Essays on Labor Dynamics and on Endogenous Networks

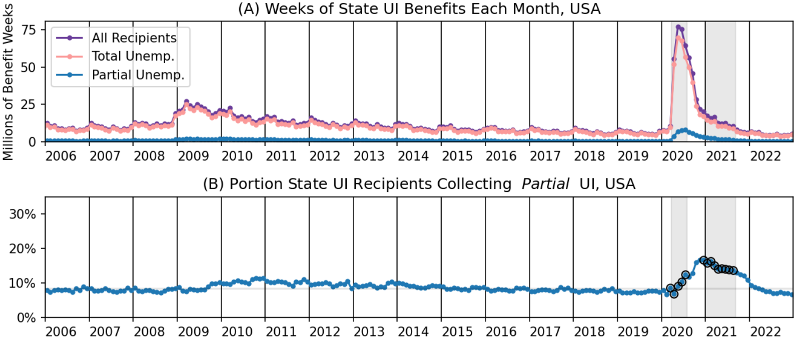
Thesis Defense

Robert Winslow

July 16th, 2024

Partial Unemployment Insurance During the Pandemic

Regular State UI Recipients Over Time, All US

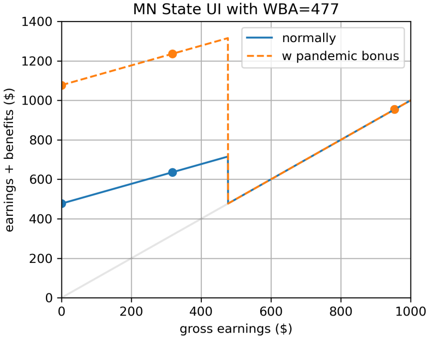


Example: State UI Benefits in Minnesota

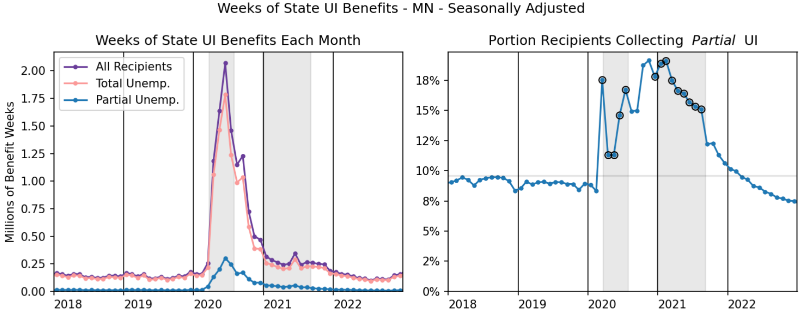
In Minnesota, the rule is that the benefits for a given week are determined by:

$$benefits = \begin{cases} WBA - \frac{earnings}{2} & \text{if } earnings < WBA \\ 0 & \text{if } earnings \geq WBA \end{cases}$$

Figure on right: earnings and benefits for a hypothetical Minnesota worker with a WBA of 477 USD



Regular State UI Recipients Over Time, MN



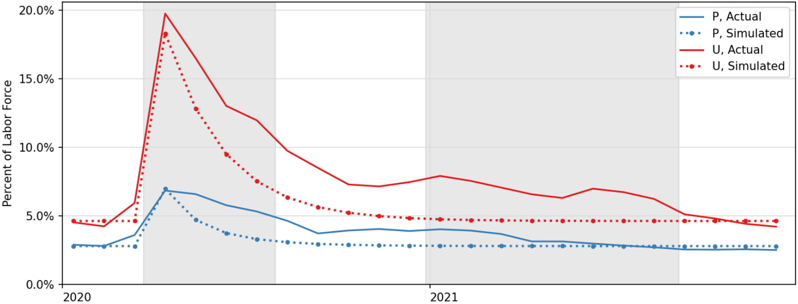
My Model

- Model of unemployment insurance with partial employment and moral hazard.
- Workers stochastically transition between three levels of employment opportunity.
  - Full Employment, Partial Employment, Unemployment
- Workers receive UI benefits when partially employed or unemployed.
- Workers can *choose* to work at a level below their employment opportunity, but only have a small *chance* of receiving UI benefits if they do so.

My Model

- I model the pandemic as a shock to employment levels which lasts only one month.
- I match the pattern of the ensuing months by calibrating how well unemployment insurance requirements are enforced.
- I then suppose we made the bonuses permanent and compare welfare in stationary equilibrium.

Simulation without bonus UI payments



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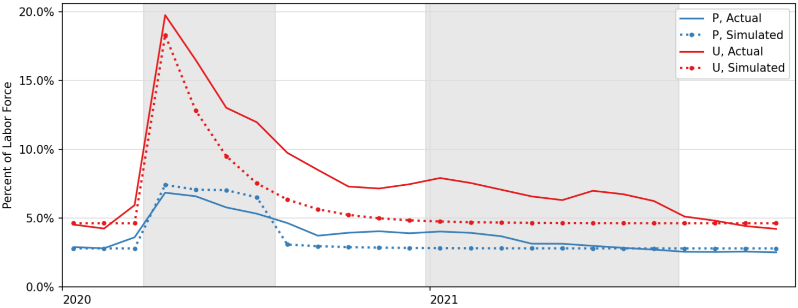

Who Wins? Who Loses?

	% Consumption Equivalent to Welfare Change					
Quintile	1	2	3	4	5	all
Pre-pandemic Baseline	0	0	0	0	0	0
Pandemic Bonus, Unbalanced Budget	11.1	7.2	5.1	3.7	2.1	5.8
Pandemic Bonus, Balanced Budget	7.0	2.9	0.7	-0.8	-2.4	1.5
Higher RR, Unbalanced Budget	1.7	1.7	1.7	1.7	1.7	1.7
Higher RR, Balanced Budget	0.2	0.2	0.2	0.2	0.2	0.2
Transfer to Everyone	7.5	3.4	1.0	-0.6	-2.3	1.8
Transfer to Bottom Two Quintiles	21.0	13.2	-4.4	-4.4	-4.4	4.2

Key Takeaways

- The relative spike in Partial Unemployment was large.
- But if people could freely respond, it should have been much larger.
  - Suggests that for the most part, workers were unable to freely maximize their income in this way.
- Nonetheless, alternate programs could have spent the money more effectively.

What's Next?

- Empirical Analysis: Some states ended the program early. Add to the body of literature on the results of this policy.

Behavioral Choice in a Branching Process Model of Disease

How Contagion Spreads

- (Newman 2002) describes a class of networks on which an SIR model can be solved exactly.
- Social network is an infinite random graph described by degree distribution $\{p_k\}$
- Contagion can spread along each edge with probability T

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- Given degree distribution, there is a critical transmissibility threshold T_c

$$T_c = \frac{\sum_k (p_k k)}{\sum_k (p_k k(k-1))}$$

- If $T < T_c$, epidemic occurs with zero probability.

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- An "epidemic" occurs if the contagion spreads to an infinite number of nodes. (A non-zero portion.)
- Given degree distribution, there is a critical transmissibility threshold T_c
- When $T > T_c$, the probability an epidemic occurs equals the expected portion of nodes which become infected. Denoted R_∞

$$R_\infty = 1 - \sum_k \left(p_k \cdot (1 - (1 - \upsilon)\, T)^k \right)$$

where $\upsilon \in (0, 1)$ is the solution to

$$\upsilon = \frac{\sum_k \left(p_k k \cdot (1 - (1 - \upsilon)\, T)^k \right)}{\sum_k (p_k k)}$$

Important Variables so Far

- $\{p_k\}$is the degree distribution of the network.
- T is transmissibility.
- T_c is the critical transmissibility threshold.
- R_∞ is the probability and size of epidemic when $T > T_c$
- υ can be thought of as the chance a random neighbor remains uninfected.

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- R_∞ is the probability and size of epidemic when $T > T_c$
- υ can be thought of as the chance a random neighbor remains uninfected.

- Finally, define the risk of disease from a neighbor Ψ as

$$\psi \equiv \begin{cases} 0 & \text{if } T \leq T_c \\ (1-\upsilon)T & \text{if } T > T_c \end{cases}$$

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- Each person *makes this choice exactly once*, when news of a potential epidemic arrives.

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- Let there be multiple types of people, denoted by i. Let N_i be the choice of type i, and α_i be the relative population of type i.

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- The critical transmissibility threshold is given by:

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- The probability and size of the epidemic when $T > T_c$ is given by

$$R_\infty = 1 - \sum_i \left[\alpha_i e^{-(1-\upsilon)TN_i}\right]$$

where υ is the solution to

$$\upsilon = \frac{\sum_i \left(\alpha_i N_i e^{-(1-\upsilon)TN_i}\right)}{\sum_i (\alpha_i N_i)}$$

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- And finally, let $\Psi^* (\{N_i\})$be the value of Ψ, taken as a function of the set of choices.
  - When $T \leq T_c(\{N_i\})$, $\Psi^* (\{N_i\}) = 0$
  - When $T > T_c(\{N_i\})$, $\Psi^* (\{N_i\})$ is the solution $\Psi \in (0, 1)$ to:

$$\Psi = T \frac{\sum_i A_i N_i (1 - e^{-\Psi N_i})}{\sum_i A_i N_i}$$

People like being friendly, but dislike disease risk.

- The payoff for a person of type i is

$$U_i(N_i; \Psi) = u_i(N_i) - \delta_i \cdot \left(1 - e^{-\Psi N_i}\right)$$

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- $1 - e^{-\Psi N_i}$ is the probability of getting sick during this outbreak.
- δ_i is the disutility from getting sick.

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- For convenience, I'd like to choose a $u_i$such that:
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- If $\delta_i = 1$ for all i, then the following function has these properties:

$$u_i(N) = \ln\left(\frac{N}{\theta_i}\right) - \frac{N}{\theta_i}$$

where θ_i is the person's optimal choice when $\Psi = 0$

Equilibrium

Given exogenous $T, \{\alpha_i\}$, an equilibrium in this model consists of Ψ, N_i such that

$$\Psi = \Psi^* \left(\{N_i\} \right)$$

$$N_i = N_i^*(\Psi) \equiv \arg\max U_i(N_i; \Psi)$$

Equilibrium Existence

- **Proposition 1:** If for each i, the optimal policy function $N_i^*(\Psi)$is a continuous non-negative function on $\Psi \in [0, 1]$,then an equilibrium exists.

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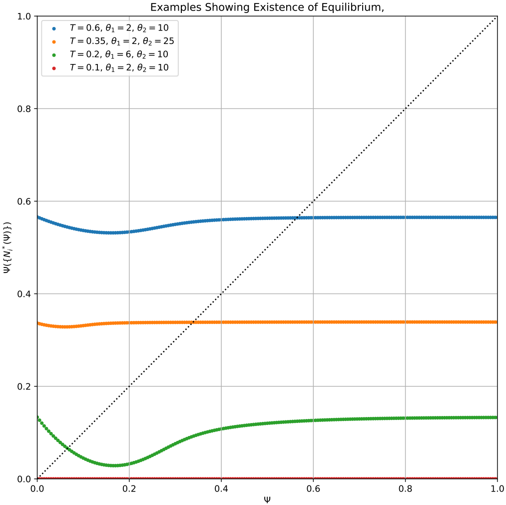

Equilibrium Existence

- **Proposition 1:** If for each i, the optimal policy function $N_i^*(\Psi)$is a continuous non-negative function on $\Psi \in [0,1]$,then an equilibrium exists.
- **Proposition 2:** Iff $T \leq T_c(\{N_i^*(0)\})$, then there is an equilibrium without any risk of epidemic exists, where $\Psi = 0$ and $N_i = N_i^*(0)$ for all i.

Individual Fatalism

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- However, the marginal disease risk from N_i may sometimes *decrease* as Ψ increases.

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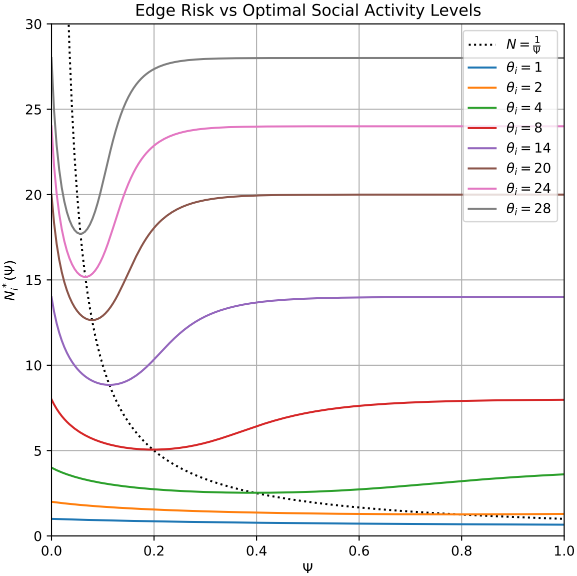
- When $\Psi > \frac{1}{N_i}$, an *increase* in disease risk may lead to individuals trying *less* hard to avoid getting sick.

Individual Fatalism



When can N_i have *positive* externalities?

- **Proposition 3:** Suppose $\{N_i\}$ is such that $T > T_c(\{N_i\})$. In this case,

$$\frac{\partial \Psi^*(\{N_i\})}{\partial N_j} < 0$$

$$\Updownarrow$$

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  - there is only a singular type
  - $N_j > \frac{1}{\Psi^*(\{N_i\})}$

What's Next?

- Preferential matching with certain types
- Different degree distribution - Negative binomial
- Incorporate site percolation

Forecasting Individual Unemployment

Details About the Task

- Binary prediction about whether each person will be unemployed in one year's time.
- Unbalanced data: Only 5 percent of individuals will be unemployed in one year's time.
- The competition's scoring metric placed equal weight on accurate predictions of unemployment and accurate predictions of non-unemployment:
  - $GF \equiv \frac{\text{\# Correctly Predicted Unemployed}}{\text{\# Unemployed}} \cdot \frac{1}{2} + \frac{\text{\# Correctly Predicted Not Unemployed}}{\text{\# Not Unemployed}} \cdot \frac{1}{2}$
- Data is drawn from the CPS outgoing rotation groups
  - people aged 20-64
  - years 1999-2018 (Mebdi Competition covered years 2008-2014)
    - 1.4 million observations, roughly 3% of whom will be unemployed in one year's time.

Demographic Comparisons

	Pr(E')	Pr(U')	Pr(U'|E)
All	74.0	3.5	2.4
White	75.1	3.1	2.2
Black	66.9	5.7	3.6
Men	80.2	4.0	2.6
Women	67.9	3.0	2.1
No College Degree	68.4	4.2	2.9
College Degree	82.2	2.4	1.6

Traits with Lowest Future Unemployment

	Pr(E')	Pr(U')	Pr(U'|E)
All	74.0	3.5	2.4
Occ: Physicians	97.2	0.4	0.3
Occ: Dentists	97.6	0.5	0.4
Occ: Dental hygienists	93.9	0.5	0.5
Occ: Occupational therapists	95.3	0.5	0.4
Occ: Speech therapists	94.3	0.6	0.3

Traits with Highest Future Unemployment

	Pr(E')	Pr(U')	Pr(U'|E)
All	74.0	3.5	2.4
Unemployed, seeking full-time work	48.9	27.6	
Why Unemployed: "Other job loser"	50.8	28.5	
Why Unemployed: Temp job ended	47.6	29.4	
Unemployment Duration: 4-12 months	44.2	29.4	
Unemployment Duration: $>$ 52 weeks	31.5	36.4	

Traits with High Future Unemployment When Employed

	Pr(E')	Pr(U')	Pr(U'|E)
All	74.0	3.5	2.4
Ind: Personnel supply services	76.3	10.9	7.3
Absent: weather affected job	80.3	9.1	9.1
Unemployed 3 months ago	52.1	21.0	11.0
Unemployed 2 months ago	51.3	22.9	12.0
Unemployed 1 month ago	49.8	24.7	13.3

Model Accuracy Overview

	LASSO	Ridge	Gradient Boosted Decision Trees	Simple Ensemble	ENU Ensemble
Balanced Accuracy (GF)	**73.4**	**73.4**	**73.0**	**73.7**	**73.8**
Will Be Unemployed	**73.2**	**73.8**	**65.9**	**71.0**	**70.8**
Employed→Unemployed	56.3	57.2	44.7	52.6	52.3
NILF→Unemployed	78.5	79.3	72.3	77.1	77.0
Unemployed→Unemployed	100	100	99.8	100	100
Won't Be Unemployed	**73.6**	**73.0**	**80.1**	**76.3**	**76.7**
Employed→Employed	78.2	77.8	85.4	81.1	81.8
NILF→Employed	40.7	39.4	47.1	42.2	39.1
Unemployed→Employed	0	0	0.7	0	0.5
Employed→NILF	64.1	63.6	71.4	66.8	64.6
NILF→NILF	74.9	73.9	79.5	77.4	78.2
Unemployed→NILF	0	0	1.3	0	0.6

Model: Decision Tree

Decision Trees are model which make sequences of binary comparisons to classify data.

When trained on this data, the first few branches of the tree look like this:

- Is the individual is currently unemployed?
  - If yes, predict that they *will* be unemployed in one year's time.
  - If not, then were they unemployed three months prior (in their first appearance in the CPS)?
    - If yes, predict that they *will* be unemployed in one year's time.
    - If not, the algorithm goes on to make additional comparisons.

Model: Gradient Boosted Decision Trees

- Many small trees are trained, each trying to predict the residuals unexplained by the previous trees.
- The predictions of the trees are then averaged together in an ensemble.
- The most important variables in this model, as measured by "reduction in Gini impurity", are:
  - Duration of unemployment.
  - Dummies for whether the individual was unemployed 1 month ago, 2 months ago, 3 months ago

Model: Lasso and Ridge

- Two varieties of regularized linear regressions
- As with a standard regression, we minimize some error term.
- With Lasso, we add the absolute values of the coefficients:

$$\min_{\beta} \sum_{i} (X_i\beta - y_i)^2 + \alpha \sum |\beta|$$

- With Ridge, we add the squared coefficients:

$$\min_{\beta} \sum_{i} (X_i\beta - y_i)^2 + \alpha \sum \beta^2$$

- Practical difference is that Lasso tends to set coefficients to zero.

Model: Ensembles

- "Simple Ensemble":
  - I averaged the predictions from the Lasso, Ridge, and Gradient Boosted Decision Tree Models.
- "ENU Ensemble":
  - Split the training data based on current employment status.
  - Trained the same three models on each subset of the data, and used it to form a simple ensemble for each.
  - Merged the predictions together.
- Both ensemble methods consistently improved GF in cross-validation, though the gains from the latter ensemble were relatively small.

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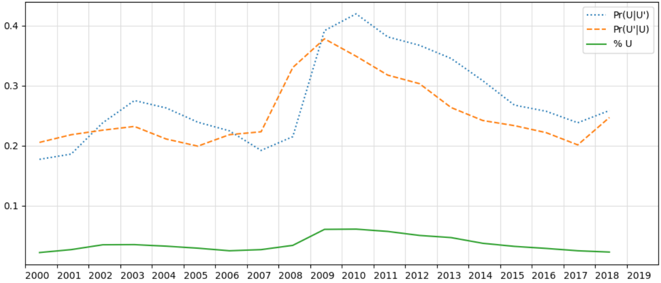
Current Unemployment Predicts Future Unemployment

- In each of these models, all or nearly all of the currently unemployed are predicted to be unemployed in one year's time.
- A single-variable model using only current employment status can achieve a score of $GF = 64\%$ by itself.
  - This heuristic faired even better in the competition sample.



Which Variables Are Most Important to the Model?

- Permutation Importance:
  1. Fit a model and evaluate predictions.
  2. Permute a feature or set of features.
  3. Make predictions with permuted X, and re-evaluate.
  4. Take the difference in scores.
- In the simple ensemble, the most important groups of features are:

	LASSO	Ridge	Gradient Boosted Decision Trees	Simple Ensemble
Histories	0.050	0.043	0.044	0.042
Employment Status	0.034	0.038	0.056	0.035
Class of Worker	0.019	0.024	0.007	0.015
Work Status	0.018	0.025	0.002	0.013
Time Period	0.012	0.012	0.013	0.013
Earnings/hourly wages	0.008	0.013	0.005	0.007

Importance For Each Type of Employment Status

- Take the ensemble trained on each employment status type (ENU)
- Calculate the permutation importances for each simple ensemble.
- Normalize by maximum possible reduction in *GF* score.
- Compare the ensemble trained on each subset to the simple ensemble trained on the entire sample.

Currently Employed		Currently NILF		Currently Unemployed	
Employment Status	-10.6	Employment Status	25.0	Histories	10.0
Time Period	8.9	Spouse Info	5.7	Time Period	8.0
Industry	4.2	Class of Worker	-5.0	Duration of Unemployment	7.6
Spouse Info	3.2	Work Status	-4.8	Class of Worker	-6.1
Location	2.5	Time Period	-4.5	Marital Status	5.8

Splitting by Recession/Expansion

- I repeated the exercise, this time splitting by years instead of employment status.
  - 2001-02, 2008-10 for recession years
  - all other years in sample for expansion years
- As in previous slide, I trained an ensemble on each subsample, calculated normalized permutation importances, and compared them to baseline importances.

Recession		Expansion	
Earnings/hourly wages	-2.6	Histories	3.3%
Time Period	-2.3	Time Period	-3.2%
Class of Worker	1.7	Earnings/hourly wages	3.0%
Location	1.5	Marital Status	1.7%
Hispanic	1.5	Employment Status	1.4%

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- But I suspect the models are already fairly close to the frontier of information for this particular dataset.
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- Better still: long-term panel data on employment and income
  - Recurrent Neural Networks might be well suited to analysis of data of this type.
  - A tangential research question: to what extent are idiosyncratic job finding and separation rates persistent across a person's lifespan?