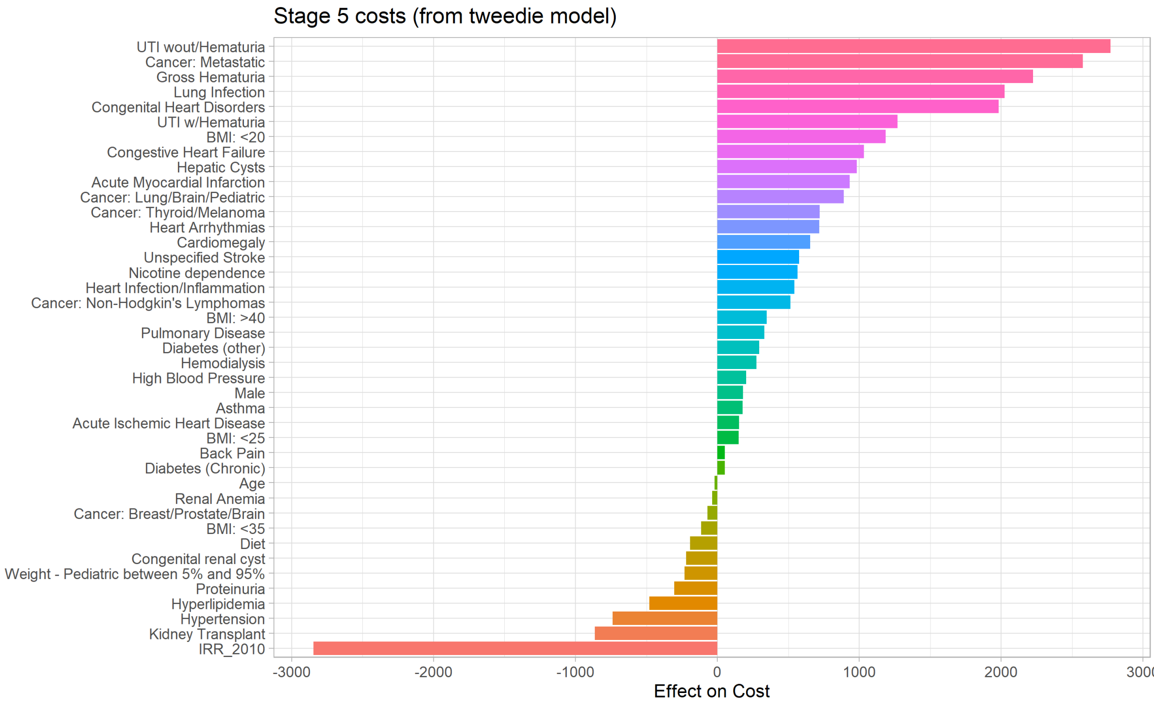


Figure A45: Medicare Tweedie Regression Cost Model for Stage 5

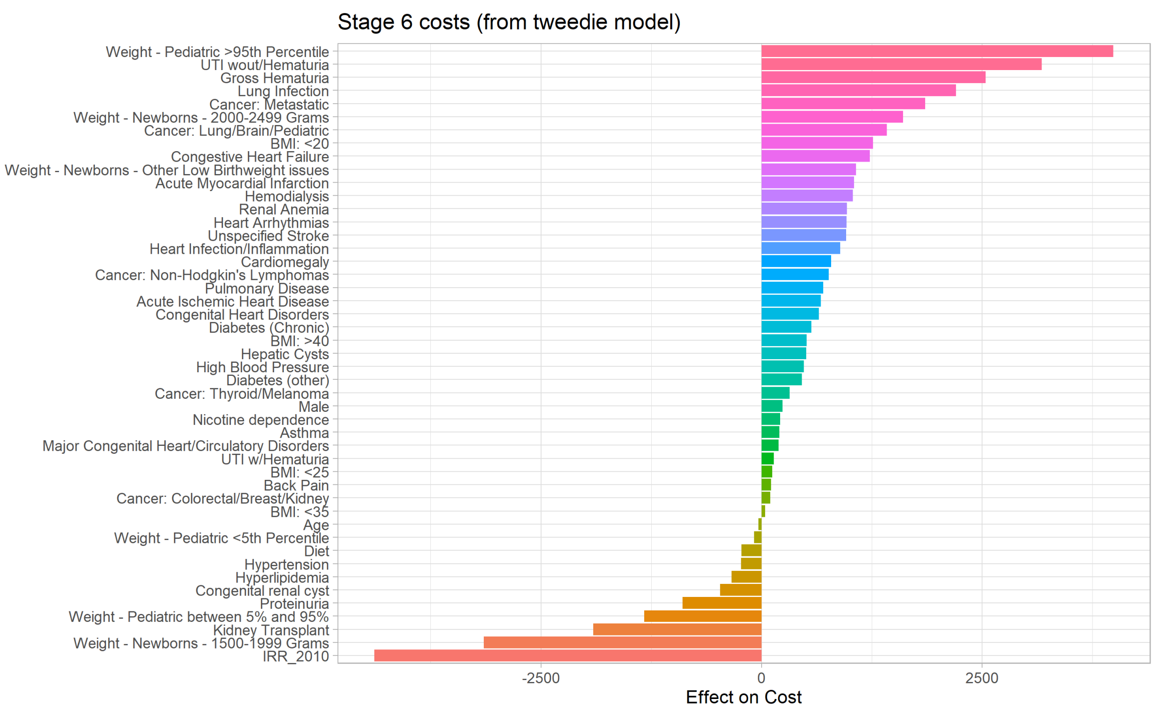


Figure A46: Medicare Tweedie Regression Cost Model for Stage 6