Mental Health, Human Capital, and the Labor Market

Christopher J. Cronin, University of Notre Dame
Matthew P. Forsstrom, Wheaton College
Nicholas W. Papageorge, Johns Hopkins University

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Motivation

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However, such models have rarely been used to understand the tradeoffs patients face when choosing among mental health treatments.

- Lack of data
- Empirical challenges associated with selection into treatment
- Mental illness seen as fundamentally different than physical illness
  - Only 4% of US adults experience serious mental illness (NIMH, 2016)

Motivation

Mental illness and treatment is highly prevalent.

- 1 in 5 US adults experiences mental illness each year (NIMH, 2016)
- Among individuals over 12, 13% took an antidepressant within past month (CDC).
  - A 65% increase since 2000.
- $16 billion spent annually on antidepressants.

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The medical literature suggests therapy is highly effective in treating depression and anxiety, but <u>very few individuals use therapy relative to medication</u>.

Objectives

We design a dynamic, structural model of mental health treatment decisions that incorporates labor market decisions and outcomes.

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We use the model to evaluate counterfactual policy proposals. E.g., suppose we want to determine the most effective way to encourage therapy use:

- Reduce out-of-pocket costs of therapy
- Increase work flexibility or reduce the time costs of therapy
- Reduce patient uncertainty with respect to therapy match

Data Overview

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- Highlights
  - Treatment decisions (e.g., consumption units, prices, dates)
  - Mental health (e.g., subjective and diagnoses)
  - Employment (e.g., hours, wages, occupation)
  - Demographics (e.g., education, age, sex, race, location, etc.)
  - Observe both uninsured and unemployed individuals.

Motivating Features of the Data

The following features in the data motivate the model:

1. The incidence of mental illness and treatment patterns vary over the lifecycle and by sex.

Lifecycle Mental Health and Treatment

	Subjective MH	Depression/Anxiety	Medication	Psychotherapy
Age				
22-24	4.207	0.026	0.024	0.007
25-29	4.153	0.046	0.034	0.010
30-34	4.081	0.048	0.039	0.011
35-39	4.029	0.058	0.047	0.011
40-44	3.941	0.082	0.066	0.013
45-49	3.881	0.095	0.082	0.018
50-54	3.844	0.116	0.099	0.019
55-59	3.831	0.102	0.087	0.013
60-64	3.798	0.118	0.102	0.017
Gender				
Male	3.987	0.058	0.051	0.010
Female	3.890	0.117	0.098	0.017

Notes: An observation is an interview period; thus, sample statistics are calculated across all 376,234 observations in the estimation sample (98,056 individuals). "Subjective MH" is the respondent's subjective assessment of own mental health and ranges from 1 (poor) to 5 (excellent). Depression and anxiety indicators are based on the ICD-9 codes associated with reported diagnoses.

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2. Therapy is highly effective on average

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Mental Health Production Function

- Estimating health production functions is difficult because health behaviors, including medical treatment, are endogenous.
    - More pre-disposed to illness $\Rightarrow$ more likely to choose treatment
    - Negative health shocks $\Rightarrow$ more likely to choose treatment
- Instruments for therapy and medication:
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  - County has Walmart post 3Q2006

Mental Health Production Function

	OLS	2SLS
Any RX	-0.36***	0.74**
Any Therapy	-0.41***	1.27*
Lagged Mental Health		
Excellent	2.06***	2.92***
Very good	1.57***	2.38***
Good	1.11***	1.83***
Fair	0.51***	0.89***
FS Sanderson-Windmeijer F-stat, Rx	–	16.3***
FS Sanderson-Windmeijer F-stat, Therapy	–	24.3***
Kleibergen-Paap rk LM Stat. (H_0: Underidentified)	–	6.91*
Hansen J Stat (H_0: Inst. Exog.)	–	2.92
Observations	179,259	

- Perceived MH takes values from 5 (excellent) to 1 (poor).
- Controls: county and time FE, age, gender, race, family structure, income, edu.
- Sample: MEPS 1996-2012, age $\in \{22, 64\}$, privately insured
- Instruments: Psych per cap $\times$ (Nonwhite, Prev. Married, Male), Walmart$*\mathbb{1}_{Year>2006}$

First Stage

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- CBT more efficacious than ADs for patients with moderate depression (Gloaguen et al., 1998, Hollon et al., 2005).
- ADs no more effective in treating moderate depression than a placebo, while somewhat effective for seriously depressed patients (Kirsch et al., 2008; Cipriani et al., 2018).
- Baranov et al. (2017) use RCT to show that CBT has large, positive short- and long-run effects on depressed mothers in rural Pakistan.

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Average individual is roughly 4 times more likely to use pills than therapy.

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3. Many individuals attend therapy once or twice and then quit

   … these sessions appear to be unproductive and make-up about 40% of treatment episodes.

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4. Mental health is positively associated with wages and employment.

   ... and conditional on mental health, therapy use is negatively associated with hours/employment.

Model Overview

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- A decision-period is defined as 6 months.
- Each period the individual receives flow utility that is a function of the choice, the individual's state vector, and consumption.
- Choices in each period impact the distribution of the state vector in the next period, and the individual solves the dynamic problem to maximize expected lifetime utility.

Model Timing

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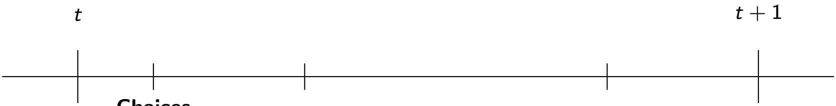

Choices

$$\text{Rx}, \, r_t = \begin{cases} \text{Y} \\ \text{N} \end{cases}$$

$$\text{Couch}, \, c_t = \begin{cases} \text{Y} \\ \text{N} \end{cases}$$

$$\text{Employment}, \, e_t = \begin{cases} \text{Full} \\ \text{Part} \\ \text{None} \end{cases}$$

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t $\qquad\qquad$ $t+1$

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State Variables

Mental Health, mh_{t+1}

Experience, exp_{t+1}

Price Variables

Wages, $\mathbf{w_{t+1}}$

Treatment Prices, $\mathbf{p_{t+1}}$

Estimation

- The utility function, price equations, mismatch probability, and state transition functions are parameterized and the parameters are estimated via a nested maximum likelihood.
  - An inner algorithm solves the model via backwards recursion to calculate choice probabilities given a set of parameters.
  - An outer algorithm uses the solution to calculate the likelihood function and updates the parameter vector

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  - Assume K types in population

$$\epsilon_{a,it} = \mu^k_{a,i} + \eta_{a,it} \qquad k = 1, \ldots, K$$

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  - For fixed K, can estimate $\{\theta^k, \mu^k\}^K_{k=2}$ (Heckman and Singer, 1984), where
    - $\sum_{k=1}^K \theta^k = 1$ (i.e., θ^k is the probability of being type k)
    - $\mu^k = \{\mu^k_1, \mu^k_2, \ldots, \mu^k_{10}\}$

Model Fit

Age	Subj. MH		Rx		Therapy		Part Time		Full Time	
	obs.	sim	obs.	sim	obs.	sim	obs.	sim	obs.	sim
25-29	4.150	4.134	0.037	0.045	0.015	0.018	0.181	0.156	0.579	0.580
30-34	4.073	4.070	0.054	0.056	0.015	0.021	0.166	0.167	0.593	0.596
35-39	4.035	4.026	0.061	0.062	0.019	0.022	0.175	0.173	0.610	0.606
40-44	3.946	3.946	0.080	0.082	0.023	0.023	0.176	0.169	0.608	0.600
45-49	3.889	3.883	0.090	0.097	0.026	0.027	0.164	0.170	0.617	0.587
50-54	3.806	3.836	0.110	0.113	0.025	0.027	0.156	0.161	0.577	0.570

Key Treatment Decision Tradeoffs

- Direct Benefits of Treatment

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  - $\uparrow U_t$
  - $\downarrow$ disutility from work $\implies \uparrow$ employment
  - $\uparrow$ wages $\implies \uparrow$ employment
  - $\uparrow$ employment $\implies \uparrow$ future wages

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- Costs of treatment
  - 50% (10%) of therapy (Rx) is free.
  - Therapy is 1.6 times as expensive as Rx when price is non-zero.
  - Average person has a $\sim$ 40% chance of therapy mismatch.
  - Both therapy and Rx consumption result in disutility.
  - Average FT employee experiences 8.9% (16.3%) more disutility from therapy (Rx) than an unemployed individual.

WTP to avoid therapy

How many dollars would an individual be willing to pay in every future period in order to avoid the period t flow utility cost from treatment?

	Therapy		Rx	
Subsample	Inexp.	Exp.	Inexp.	Exp.
employment status				
part-time	207.47	27.20	57.19	-14.01
full-time	242.06	43.61	69.57	-8.71
insurance type				
public	171.73	12.14	46.86	-17.28
private	229.24	35.56	64.93	-11.46

Simple Counterfactuals

	Base	Sim 1		Sim 2		Sim 3	
		Level	% Δ	Level	% Δ	Level	%Δ
Therapy	0.023	0.038	65.2	0.070	204.3	0.044	91.3
Medication	0.078	0.075	-3.8	0.061	-21.8	0.077	-1.3
Avg. MH	3.895	3.914	0.5	4.035	3.6	3.921	0.7
Avg. MH if initial MH<4	3.609	3.650	1.1	3.892	7.8	3.662	1.5
Avg. MH if initial MH$=1$	3.359	3.468	3.2	3.906	16.3	3.493	4.0
Avg. FT	0.592	0.594	0.3	0.610	3.0	0.597	0.8
Avg. FT if initial MH<4	0.546	0.549	0.5	0.582	6.6	0.554	1.6
Avg. FT if initial MH$=1$	0.507	0.515	1.6	0.579	14.2	0.523	3.2

Notes:

- Sim 1: Remove monetary cost of therapy
- Sim 2: Remove possibility of mismatch
- Sim 3: Remove employment cost of therapy

Conclusion

- Designing and estimating a dynamic, stochastic model of mental health treatment and labor supply decisions.
- Testing multiple policies that alter the costs associated with therapy.
- Open Questions:
  - Are there policies that "pay for themselves"?
  - How does reduction of treatment costs at different points in the life-cycle impact outcomes?
  - How do treatment cost reductions impact outcomes for men and women differently?