Does Encounter History Influence Future Hospital Readmissions?

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Agenda

- Background on Readmissions
- Motivation
- Research Objectives
- Data
- Model
- Findings
- Contributions
- Future Directions

Hospital Readmission

- Patient is readmitted to a hospital after discharge from a hospital visit
- If a high proportion of patients are being readmitted, that may indicate inadequate quality of care or a lack of proper coordination of post-discharge care
- Hospitals can employ strategies to avert readmissions

Hospital Readmissions Reduction Program (HRRP)

- Affordable Care Act established the HRRP in 2012
- HRRP requires CMS to reduce payments to hospitals with excess readmissions
- Currently CMS employs 6 measures in calculating a hospital’s readmissions payment adjustment factor:
  - Heart Failure (HF)
  - Acute Myocardial Infraction (AMI)
  - Pneumonia
  - Chronic Obstructive Pulmonary Disease (COPD)
  - Coronary Artery Bypass Graft (CABG) Surgery
  - Elective Total Hip Arthroplasty and/or Total Knee Arthroplasty (THA/TKA)

Research Motivation

- Because of the changes brought in by HRRP, it has become strategically important to predict a patient's probability of readmission
- Hospitals should identify patients at greater risk of readmission and take steps to prevent those readmissions

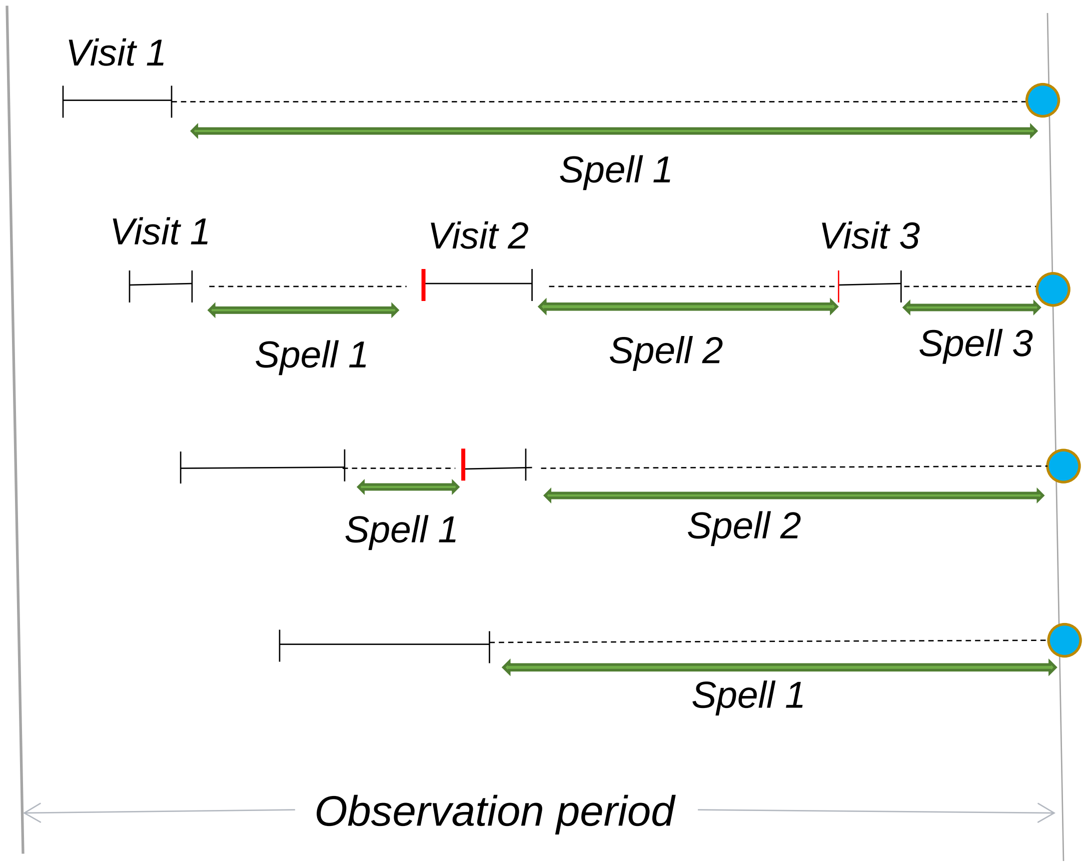
Gap in Literature

- One of the missing links in extant research on readmission is the patient's hospital encounter history
- Extant studies have examined the details of a patient's most recent encounter with the hospital, but they have not looked at prior hospital encounters
- Patients with multiple encounters experience different diagnoses, procedures, visit durations, and spell times

Research Objective

- *To predict the probability of readmission by taking into account the history of a patient's hospital encounters*
- Hospitals have data on:
  - the history of diagnoses and procedures that were carried out in earlier hospital visits
  - the history of prior visit durations & spell times

Readmissions & Censored Observations



Readimssion/Failure event

Censored observation

Requirements for the Model

- The model needs to incorporate the following dynamics of the readmission process:
  - History of hospital stays
    - Visit duration
    - Diagnoses
    - Procedures
  - History of spell times

Readmissions Data Set

- Obtained from an HIE in Texas
- The HIE includes around 70 hospital branches/ clinics and 5600 physicians located in the region
- In addition to age, gender, race, marital status, type of insurance, primary diagnosis, number of diagnoses, and number of procedures, the data set includes two types of duration data:
  - the length of each hospital stay for a patient
  - the readmission time interval, if any, for the patient
- The data set contains over 90,000 inpatient hospital admissions/readmissions during 2011 and 2012

Hazard Function

- Relative likelihood of readmission at time *t*, conditional on the patient's survival up to time *t* :

$$h(t) = \frac{f(t)}{S(t)}$$

which is the instantaneous rate of readmission at time *t* and *S(t)* is the survivor function

$$h(t) = \lim_{\Delta t \to 0} \left(\frac{P(t \leq T < t + \Delta t \mid T \geq t}{\Delta t} \right)$$

Cox Proportional Hazards Model

- Hazard function is specified as:

$$h(t;\boldsymbol{Z_i}) = h_0(t)\ \exp(\boldsymbol{\beta Z_i})$$

where $h_0(t)$ is the baseline hazard function and $\boldsymbol{\beta}$ is a parameter vector that describes the effects of the covariates Z_i .

Variables in Model

- Spell duration (*T*): Number of days since patient was last discharged from hospital
- Visit duration: Length of stay in days at the hospital during the patient’s last hospital visit
- Age, Gender, Race, Marital Status
- Diagnosis group: Category of the primary diagnosis (ICD9 code) of the patient during the hospital visit
- Number of diagnoses, Number of procedures
- Insurance: Insurance carrier of the patient
- State: Censoring indicator (1:readmitted, 0:censored)

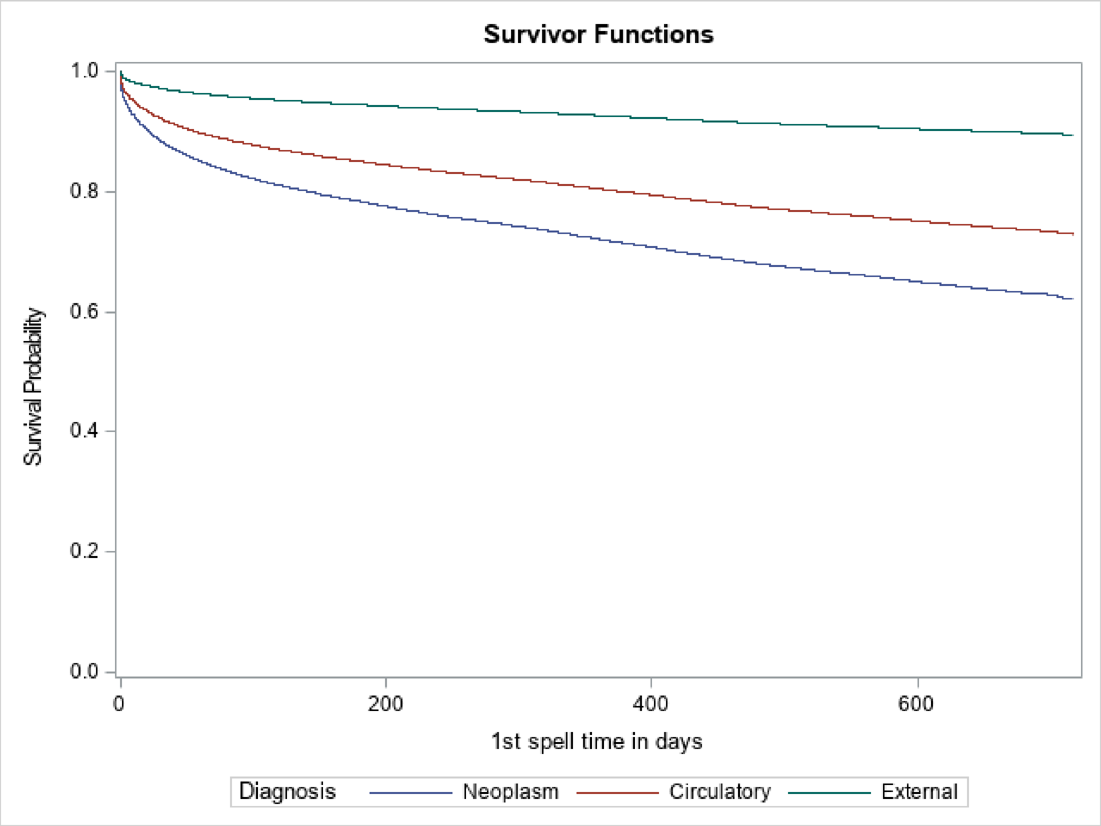
Max Likelihood Estimates for First Spell

	Parameter	DF	Parameter Estimate	Chi-Square	Pr > ChiSq
Demog	Age	1	0.01013	218.0579	<.0001
	Male	1	0.02493	1.276	0.2586
	Black	1	0.1581	14.651	0.0001
	White	1	0.08474	6.5013	0.0108
	Married	1	-0.12052	23.8684	<.0001
Insnce	CHIP	1	-0.22825	10.029	0.0015
	Charity	1	-0.02907	0.3329	0.564
	Medicaid	1	0.24911	24.5557	<.0001
	Medicare	1	-0.06505	1.0136	0.3141
	SelfPay	1	-0.16233	9.6838	0.0019
Visit	Number of diagnoses	1	0.13608	158.4346	<.0001
	Number of procedures	1	-0.08916	126.0741	<.0001
	Visit duration	1	0.01546	297.6154	<.0001

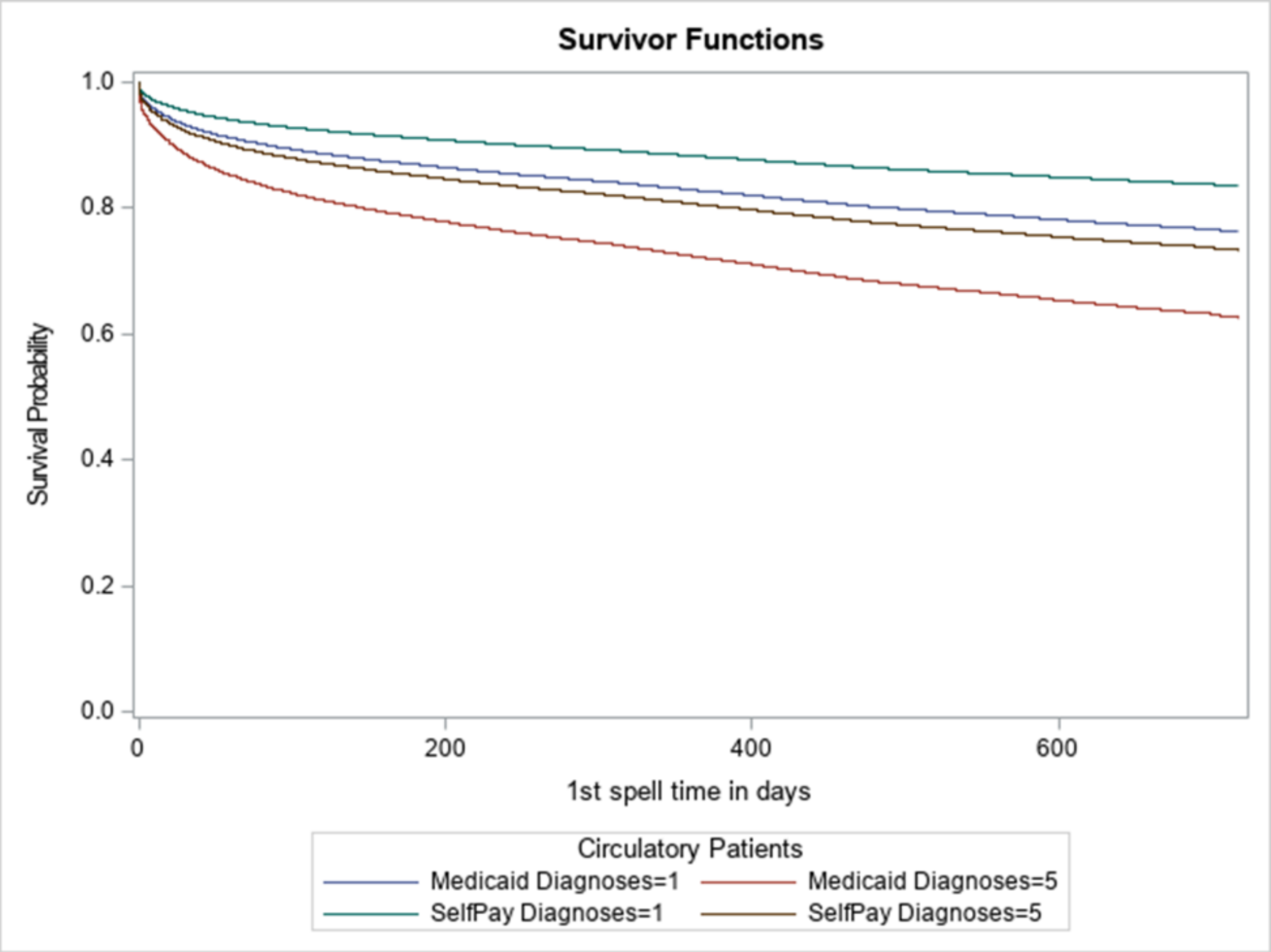
Findings for First Spell

- Older patients, black/white patients, and single patients have higher readmission risk
- Medicaid patients have the highest readmission risk
- CHIP and Self Pay patients have the lowest readmission risk
- Neoplasm & Blood patients have the highest risk
- External & Pregnancy patients have the lowest risk
- Higher the number of diagnoses, higher is the readmission risk
- Higher the number of procedures a patient undergoes, lower is the risk
- Longer the stay at the hospital, higher is the readmission risk

1st Spell Survival Probabilities for Different Diagnoses



1st Spell Survival Probabilities for Medicaid & SelfPay Patients



Max Likelihood Estimates for Second Spell

	Parameter	DF	Parameter Estimate	Chi-Square	Pr > ChiSq
Demog	Age	1	0.0059	25.3095	<.0001
	Male	1	0.06966	3.6234	0.057
	Black	1	0.1729	5.5358	0.0186
	White	1	0.07731	1.5559	0.2123
	Married	1	-0.07684	3.2748	0.0704
Insnce	CHIP	1	-0.4166	5.8269	0.0158
	Charity	1	-0.07918	0.8751	0.3496
	Medicaid	1	0.05195	0.3778	0.5388
	Medicare	1	-0.22215	4.0774	0.0435
	SelfPay	1	-0.15825	2.9858	0.084
Visit	Number of diagnoses	1	0.09523	14.1889	0.0002
	Number diagnoses Lag1	1	0.14229	34.5111	<.0001
	Number of procedures	1	-0.0405	9.7173	0.0018
	Visit duration	1	0.00349	2.6321	0.1047
	Spell time Lag1	1	-0.0007856	31.6068	<.0001

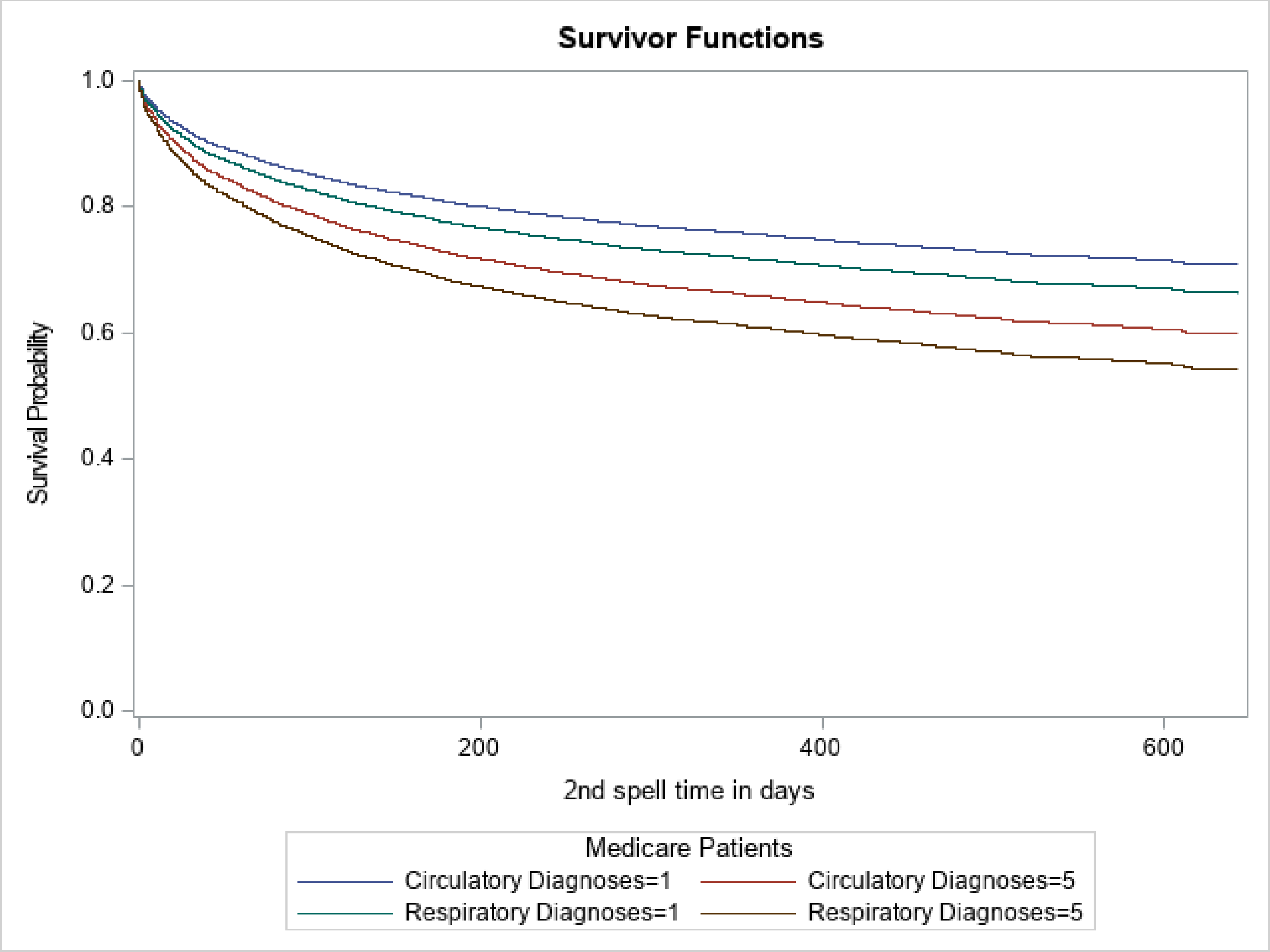
Second Spell Hazard Rates

- Previous spell time of 10 days shrinks the hazard rate by only ~ 1%
- Previous spell time of 20 days shrinks the hazard rate by ~ 2%
- Previous spell time of 30 days shrinks the hazard rate by ~3%
- Previous spell time of 60 days shrinks the hazard rate by ~6%

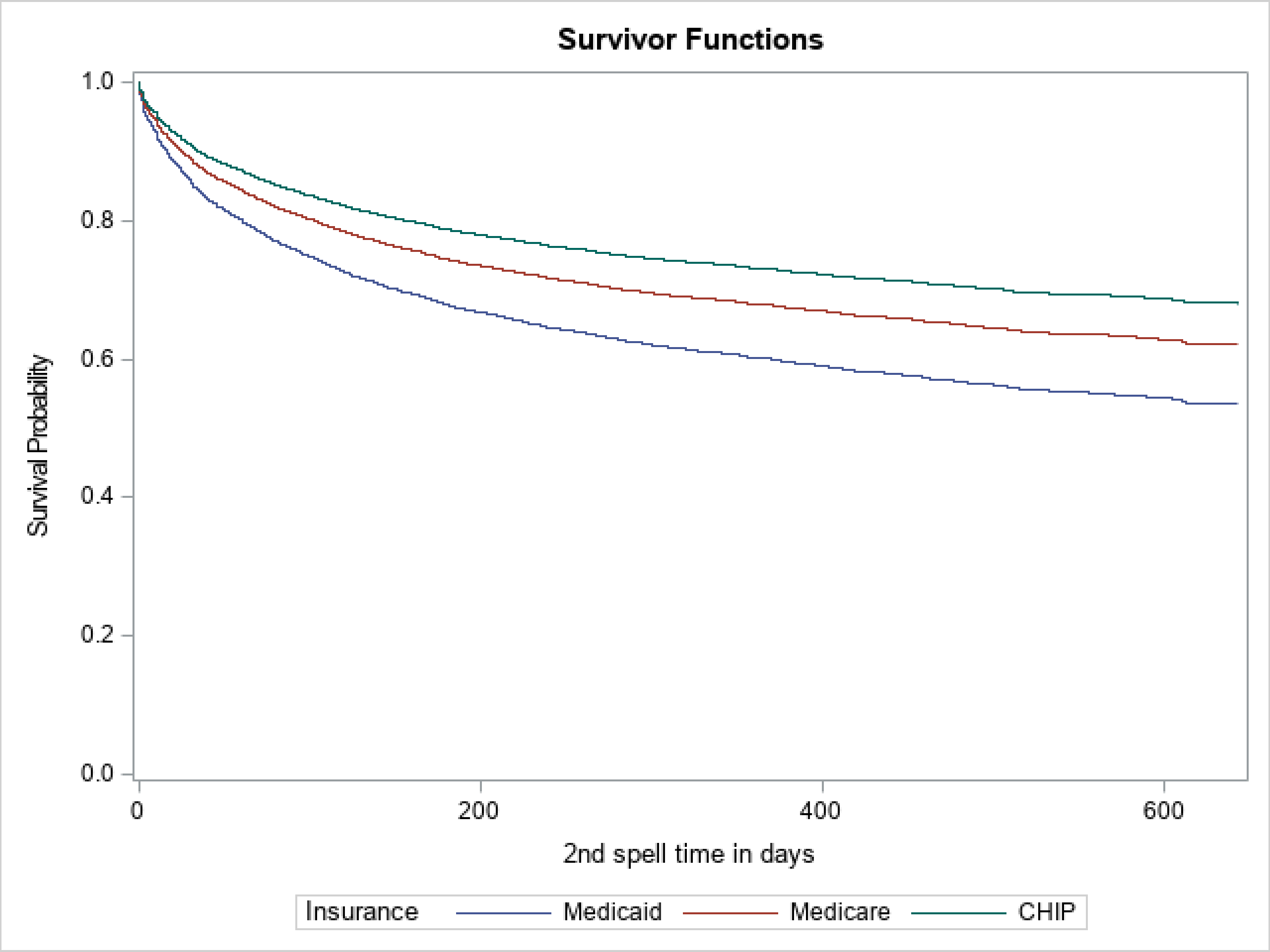
Findings for Second Spell

- Results for the second spell are generally consistent with those for the first spell
- Effects of Age, Number of diagnoses and Number of procedures on readmission time are similar to those for the first spell
- History (1st spell information) has a significant influence on readmission risk:
  - Primary diagnosis in first spell influences risk
  - Higher the number of diagnoses in the first spell, higher is the risk
  - Longer the first spell, lower is the risk

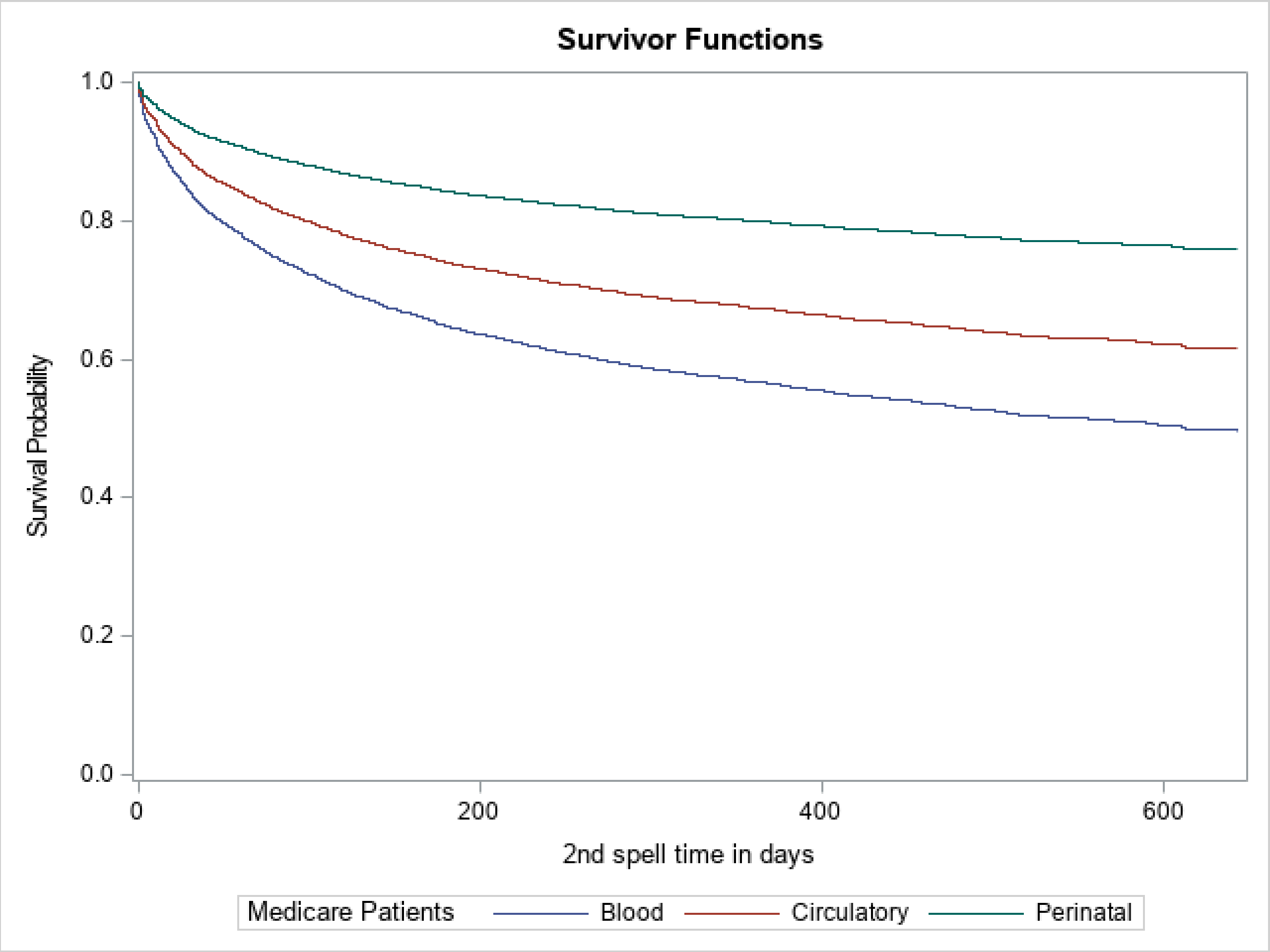
2nd Spell Survival Probabilities for Medicare



2nd Spell Survival Probabilities for Medicaid, Medicare & CHIP Patients



2nd Spell Survival Probabilities for Medicare Patients – Influence of Diagnosis



Contributions

- We employ the entire history of a patient's hospital encounters – not just the latest visit – to predict the probability of readmission
- The readmission probabilities could be calculated for any number of hospital visits by a patient, because we can derive the parameter estimates for any number of spells

Limitations & Future Directions

- We have analyzed data for only the first two spells
- Analysis was done for 19 diagnosis groups, not for specific diseases (ICD9 codes)
- Model could be tested beyond the first two spells
- 30-day readmission risks for specific diagnoses (e.g, HF, AMI, COPD) could be investigated
- Costs (readmission penalties) could be incorporated into the model