Health Shocks, Health Insurance, and the Dynamics of Earnings and Health

(Previously "Health Shocks and the Evolution of Earnings over the Life-Cycle")

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Ordered Logit Regression, H, ages 25-64, MEPS

H=Poor	-4.483***
	(0.105)
H=Fair	-1.818***
	(0.041)
Some College	0.128***
	(0.049)
College	0.353***
	(0.049)
H Shock (dp)	-0.726***
	(0.057)
H Shock (du)	-0.675***
	(0.046)
ESHI	0.446***
	(0.050)
Inc=1st	-0.301***
	(0.064)
Inc=2nd	-0.100*
	(0.061)
Inc=4th	0.093
	(0.064)
Inc=5th	0.191***
	(0.067)
Pseudo R^2	0.271

Model

- Life-cycle model with the following features:
  - Individuals enter at age 25, face survival risk each period, and live to a max of 100 years
  - Retirement is mandatory at age 65
  - Education is exogenous, three types: $<=$High School, Some College and College
  - Within education: 3 fixed skill types and 2 fixed health types
  - Model solved in partial equilibrium
  - Calibrated to US white males for the time period 2000-2013

Modeling health: Key features

1. Latent permanent health types correlated with latent skill types (De Nardi et al. (2022))
2. Multi-dimensional health:
   - Functional Health (H); Risk (R) factors (e.g., hypertension, cholesterol); Health shocks (differ in predictability and persistence)
3. Endogenous health: individuals choose whether to treat health shocks
4. Model lack of access to health care by uninsured
5. Correction model for under-reporting of health shocks by those who are not treated

Health Process

1. Two stocks:
   1.1 Functional health H_t, affecting productivity
   1.2 Underlying health risk R_t, affecting future shocks
2. Three types of health shocks:
   2.1 predictable persistent shocks d_t^p that affect H_{t+1}
   2.2 unpredictable persistent shocks d_t^u that affect H_{t+1}
   2.3 unpredictable shocks s_t that are transitory

- Estimated using MEPS Medical Conditions files
  - Conditions coded according to the International Classification of Diseases (ICD)
  - Medical doctor classified these into: affects productivity/ risk factor/ temporary/ long-lasting

Health Process and Medical Treatment Cost

Variable	Probability/ Value
H_t	$\Lambda_H(H' \mid H, e, \varepsilon^h, t, d^p, d^u, (I_\Upsilon, I_{treat}))$
R_t	$\Lambda_R(R' \mid R, t, H)$
d_t^p	$\Gamma^{dp}(R, H, t, e)$
d_t^u	$\Gamma^{du}(R, H, t)$
s_t	$\Gamma^s(R, H, t)$
I_{surv}	$\varphi(H, t, e, M)$

State Variables and Decisions

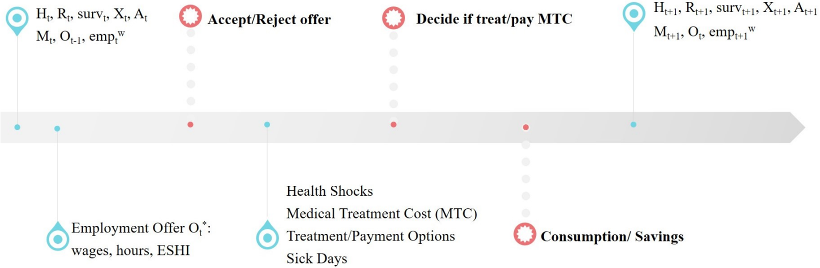
State Variables:

- Fixed: Education (e), Skill type (ε^s), health type (ε^h)
- H= Health
- R= Risk Factor
- X= Human Capital (experience)
- A= Assets
- M and emp^w = marital status and wife employment
- O_{t-1} = Past employment and health insurance

Decision Variables:

- Discrete labor supply (FT/PT/NE)
- Decisions to treat and pay medical bills
- Continuous consumption/saving

Timeline


H_t, R_t, $surv_t$, X_t, A_t
M_t, O_{t-1}, emp_t^w
Accept/Reject offer
Decide if treat/pay MTC
H_{t+1}, R_{t+1}, $surv_{t+1}$, X_{t+1}, A_{t+1}
M_{t+1}, O_t, emp_{t+1}^w
Employment Offer O_t^*:
wages, hours, ESHI
Health Shocks
Medical Treatment Cost (MTC)
Treatment/Payment Options
Sick Days
Consumption/ Savings

Employment Offers, Wages, Hours and HC

- Employment offer: $O^* = \{W^*, h^*, ins^*\}$
  - $h^* \in \{0, PT, FT\}$ and $ins^* \in \{0, 1\}$ (ESHI)
  - received with probability: $\Pi(O^*, O_{-1}, e, t)$
- Wage offers: W^*:

$$lnW^* = w(e, h_{-1}, X, H, h^*) + \varepsilon^s + \varepsilon^W$$

- Hours worked: $h = I_w(h^* - sd(e, H_t, \Upsilon_t))$
- Human capital: $X_{t+1} = X_t + h_t$

Treatment Costs and Social Insurance

- Treatment costs: $MTC(ins, t, d^u, d^p, s, H, \varepsilon^{CAT})$
- **Means-tested transfers captured by consumption floor**
  - Consumption floor $\bar{c}(e, I_{H=Poor}, M)$
  - Captures array of programs: Medicaid, Food-stamps, etc.
  - Disability Insurance modeled as higher consumption floor if $H = Poor$

Treatment and Payment Options

Options to treat and pay depend on ESHI status:

- **Those with ESHI have 3 options**
  1. treat and pay MTC
  2. treat and not pay MTC (suffer utility cost κ)
  3. not treat (suffer worse H transitions)
- **No ESHI: 3 sets of options - prob. depends on H**
  1. All 3 options available; e.g., ER visits
  2. Can treat but must pay MTC ((1) and (3)); e.g., refill prescription
  3. Cannot be treated; e.g., elective surgery

Family Status

- $M_t \in \{\text{Single}, \text{Married}\}$
- transition probability: $\Lambda^M(M', M, e, t, H, inc, O)$
- spouse employed with probability $\Pi^w(e, t, H, \varepsilon^s)$
- spouse income given by: $inc^w(emp^w, e, t, H, \varepsilon^s)$
- all working spouses have ESHI, while those not employed do not
- spouse's medical costs $MTC^w(ins^w, ins, t, e)$ are always paid

Preferences

- Utility:

$$u(c, l, I_{pay}, B) = \frac{1}{1-\sigma}[c^{\alpha} l^{(1-\alpha)}]^{(1-\sigma)} - (1 - I_{pay})\kappa + (\zeta + U_{Beq}) I_{death}$$

- Leisure:

$$l = 1 - h - sd - F(I_w, H) - hw(M, h^* \cdot I_w, emp^w).$$

- Bequest utility:

$$U_{Beq}(B) = \theta_{Beq} \frac{(B + k_{Beq})^{(1-\gamma)}}{1-\gamma}$$

Calibration Strategy

- Model calibrated to the U.S. white male population for 2000-2013
- Medical Expenditure Panel Survey (MEPS), CPS, HRS, PSID.

1. Measurement model for health shocks - those not treated often under-report health shocks and R
2. Most parameters estimated inside the model targeting moments on wages, income, assets, health, etc.

Medical Treatment Costs

Treatment costs: $MTC(ins, t, d^u, d^p, s, H, \varepsilon^{CAT})$

- In MEPS, we observe both Medical Charges and OOP.
  - Medical Charges: sum of all charges for care received; usually does not reflect actual payments made for services, which can be substantially lower due to factors such as negotiated discounts, bad debt, and free care.
- If ESHI, the MTC equals the OOP (Guess and verify all those with ESHI get treated)
- If no ESHI, the MTC is the actual cost of treatment.
  - Set to 0.6* Medical Charges of those with ESHI (Lockwood (2021) and Mahoney (2015))

Ordered Logit Regression, H, ages 25-64

	Data	Model
H=Poor	-4.483***	-4.332***
	(0.105)	(0.019)
H=Fair	-1.818***	-1.748***
	(0.041)	(0.008)
Some College	0.128***	0.168***
	(0.049)	(0.010)
College	0.353***	0.443***
	(0.049)	(0.011)
H Shock (dp)	-0.726***	-0.745***
	(0.057)	(0.012)
H Shock (du)	-0.675***	-0.701***
	(0.046)	(0.009)
ESHI	0.446***	0.598***
	(0.050)	(0.009)
Inc=1st	-0.301***	-0.241***
	(0.064)	(0.014)
Inc=2nd	-0.100*	-0.100***
	(0.061)	(0.012)
Inc=4th	0.093	0.041***
	(0.064)	(0.012)
Inc=5th	0.191***	0.130***
	(0.067)	(0.014)
Pseudo R^2	0.271	0.295

Ordered Logit Regression, H, ages 25-64, Model

	1	2	3	4
ESHI	0.593***	0.647***	-0.014	0.025**
	(0.010)	(0.010)	(0.011)	(0.011)
Inc: 1st	-0.170***	-0.016	-0.160***	0.007
	(0.013)	(0.014)	(0.014)	(0.014)
Inc: 2nd	-0.044***	-0.021*	-0.025**	0.000
	(0.012)	(0.012)	(0.012)	(0.013)
Inc: 4th	0.026**	0.008	-0.002	-0.023*
	(0.013)	(0.013)	(0.013)	(0.013)
Inc: 5th	0.133***	0.069***	0.079***	0.010
	(0.014)	(0.015)	(0.015)	(0.015)
Latent health = Bad		-0.935***		-1.000***
		(0.008)		(0.009)
Not treat shock=1			-2.420***	-2.486***
			(0.018)	(0.018)
Pseudo R^2	0.294	0.314	0.335	0.357

$^{*}\ p < 0.1$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$

Calibration Strategy

Table: Summary of Key Health Parameters Estimation

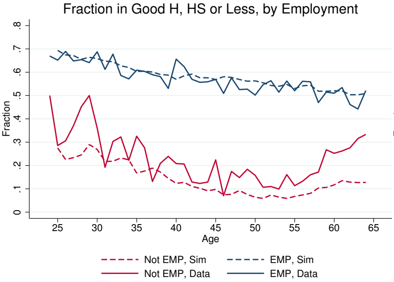
To be identified	Target
1. Effect of latent types in Λ_H	H transitions and H dist'n by age
2. Effect of treatment in Λ_H	H transitions for insured vs uninsured
3. Latent types dist'n $\Lambda^{\varepsilon}(\varepsilon^h, \varepsilon^s, e)$	Corr. btw income, emp, wealth and H
4. Stigma of not paying bills (κ)	Average OOP/Charges for uninsured
5. Treat/pay option prob $\psi(J(ins = 0)\|H)$	Medical charges by insurance status;
	% uninsured who treat and who do not pay

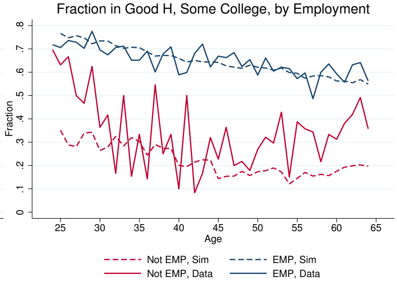
Latent Skill and Health Types Distribution

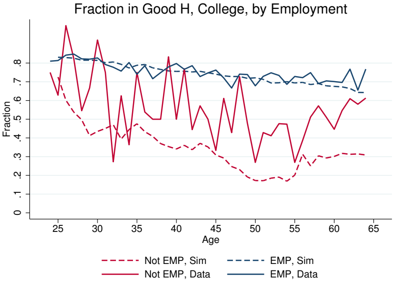
- Probability of each skill type is 1/3 in each educ group
- The probability of being a good health type conditional on education and skill type is:

Latent Skill	HS or Less	Some College	College
Low	0.37	0.45	0.5
Medium	0.435	0.5	0.6
High	0.5	0.55	0.7

Latent Skill and Health Types: (1) H and Emp







Latent Skill and Health Types: (2) H and Income

Coefficients on $H = Good$, regression of Income (thousands) on H and cubic age, by education

All	**Data**	**Model**
HS or Less	8.6	9.2
Some College	8.5	10.6
College	14.0	14.3
Employed FT		
HS or Less	4.9	4.8
Some College	4.3	5.5
College	10.5	10.3

Latent Skill and Health Types: (3) H and Wealth

Table: Health distribution within wealth terciles, by education, ages 56-60, HRS

	Health		
	H=Poor	H=Fair	H=Good
Education			
HS or Less			
Wealth Tercile			
1st	23.6	51.9	24.5
2nd	13.4	44.3	42.3
3rd	8.1	41.5	50.3
Some College			
Wealth Tercile			
1st	14.3	43.4	42.3
2nd	6.2	34.5	59.3
3rd	4.0	29.8	66.2
College			
Wealth Tercile			
1st	8.5	32.5	59.0
2nd	2.7	28.4	68.8
3rd	1.7	23.2	75.1

Latent Skill and Health Types: (3) H and Wealth

Table: Health distribution within wealth terciles, by education, ages 56-60, Model

	Health		
	H = Poor	H = Fair	H = Good
Education			
HS or Less			
Wealth Tercile			
1st	42.7	43.7	13.6
2nd	9.8	46.8	43.4
3rd	8.8	40.3	51.0
Some College			
Wealth Tercile			
1st	23.1	45.9	31.0
2nd	9.2	37.6	53.1
3rd	5.7	39.4	54.9
College			
Wealth Tercile			
1st	8.4	38.0	53.6
2nd	3.9	30.1	66.0
3rd	2.2	27.5	70.3

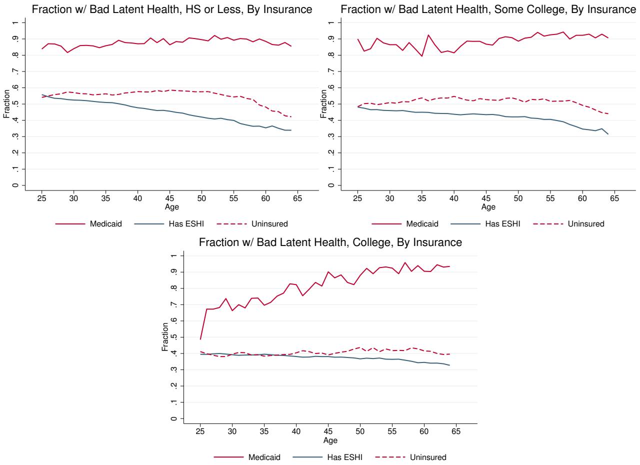
Health Transitions by Insurance

Table: Estimated Probability of staying in Good health at age 45

	Data	Model
Private	0.794***	0.830***
	(0.006)	(0.001)
Public	0.629***	0.726***
	(0.029)	(0.009)
Uninsured	0.717***	0.705***
	(0.012)	(0.002)

- Two possibilities: latent types or non-treatment?

Latent Health Distribution by Insurance



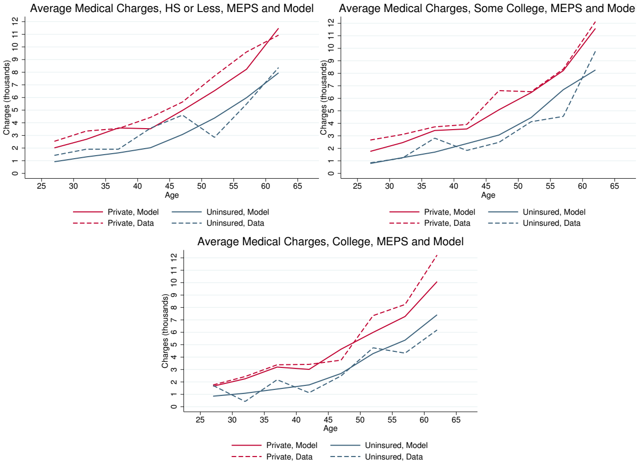
- Latent types explain bad transition of Medicaid group & non-treatment explains bad transitions of uninsured

Probability of Treatment/Paying if no ESHI

Health	Can treat and not pay	Can treat but must pay	Cannot treat
Poor	0.78	0.22	0
Fair	0.45	0.20	0.35
Good	0.38	0.17	0.45

- Stigma cost of not paying very small.

Medical Charges by Insurance



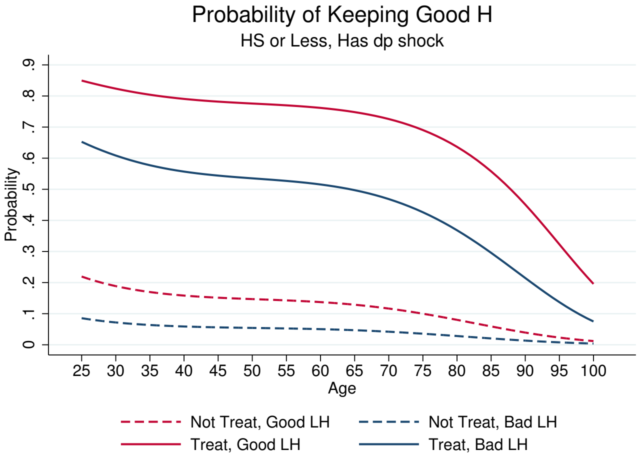
Fractions treated and paying bills

Table: Statistics on Medical Bills, MEPS, Uninsured, ages 25-64 with **reported health shock**

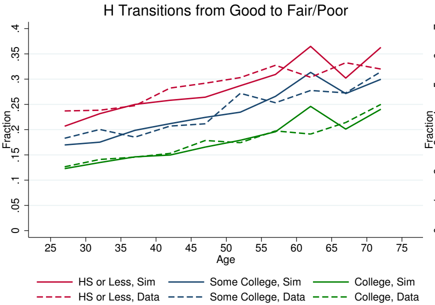
Health	**% treat**	**% pay if treat**	**OOP/MC if treat**
Poor	0.90	0.16	0.13
Fair	0.71	0.24	0.20
Good	0.65	0.23	0.20
Total	0.75	0.21	0.18

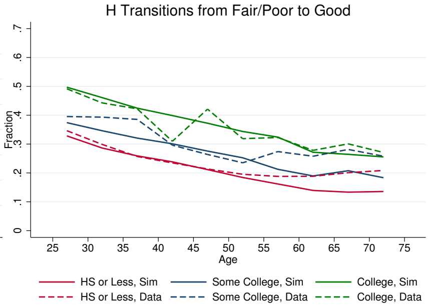
Classified as "treated" if medical charges > $500/year.
Classified as "paying" if OOP > 0.6* Medical charges.

Health Transitions - Types and Treatment

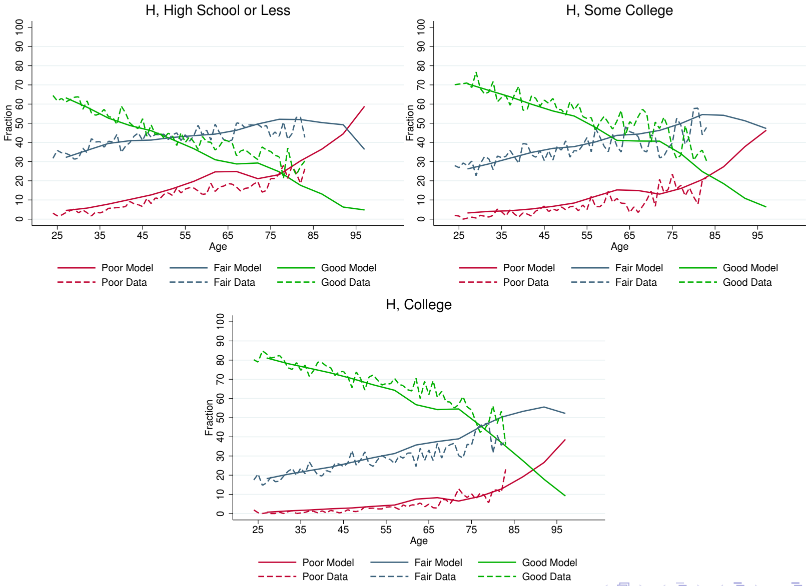


Health Transitions





Health Profiles



Medical Bills by Source of Payment

	Total cost of treated	By Source of Payment: OOP (Self)	ESHI	Medicaid	Unpaid	Cost of untreated
No ESHI	3,753	320	0	2,097	1,336	1,185
		(8%)	(0%)	(56%)	(36%)	(+32%)
ESHI	2,524	549	1,967	8	0	4
		(22%)	(78%)	(0%)	(0%)	(0%)
All	3,045	452	1,134	893	566	504
		(15%)	(37%)	(29%)	(19%)	(+17%)

Key Results: Health Process

- Endogenous health, treatment and payment decisions:
  - almost all individuals want to treat (the value of good health is very high)
  - high fraction of uninsured are not treated due to lack of access to health care (32%)
  - high fraction of uninsured do not pay bills (30%)
- Implications:
  - Health insurance valuable as a ticket to accessing health care (insuring OOP risk is secondary)

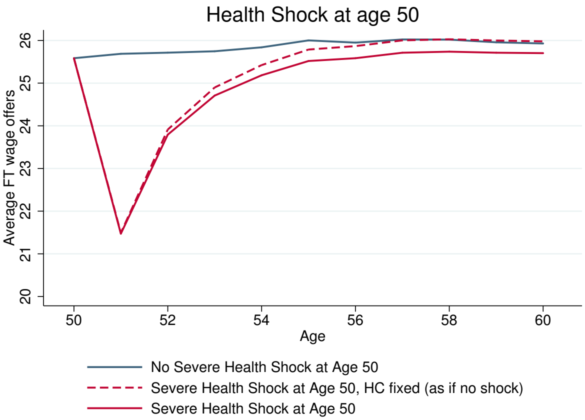
Health Shocks and Human Capital

- We decompose effects of health shocks on earnings into direct and indirect effects:
- Effects of health shocks on PV of Earnings:
  - Direct effects:
    $\uparrow$ sick days, $\downarrow$ health

  The drop in health directly reduces wages, tastes for work and labor supply, thus reducing earnings.
  - Indirect effects:
    Lower rate of human capital accumulation amplifies the drop in the wage rate in long-run

Effects of Major Health Shocks on Wage Offers

Simulated effect of major health shock d^u at age 50



Human capital effect generates long-run drop in offer wages.

Effects of Major Health Shocks on PV Earnings

Effect of major d^u shock on PV of earnings (from age of shock to age 65)

Age of Shock	**Δ PV Earnings**				
	***HC* fixed**		**Total Effect**		**Due to *HC***
		%		**%**	**% of total**
≤High School					
40	-25,015	-5.9	-33,410	-7.9	25.1
50	-29,348	-11.1	-33,848	-12.8	13.3
60	-13,777	-21.6	-13,959	-21.9	1.3
College					
40	-26,733	-2.7	-44,749	-4.5	40.3
50	-33,487	-4.9	-40,214	-5.9	16.7
60	-25,227	-13.6	-26,462	-14.2	4.7

Absolute loss bigger for college types, % loss bigger for ≤HS.

Results: Health Shocks and Earnings Inequality

Effects of Health Shocks on PV of Lifetime Earnings
(Decompose Direct vs. Behavioral Effects)

	Benchmark		No Health Shocks			
			Decision Rules Fixed		Decision Rules Change	
	Mean	CV	Mean	CV	Mean	CV
All	762,177	0.555	+5.56%	0.528	+9.26%	0.479
$\leq$HS	523,423	0.376	+7.41%	0.350	+11.83%	0.286
$<$College	711,746	0.435	+5.72%	0.411	+9.94%	0.350
College	1,091,345	0.445	+4.42%	0.425	+7.41%	0.375

Coefficient of variation (CV) of PVE decreases from 0.555 to 0.528 or 4.9% if we hold decision rules fixed. It decreases to 0.479 or 13.7% if we let decision rules adapt to the new environment.

Results: Health Shocks and Earnings Inequality

Effects of Health Shocks on PV of Lifetime Earnings

	Benchmark		No Health Shocks			
			Decision Rules Fixed		Decision Rules Change	
	Mean	**CV**	**Mean**	**CV**	**Mean**	**CV**
≤High School						
Low Prod.	293,730	0.300	+12.85%	0.273	+37.49%	0.169
Med Prod.	539,185	0.150	+7.14%	0.130	+7.43%	0.125
High Prod.	734,667	0.134	+5.47%	0.122	+5.36%	0.124

Low skill types earn much more if health shocks are eliminated.

Conclusion

- Health Shocks account for 15% of lifetime earnings inequality
- About 1/3 of this is due to direct effects and 2/3 is due to behavioral effects.
- Lack of health insurance creates a perverse incentive for low-skill workers to work less and accumulate less human capital to maintain eligibility for means tested transfers.
- Health insurance is very valuable for providing access to health care rather than insuring OOP risk
- Provision of public insurance for the uninsured eliminates incentive to work less to qualify for Medicaid and improves health outcomes which further increase employment