Job Loss: Eat, Drink and Try to be Merry?[1]

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Introduction

- Losing a job can be stressful
- Each phase of job loss can produce a forceful emotional response
  - Anticipation
  - Termination
  - Unemployment
  - Job search
- Individuals may respond to stress by eating or drinking

Introduction

- Individuals over 50 have been disproportionately represented among displaced workers in recent decades
- Alcohol misuse is of special concern for older individuals
  - Alcohol can contribute to difficulties with reaction, balance and elements of cognitive function
- Obesity may be similarly problematic for the middle aged and near elderly
  - Obesity is a well-established risk factor for cardiovascular disease, high blood pressure, and diabetes

- Using data on older workers, our goal is to assess the effect of business closures on
  - alcohol use
  - body mass index (BMI)

- We use business closings as our measure of job loss
  - In the literature, job loss is often represented by layoff or some combination of involuntary termination (e.g., layoff, plant closing, and firing)
- We use finite mixture model (FMM) models to address the complicated potential relationships among job loss, alcohol use, and BMI
  - Traditional statistical analyses have been unable to account for individual differences in response to the stress of job loss
- Our research topic is timely and germane to the ongoing conversation on the impacts of job loss
  - Adverse impacts of business closings are presently of interest to policy makers

- Research has linked late-career job loss to adverse health and chronic disease outcomes
    - Falba, Teng, Sindelar, and Gallo 2005
    - Gallo, Bradley, Dubin, Jones, Falba, Teng, and Kasl 2006
    - Gallo, Bradley, Siegel, and Kasl 2000
    - Gallo, Teng, Falba, Kasl, Krumholz, and Bradley 2006

- Evidence on the effects of job loss on health behaviors is mixed
- Increase in alcohol consumption
  - Catalano, Dooley, Wilson, and Hough 1993
  - Janlert 1992
- Decrease in alcohol consumption
  - Iversen and Klausen 1986
  - Ruhm 2000, 2005
- No effect
  - Broman, Hamilton, Hoffman, and Mavaddat 1995
  - Cook, Cummins, Bartley, and Shaper 1982
  - Gallo, Bradley, and Kasl 2001

- Evidence on the effects of job loss on health behaviors is mixed
- Increase in BMI
  - Leino-Arjas, Liira, Mutanen, Malmivaara, and Matikainen 1999
  - Morris, Cook, and Shaper 1994
- Decrease in BMI
  - Morris, Cook, and Shaper 1992
- No effect
  - Leino-Arjas, Liira, Mutanen, Malmivaara, and Matikainen 1999

- Several potential mechanisms explain the variation in the individual behavioral responses to the stress of job loss

- Differences in stress-reactivity
- Income and substitution effects
- Use of discretionary time due to unemployment

Outline of talk

- Introduction

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- Data
  - Sample
  - Variables

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  - Standard specifications
  - Finite mixture models

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  - Data characteristics
  - Estimates of effects
  - Characteristics of latent classes

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- Conclusions

Data
Sample

- Data from the Health and Retirement Study (HRS)
  - 12,652 individuals from 7,702 households at baseline
  - 6 waves: 1992-2002
- Sample restricted to individuals who met the following criteria at the 1992 baseline
  1. were between ages 51 and 61
  2. were working for pay but not self employed
  3. minimum of two years of continuous employment
  4. provided at least one follow-up response
- Limit the sample to those who reported continuous employment in the previous wave
- Number of individuals: 3,366
- Number of observations: 6,726

- Business closure
  - Why did you leave that employer? Did the business close, were you laid off or let go, ...?
- DRINKS
  - In the last three months, on the days you drink, about how many drinks do you have?
  - Non-drinkers were assigned a 0 value for this variable
- BMI

Standard specifications

- For DRINKS

$$E(DRINKS_t) = \exp(\alpha BC_{t-1} + \gamma \ln(DRINKS_{t-1} + 1) + X_{t-1}\boldsymbol{\beta})$$

- Estimate by Poisson regression

Standard specifications

- For DRINKS

$$E(DRINKS_t) = \exp(\alpha BC_{t-1} + \gamma \ln(DRINKS_{t-1} + 1) + X_{t-1}\boldsymbol{\beta})$$

- Estimate by Poisson regression

- For BMI

$$E(BMI_t) = \alpha BC_{t-1} + \gamma BMI_{t-1} + X_{t-1}\boldsymbol{\beta}$$

- Estimate by OLS

Finite Mixture Models

- The density function for a C-component finite mixture is

$$f(y|\mathbf{x};\theta_1,\theta_2,...,\theta_C;\pi_1,\pi_2,...,\pi_C) = \sum_{j=1}^{C} \pi_j f_j(y|\mathbf{x};\theta_j)$$

where $0 < \pi_j < 1$, and $\sum_{j=1}^{C} \pi_j = 1$

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where $0 < \pi_j < 1$, and $\sum_{j=1}^{C} \pi_j = 1$

- To ensure $0 < \pi_j < 1$, and $\sum_{j=1}^{C} \pi_j = 1$

$$\pi_j = \frac{\exp(\gamma_j)}{\exp(\gamma_1) + \exp(\gamma_2) + ... + \exp(\gamma_{C-1}) + 1}$$

Finite Mixture Models

Properties

- The finite mixture model approximates a statistical distribution by a mixture (or weighted sum) of other distributions
- It provides a natural representation of heterogeneity in a finite number of latent classes
- FMM is a semiparametric / nonparametric estimator of the density (Lindsay)
- Experience suggests that usually only few latent classes are needed to approximate density well (Heckman)
- In practice FMM are flexible extensions to basic parametric models
  - can generate skewed distributions from symmetric components
  - can generate leptokurtic distributions from mesokurtic ones

- For DRINKS

$$f_j(y|\mathbf{x};\theta_j) = \sum_{j=1}^{C} \pi_j \frac{\mu_j \exp(\mu_j)}{\Gamma(y+1)}$$

where $\mu_j = \exp(\alpha_j BC_{t-1} + \gamma_j \ln(DRINKS_{t-1}+1) + X_{t-1}\boldsymbol{\beta}_j)$

- For DRINKS

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where $\mu_j = \exp(\alpha_j BC_{t-1} + \gamma_j \ln(DRINKS_{t-1} + 1) + X_{t-1}\boldsymbol{\beta}_j)$

- For BMI

$$f_j(y|\mathbf{x};\theta_j) = \sum_{j=1}^{C} \pi_j \frac{1}{\sqrt{2\pi\sigma_j^2}} \exp\left(-\frac{1}{2\sigma_j^2}(y-\mu_j)^2\right)$$

where $\mu_j = \alpha_j BC_{t-1} + \gamma_j BMI_{t-1} + X_{t-1}\boldsymbol{\beta}_j$

- Maximum likelihood

$$\max_{\boldsymbol{\pi},\boldsymbol{\theta}} \ln L = \sum_{i=1}^{N} \left(\log(\sum_{j=1}^{C} \pi_j f_j(y|\theta_j) \right)$$

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$$\max_{\pi,\theta} \ln L = \sum_{i=1}^{N} \left(\log\left(\sum_{j=1}^{C} \pi_j f_j(y|\theta_j)\right) \right)$$

- Robust standard errors - clustered at the individual-level

- Prior probability that observation y_i belongs to component c:

$$\Pr[y_i \in \text{population } c|\mathbf{x}_i, \boldsymbol{\theta}] = \pi_c$$

$c = 1, 2, ..C$

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$c = 1, 2, ..C$

- Posterior probability that observation y_i belongs to component c:

$$\Pr[y_i \in \text{population } c | \mathbf{x}_i, y_{i;} \boldsymbol{\theta}] = \frac{\pi_c f_c(y_i | \mathbf{x}_i, \boldsymbol{\theta}_c)}{\sum_{j=1}^{C} \pi_j f_j(y_i | \mathbf{x}_i, \boldsymbol{\theta}_j)}$$

$c = 1, 2, ..C$

- Stata package `fmm`

```
fmm depvar [indepvars] [if] [in] [weight],
components(#) mixtureof(density)
```

- where density is one of

```
gamma
negbin1
negbin2
normal
poisson
studentt
```

- `predict` and `mfx` give predictions and marginal effects of means, component means, prior and posterior probabilities

Example

Color of Wine

Results of a chemical analysis of wines grown in the same region in Italy but derived from three different cultivars (grape variety)

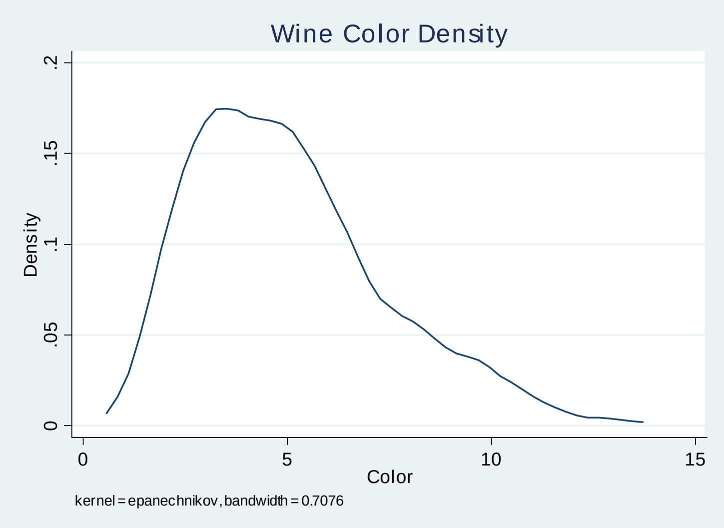
Data characteristics

Cultivar	Freq.	% of total	Color intensity (mean)
1	59	33.15	5.528
2	71	39.89	3.086
3	48	26.97	7.396
Total	178	100	5.058

Estimate a finite mixture of 3 normal densities

Example

Color of Wine



Estimates from finite mixture of normals with 3 components

Parameter	component 1	component 2	component 3
Constant	4.929	7.548	2.803
	(0.334)	(0.936)	(0.244)
π	0.365	0.312	0.323
	(0.176)	(0.117)	(0.107)

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Example

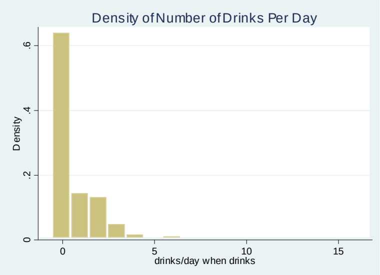
Color of Wine

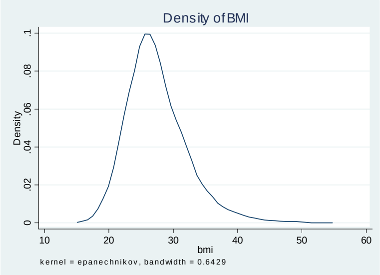
	Posterior probability (median)		
Cultivar	component 1	component 2	component 3
1	0.737	0.195	9.00e-5
2	0.048	0.023	0.923
3	0.030	0.970	7.54e-14

Data characteristics

Cultivar	Freq.	% of total	Color (mean)
1	59	33.15	5.528
2	71	39.89	3.086
3	48	26.97	7.396
Total	178	100	5.058

Results
Data characteristics





Summary statistics by business closing status

Variable	No	Yes
BMI	27.451	27.488
Daily number of drinks	0.741	0.744
Age	61.152	61.669
Married	0.717	0.785
Ln(income)	1.459	1.290
Manufacturing	0.155	0.140
Administrative, clerical	0.187	0.215
Sales	0.063	0.091
Mechanical	0.095	0.149
Service	0.148	0.116
Operator	0.146	0.174
Farming, fishing	0.016	0.025

Results

Data characteristics

Summary statistics by business closing status

Variable	No	Yes
Depressive symptoms	-0.031	0.053
Black race	0.162	0.190
Male	0.502	0.479
Years of education	12.848	11.669
Job stress	0.181	0.190
Physical effort	2.818	2.860
Risk aversion	3.369	3.257
Financial planning horizon	3.149	2.915
Cognitive score	15.607	15.444
Observations	6601	121

Parameter estimates for models of daily drinks

	Poisson	FMM Poisson	
VARIABLES		component1	component2
Business closure	0.228	0.131	0.844***
	(0.173)	(0.109)	(0.242)

Parameter estimates for models of daily drinks

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VARIABLES		component1	component2
Business closure	0.228	0.131	0.844***
	(0.173)	(0.109)	(0.242)
Age	-0.009*	-0.015**	0.014
	(0.006)	(0.007)	(0.022)

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Business closure	0.228	0.131	0.844***
	(0.173)	(0.109)	(0.242)
Age	-0.009*	-0.015**	0.014
	(0.006)	(0.007)	(0.022)
Ln(income)	0.082***	0.119***	-0.211
	(0.028)	(0.034)	(0.172)

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	(0.006)	(0.007)	(0.022)
Ln(income)	0.082***	0.119***	-0.211
	(0.028)	(0.034)	(0.172)
Administrative occupation	-0.066	-0.158**	0.233
	(0.058)	(0.064)	(0.147)

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Ln(income)	0.082***	0.119***	-0.211
	(0.028)	(0.034)	(0.172)
Administrative occupation	-0.066	-0.158**	0.233
	(0.058)	(0.064)	(0.147)
Farming occupation	-0.276*	-0.674**	0.397
	(0.153)	(0.334)	(0.512)

2.7 additional drinks per day among individuals who drink 2 drinks per day

Parameter estimates for models of daily drinks

Variable	Poisson	FMM Poisson component1	FMM Poisson component2
CESD	-0.086***	-0.146***	0.064
	(0.029)	(0.050)	(0.130)

Parameter estimates for models of daily drinks

	Poisson	FMM Poisson	
Variable		component1	component2
CESD	-0.086***	-0.146***	0.064
	(0.029)	(0.050)	(0.130)
Lagged ln(DRINKS+1)	1.587***	1.986***	0.191
	(0.040)	(0.067)	(0.189)

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Lagged ln(DRINKS+1)	1.587***	1.986***	0.191
	(0.040)	(0.067)	(0.189)
π_1		0.939	
		(0.009)	

Parameter estimates for models of DRINKS: Robustness checks

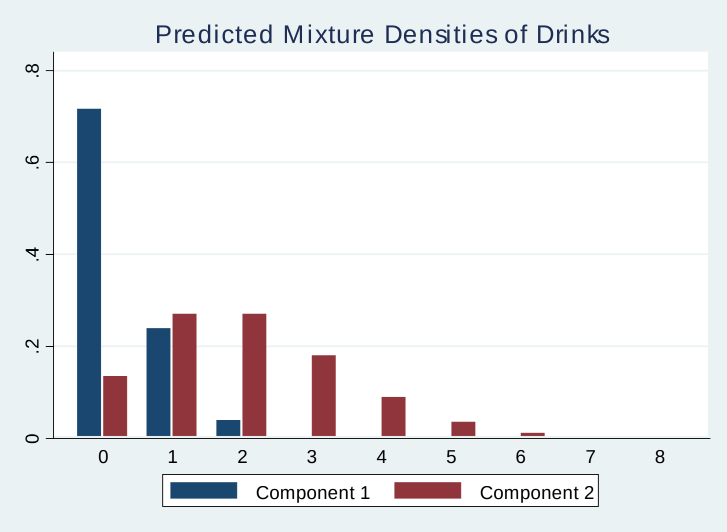
	FMM Poisson		FMM Poisson	
Variable	component1	component2	component1	component2
Bus. closure	0.189*	1.701***	0.216*	1.967***
	(0.105)	(0.289)	(0.112)	(0.317)
+	race, gender, region		race, gender, region high stress, physical job	

Parameter estimates for models of DRINKS: Robustness checks

	FMM Poisson		FMM Poisson	
Variable	component1	component2	component1	component2
Bus. closure	0.189*	1.701***	0.216*	1.967***
	(0.105)	(0.289)	(0.112)	(0.317)
+	race, gender, region		race, gender, region high stress, physical job	
π_1	0.920		0.916	
	(0.013)		(0.012)	

Results

Predicted densities of DRINKS



Parameter estimates for models of BMI

Variable	OLS	FMM Normal	
		component1	component2
Business closure	0.081	-0.192	1.083**
	(0.149)	(0.119)	(0.541)

Results

Estimates for BMI

Parameter estimates for models of BMI

Variable	OLS	FMM Normal	
		component1	component2
Business closure	0.081	-0.192	1.083**
	(0.149)	(0.119)	(0.541)
Age	-0.023***	-0.009*	-0.086***
	(0.006)	(0.005)	(0.028)

Parameter estimates for models of BMI

Variable	OLS	FMM Normal	
		component1	component2
Business closure	0.081	-0.192	1.083**
	(0.149)	(0.119)	(0.541)
Age	-0.023***	-0.009*	-0.086***
	(0.006)	(0.005)	(0.028)
Manufacturing occupation	-0.049	0.017	-0.495*
	(0.055)	(0.049)	(0.283)

Parameter estimates for models of BMI

Variable	OLS	FMM Normal	
		component1	component2
Business closure	0.081	-0.192	1.083**
	(0.149)	(0.119)	(0.541)
Age	-0.023***	-0.009*	-0.086***
	(0.006)	(0.005)	(0.028)
Manufacturing occupation	-0.049	0.017	-0.495*
	(0.055)	(0.049)	(0.283)
Lagged BMI	0.956***	0.989***	0.850***
	(0.007)	(0.005)	(0.035)

Parameter estimates for models of BMI

Variable	OLS	FMM Normal	
		component1	component2
Business closure	0.081	-0.192	1.083**
	(0.149)	(0.119)	(0.541)
Age	-0.023***	-0.009*	-0.086***
	(0.006)	(0.005)	(0.028)
Manufacturing occupation	-0.049	0.017	-0.495*
	(0.055)	(0.049)	(0.283)
Lagged BMI	0.956***	0.989***	0.850***
	(0.007)	(0.005)	(0.035)
π_1		0.806	
		(0.026)	

7 pound gain in weight for a 5 ft, 10 inch man who weighs 180 pounds

Parameter estimates for models of BMI: Robustness checks

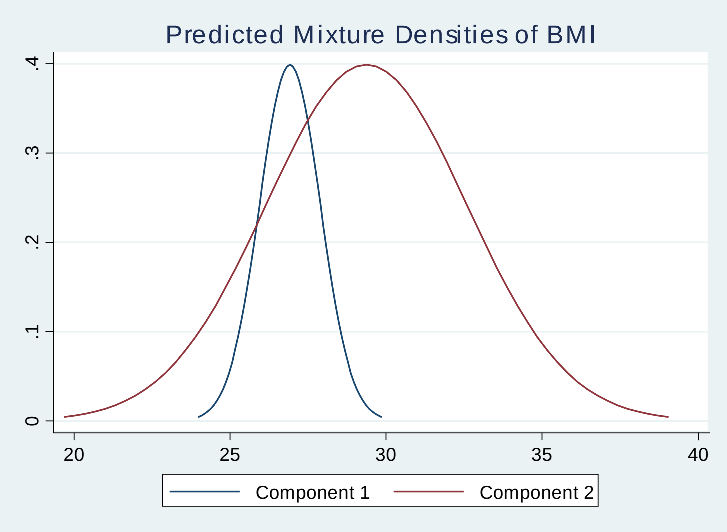
	FMM Normal		FMM Normal	
Variable	component1	component2	component1	component2
Bus. closure	-0.182	1.101**	-0.186	1.107**
	(0.120)	(0.545)	(0.120)	(0.543)
+	race, gender, region		race, gender, region, high stress, physical job	

Parameter estimates for models of BMI: Robustness checks

	FMM Normal		FMM Normal	
Variable	component1	component2	component1	component2
Bus. closure	-0.182	1.101**	-0.186	1.107**
	(0.120)	(0.545)	(0.120)	(0.543)
+	race, gender, region		race, gender, region, high stress, physical job	
π_1	0.805		0.805	
	(0.027)		(0.027)	

Results

Predicted densities of BMI



Individuals in Component 2 - 6% of population

- consumed an average of 2 drinks as compared to 0.3 drinks among individuals in Component 1
- were almost 9 percentage points more likely to be classified as being problem drinkers
- were 24 percentage points more likely to be binge drinkers
- binged 1.2 more days on average

Results

Characteristics of latent classes: DRINKS

Determinants of component 2 posterior probability: DRINKS

Variable	(1)	(2)	(3)	(4)	(5)
Ln(income)	0.007**	0.006*	0.006*	0.006	0.006*
	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)
Sales occupation	-0.007	-0.009	-0.011	-0.018*	-0.019*
	(0.010)	(0.011)	(0.011)	(0.011)	(0.011)
Mechanic occupation	0.010	0.008	0.004	-0.018*	-0.022**
	(0.009)	(0.010)	(0.010)	(0.011)	(0.011)
Operator occupation	0.003	0.003	-0.002	-0.018*	-0.022**
	(0.008)	(0.009)	(0.009)	(0.010)	(0.010)
Male				0.032***	0.033***
				(0.006)	(0.006)

Determinants of component 2 posterior probability: DRINKS

Variable	(1)	(2)	(3)	(4)	(5)
Years of education				-0.003**	-0.003**
				(0.001)	(0.001)
High stress job					-0.000
					(0.006)
Physical job					-0.005**
					(0.002)
Risk aversion			-0.007**	-0.006**	-0.006**
			(0.003)	(0.003)	(0.003)
Observations	4350	3907	3907	3906	3906

Individuals in Component 2 - 19% of population

- had an average BMI of 29.4 as compared to 26.9 among individuals in Component 1
- were almost 21 percentage points more likely to be obese

Determinants of component 2 posterior probability: BMI

Variable	(1)	(2)	(3)	(4)	(5)
Age	-0.002*	-0.002**	-0.002**	-0.002**	-0.002*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Ln(income)	-0.020***	-0.020***	-0.019***	-0.017***	-0.017***
	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)
CESD	0.013***	0.012***	0.011***	0.010***	0.010***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)
Black				0.017*	0.017*
				(0.010)	(0.010)
Male				-0.025***	-0.025***
				(0.007)	(0.007)

Determinants of component 2 posterior probability: BMI

Variable	(1)	(2)	(3)	(4)	(5)
High stress job					0.014*
					(0.008)
Physical job					0.000
					(0.003)
Risk averse			0.004	0.003	0.003
			(0.004)	(0.004)	(0.004)
Observations	6727	6089	6089	6088	6086

Conclusions

- Use of all job losses may produce misleading estimates - business closure is exogenous
- Focus on the average effect of job loss rather than the heterogeneous effects of job loss across the population may be limiting
- FMM can uncover otherwise hidden relationships
- The smaller proportion of individuals who respond to job loss by increasing unhealthy behaviors are already pursuing unhealthy behaviors so that these further increases in unhealthy behaviors may be especially problematic

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- Focus on the average effect of job loss rather than the heterogeneous effects of job loss across the population may be limiting
- FMM can uncover otherwise hidden relationships
- The smaller proportion of individuals who respond to job loss by increasing unhealthy behaviors are already pursuing unhealthy behaviors so that these further increases in unhealthy behaviors may be especially problematic

- Extensions of FMM to panel data
    - Random effects models can be estimated with standard software using Mundlak-type specifications
    - Working on formulating fixed effects models