

# Employee and Employer Effects on Drug Treatment Episodes

Allen C Goodman<sup>1</sup>, Janet R Hankin<sup>1</sup>, David E Kalist<sup>1</sup>, Yingwe Peng<sup>2</sup>,  
Stephen J Spurr<sup>1</sup>,

(1) Department of Economics, Wayne State University, 656 W. Kirby,  
Detroit, MI 48202;

(2) Department of Mathematics and Statistics, Memorial University of  
Newfoundland St. John's, Newfoundland A1C 5S7 Canada

**Sources of Funding:** The research is partially supported by Grant DA10828 from the National Institute on Drug Abuse (NIDA), and from a grant from the Blue Cross Blue Shield Foundation. The data analyzed were purchased from MEDSTAT© Systems, Inc under NIDA grant DA08711.

**Acknowledgments:** We thank Thomas McLellan for his advice and technical expertise. The findings are ours and do not represent NIDA, the Blue Cross Blue Shield Foundation, or Wayne State University.

# Individual and Employer Impacts

- This study investigates the lengths of drug treatment episodes with explicit comparisons of individual and employer impacts on episode length.
- In analyzing health care utilization, researchers typically look at individual characteristics.
- With the advent of managed care, different employers and/or caregivers may act differently for similar employees.
- Rather than simply identifying employers with binary variables, employers are characterized by employer-specific year-specific measures such as **mean age**, **mean employment status**, or **mean percentage male**, for example, since employer health care benefits packages policies may be proxied by the types of workers that are covered.
- Employer-specific mean coinsurance rates and deductibles are also calculated.

# Database

- The database is a population of 34,000 individuals with either a drug or an alcoholism treatment diagnosis.
- It was selected from a large health insurance claims database of 36 self-insured employers, for all treatment events starting January 1, 1989, and ending December 31, 1991.

## Database (2)

- We included claims of all beneficiaries less than 65 years of age (to avoid Medicare overlap) who incurred at least one drug abuse or alcoholism treatment event in the 3-year period.
- For tractability we limited the database to those subjects with between one and ten episodes in the three-year period.
- This provided 153,115 episodes over 33,998 subjects.

# One-Day v. Multi-day Episodes

	<u>Total</u>	<u>1-Day</u>	<u>Multi-day</u>
<b>Number</b>	153115	63761	89354
<b>Fraction</b>	1.0000	0.4164	0.5836
<b>Duration</b>	32.5116	1.0000	54.9975
<b>Male Patient</b>	0.6828	0.6885	0.6787
<b>Age</b>	36.7794	36.2680	37.1444
<b>Hourly</b>	0.5403	0.5373	0.5424
<b>Active</b>	0.8541	0.8547	0.8537
<b>Self</b>	0.5886	0.5716	0.6008
<b>Starting Date</b>	505.5964	530.2268	488.0207
<b>Deductible</b>	36.8618	18.1130	50.2405
<b>Copay</b>	0.0870	0.0841	0.0891

# Analysis

We use the Anderson-Gill model for multiple episodes.

$$\log T_{ikm} = \sum_j \beta_j x_j + \sum_n \delta_n y_n + \sum_g \eta_g f_g + \sum_i \sum_k \sum_m \alpha_{ikm} L_{ikm} + \sum_{v=1}^{v=k} \sum_{u=1}^{u=k} \rho_{uv} z_{uv}$$

$T_{ikm}$  refers to the duration of the  $i^{\text{th}}$  episode in the sequence, with diagnosis  $k$ , at treatment location  $m$ .

$x_j$  refer to individual level variables including age, gender, and employment status.

$y_n$  refer to individual insurance variables: coinsurance, deductibles

$f_g$  characterize the employer where the subject either works or has coverage as the dependent of a worker .

# Analysis (2)

We use the Anderson-Gill model for multiple episodes.

$$\log T_{ikm} = \sum_j \beta_j x_j + \sum_n \delta_n y_n + \sum_g \eta_g f_g + \sum_i \sum_k \sum_m \alpha_{ikm} L_{ikm} + \sum_{v=1}^{v=k} \sum_{u=1}^{u=k} \rho_{uv} z_{uv}$$

$L_{ikm}$ , for example, is **EPS\_3PO** with a value of 1, indicating that the current episode is the third (3) episode in the sequence and is a psychiatric (P) outpatient (O) episode.

$z_{uv}$ , for example, is **PSY\_P\_ALC** (“**PSY**ch episode where the **P**revious episode was an **ALC**oholism episode”) has a value of 1.

**Hazard determinants**

<u>Variable</u>	<u>Coefficient</u>	<u>Std. error</u>	<u>t-stat</u>
<i>Individual</i>			
<b>Male</b>	<b>0.1102</b>	<b>0.0064</b>	<b>17.15</b>
<b>Age</b>	<b>-0.0028</b>	<b>0.0002</b>	<b>-11.50</b>
<b>Hourly</b>	<b>-0.0003</b>	<b>0.0071</b>	<b>-0.04</b>
<b>Active</b>	<b>-0.0262</b>	<b>0.0091</b>	<b>-2.87</b>
<b>Self</b>	<b>-0.0637</b>	<b>0.0067</b>	<b>-9.51</b>
<b>Starting Date</b>	<b>0.0006</b>	<b>0.0000</b>	<b>8.80</b>
<i>Insurance</i>			
<b>Episode Deductible</b>	<b>-0.0043</b>	<b>0.0000</b>	<b>-97.13</b>
<b>Episode Copay Rate</b>	<b>-0.0036</b>	<b>0.0295</b>	<b>-0.12</b>
<i>Employer</i>			
<b>MALE_AVG</b>	<b>0.1264</b>	<b>0.0809</b>	<b>1.56</b>
<b>AGE_AVG</b>	<b>-0.0010</b>	<b>0.0013</b>	<b>-0.79</b>
<b>HRLY_AVG</b>	<b>0.1615</b>	<b>0.0148</b>	<b>10.93</b>
<b>ACTV_AVG</b>	<b>-0.1302</b>	<b>0.0207</b>	<b>-6.28</b>
<b>SELF_AVG</b>	<b>-0.4878</b>	<b>0.0473</b>	<b>-10.31</b>
<b>DCT_AVG</b>	<b>0.0049</b>	<b>0.0002</b>	<b>25.65</b>
<b>CPR_AVG</b>	<b>-0.2337</b>	<b>0.0820</b>	<b>-2.85</b>



**Hazard determinants**

<u>Variable</u>	<u>Coefficient</u>	<u>Std. error</u>	<u>t-stat</u>
<i>Individual</i>			
Male	0.1102	0.0064	17.15
Age	-0.0028	0.0002	-11.50
Hourly	-0.0003	0.0071	-0.04
Active	-0.0262	0.0091	-2.87
Self	-0.0637	0.0067	-9.51
Starting Date	0.0006	0.0000	8.80
<i>Insurance</i>			
Episode Deductible	-0.0043	0.0000	-97.13
Episode Copay Rate	-0.0036	0.0295	-0.12
<i>Employer</i>			
MALE_AVG	0.1264	0.0809	1.56
AGE_AVG	-0.0010	0.0013	-0.79
HRLY_AVG	0.1615	0.0148	10.93
ACTV_AVG	-0.1302	0.0207	-6.28
SELF_AVG	-0.4878	0.0473	-10.31
DCT_AVG	0.0049	0.0002	25.65
CPR_AVG	-0.2337	0.0820	-2.85

**Hazard determinants**

<u>Variable</u>	<u>Coefficient</u>	<u>Std. error</u>	<u>t-stat</u>
<i>Individual</i>			
<b>Male</b>	<b>0.1102</b>	<b>0.0064</b>	<b>17.15</b>
<b>Age</b>	<b>-0.0028</b>	<b>0.0002</b>	<b>-11.50</b>
<b>Hourly</b>	<b>-0.0003</b>	<b>0.0071</b>	<b>-0.04</b>
<b>Active</b>	<b>-0.0262</b>	<b>0.0091</b>	<b>-2.87</b>
<b>Self</b>	<b>-0.0637</b>	<b>0.0067</b>	<b>-9.51</b>
<b>Starting Date</b>	<b>0.0006</b>	<b>0.0000</b>	<b>8.80</b>
<i>Insurance</i>			
<b>Episode Deductible</b>	<b>-0.0043</b>	<b>0.0000</b>	<b>-97.13</b>
<b>Episode Copay Rate</b>	<b>-0.0036</b>	<b>0.0295</b>	<b>-0.12</b>
<i>Employer</i>			
<b>MALE_AVG</b>	<b>0.1264</b>	<b>0.0809</b>	<b>1.56</b>
<b>AGE_AVG</b>	<b>-0.0010</b>	<b>0.0013</b>	<b>-0.79</b>
<b>HRLY_AVG</b>	<b>0.1615</b>	<b>0.0148</b>	<b>10.93</b>
<b>ACTV_AVG</b>	<b>-0.1302</b>	<b>0.0207</b>	<b>-6.28</b>
<b>SELF_AVG</b>	<b>-0.4878</b>	<b>0.0473</b>	<b>-10.31</b>
<b>DCT_AVG</b>	<b>0.0049</b>	<b>0.0002</b>	<b>25.65</b>
<b>CPR_AVG</b>	<b>-0.2337</b>	<b>0.0820</b>	<b>-2.85</b>

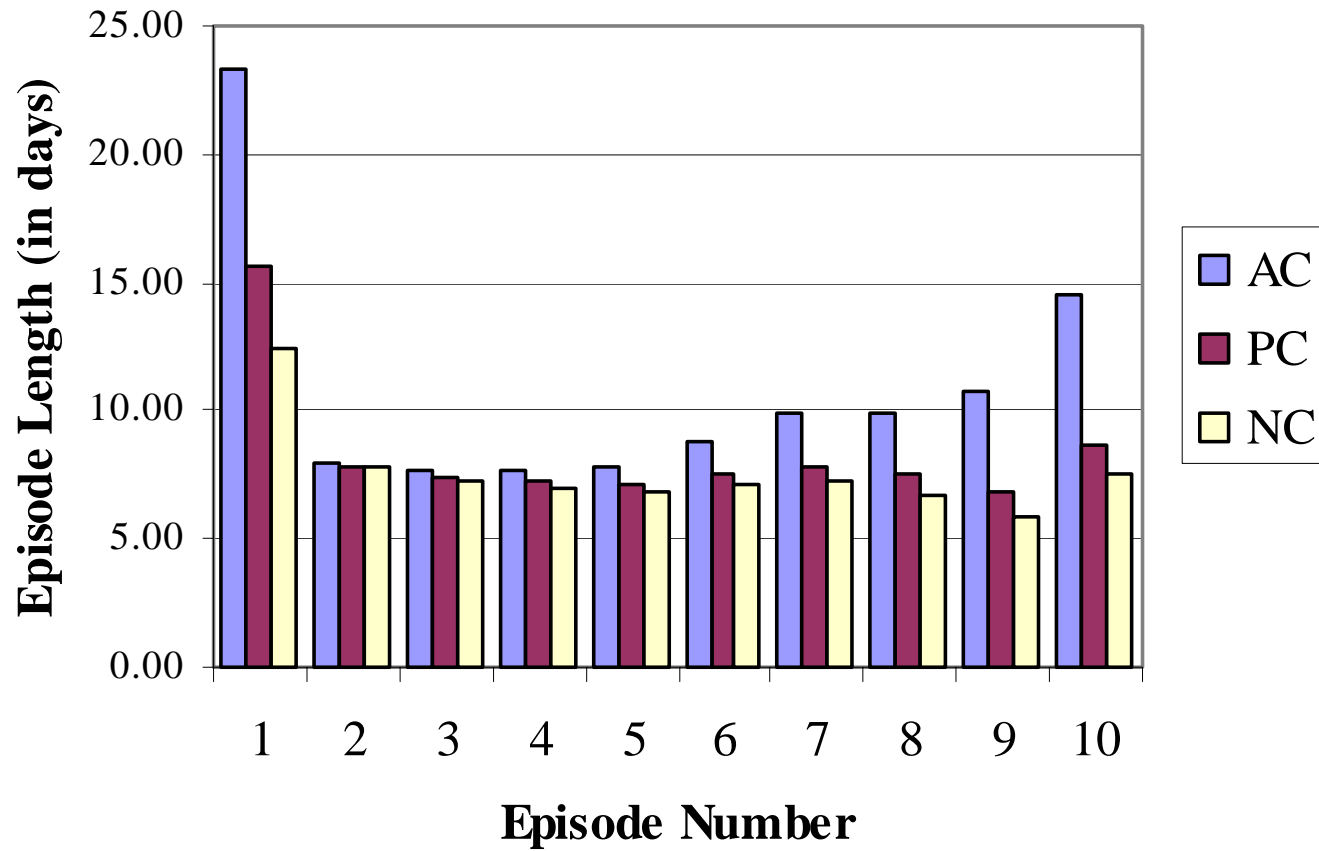
**Insurance**

<u>Variable</u>	<u>Coefficient</u>	<u>Std. error</u>	<u>t-stat</u>
<i>Individual</i>			
Male	0.1102	0.0064	17.15
Age	-0.0028	0.0002	-11.50
Hourly	-0.0003	0.0071	-0.04
Active	-0.0262	0.0091	-2.87
Self	-0.0637	0.0067	-9.51
Starting Date	0.0006	0.0000	8.80
<i>Insurance</i>			
Episode Deductible	-0.0043	0.0000	-97.13
Episode Copay Rate	-0.0036	0.0295	-0.12
<i>Employer</i>			
MALE_AVG	0.1264	0.0809	1.56
AGE_AVG	-0.0010	0.0013	-0.79
HRLY_AVG	0.1615	0.0148	10.93
ACTV_AVG	-0.1302	0.0207	-6.28
SELF_AVG	-0.4878	0.0473	-10.31
DCT_AVG	0.0049	0.0002	25.65
CPR_AVG	-0.2337	0.0820	-2.85

**Insurance**

<u>Variable</u>	<u>Coefficient</u>	<u>Std. error</u>	<u>t-stat</u>
<i>Individual</i>			
Male	0.1102	0.0064	17.15
Age	-0.0028	0.0002	-11.50
Hourly	-0.0003	0.0071	-0.04
Active	-0.0262	0.0091	-2.87
Self	-0.0637	0.0067	-9.51
Starting Date	0.0006	0.0000	8.80
<i>Insurance</i>			
Episode Deductible	-0.0043	0.0000	-97.13
Episode Copay Rate	-0.0036	0.0295	-0.12
<i>Employer</i>			
MALE_AVG	0.1264	0.0809	1.56
AGE_AVG	-0.0010	0.0013	-0.79
HRLY_AVG	0.1615	0.0148	10.93
ACTV_AVG	-0.1302	0.0207	-6.28
SELF_AVG	-0.4878	0.0473	-10.31
DCT_AVG	0.0049	0.0002	25.65
CPR_AVG	-0.2337	0.0820	-2.85

### Median Episode Length



# Conclusions

- Episodes are complex.
- We identify both individual and employer effects on episode length.
- We find that episode lengths vary by the diagnosis type, and that the lengths (and by inference cost and utilization) may depend on the treatments that occurred in previous episodes.
- We provide a method that adjusts episode lengths according to the probability of censoring.