How Important is Health Inequality for Lifetime Earnings Inequality?

Roozbeh Hosseini UGA & FRB Atlanta Karen Kopecky FRB Atlanta Kai Zhao UCONN

Guest Lecture at UMN-ECON 8181, September 25, 2020

The views expressed do not necessarily reflect the position of the Federal Reserve Bank of Atlanta or the Federal Reserve System.

Introduction

• Poor health impacts individuals through several channels:

reduces labor productivity

increases costs of working, mortality risk, medical expenses

increases chance of access to social insurance programs (e.g. SSDI)

Introduction

• Poor health impacts individuals through several channels:

reduces labor productivity

increases costs of working, mortality risk, medical expenses increases chance of access to social insurance programs (e.g. SSDI)

• Individuals in poor health have lower earnings and labor supply



Introduction

• Poor health impacts individuals through several channels:

reduces labor productivity

increases costs of working, mortality risk, medical expenses increases chance of access to social insurance programs (e.g. SSDI)

- Individuals in poor health have lower earnings and labor supply
- Question: How important is health inequality for lifetime earnings inequality?
- What are key channels?

availability/generosity of Soc Ins - vs - higher costs/lower productivity of work

▶ graph

To answer these questions

- 1. How do we measure "health"?
 - frailty index: cumulative sum of past adverse health events

To answer these questions

- 1. How do we measure "health"?
 - frailty index: cumulative sum of past adverse health events
- 2. Empirical Analysis: dynamic panel estimation using PSID data
 - estimate effect of health on current earnings
 - assess impact of health on each margin: hours, wages, participation

To answer these questions

- 1. How do we measure "health"?
 - frailty index: cumulative sum of past adverse health events
- 2. Empirical Analysis: dynamic panel estimation using PSID data
 - estimate effect of health on current earnings
 - assess impact of health on each margin: hours, wages, participation
- 3. Quantitative Analysis: structural model consistent with empirical findings
 - agents in the model have heterogeneous and risky health profiles
 - use model to assess

impact of health inequality on lifetime earnings inequality

relative importance of each channel through which health operates

- Impact of health on labor supply: Blundell et al. (2017), French (2005), Bound et al. (1999).
- SSDI and disability: Low and Pistaferri, French and Song (2014), Kitao (2014), Michaud and Wiczer (2016), Meyer and Mok (2019).
- Welfare costs of bad health: De Nardi et al. (2017), Rios-Rull and Pijoan-Mas (2019).
- Health and inequality and income distribution: Capatina (2015), O'Donnell et al. (2015), Prados (2017).
- Health and savings: De Nardi et al. (2010), Kopecky and Koreskhova (2014), Porterba et al. (2017), Scholz and Seshadri (2013).
- Dynamic panel estimation: Blundell and Bond (1998), Blundell and Bond (2000), Arellano and Bond (1991), Arellano and Bover (1995), Al-Sadoon et al. (2019), Bond (2002), Roodman (2009).
- Frailty index: Hosseini et al. (2019), Schunemann et al. (2017a), Schunemann et al. (2017b), Dalgaard and Strulik (2014).

How do we measure health?

How we measure health?

- Frailty index: cumulative sum of all adverse health events (*deficits*) proposed and widely used in gerontology literature.
- Type of deficit variables used to construct frailty index in PSID:
 - Difficulties with ADL and IADL (eating, dressing, using phone, etc)
 - Diagnosis (ever had heart disease, psychological problems, loss of memory, etc)
 - Body measurements (BMI over 30, etc)
- Assign value of 1 whenever one of these conditions exists, and value of 0 o/w.
- Add them up and normalize to a number between 0 and 1 $% \left({{\left({{{\left({{{\left({{{\left({{{}}} \right)}} \right.} \right)}_{0}}} \right)}_{0}} \right)} \right)$

▶ gerontology literature

Why use frailty index?

- 1. Easy to construct and highly predictive of health-related outcomes
- 2. Better than self-reported health in predicting decline in health with age
- 3. Measures health on finer scale \rightarrow variation of health in the unhealthy tail
- 4. Can be treated as continuous variable \rightarrow useful for estimating marginal effects
- 5. Need objective measure of health to study health-contingent policies.

tables

▶ graph

illustration

Summary Stats for Frailty

Mean	0.11
by gender:	
male	0.10
female	0.12
by age:	
25-49	0.08
50-74	0.14
75+	0.25
Median	0.07
Standard Deviation	0.12
$+\Delta$ Frailty	0.29
$-\Delta$ Frailty	0.11
Effect of 1 additional deficit	+0.037

• Sample: 2003–2017 PSID household heads + spouses, ages 25–64



Summary Stats for Frailty

Mean	0.11
by gender:	
male	0.10
female	0.12
by age:	
25-49	0.08
50-74	0.14
75+	0.25
Median	0.07
Standard Deviation	0.12
$+\Delta$ Frailty	0.29
$-\Delta$ Frailty	0.11
Effect of 1 additional deficit	+0.037

- Sample: 2003–2017 PSID household heads + spouses, ages 25–64
- Both positive and negative changes in frailty from wave to wave



Empirical Analysis

Empirical Analysis: Question

- What is the impact of adding one more deficit on earnings?
- We estimate the following regression

$$y_{i,t} = b_i + \gamma f_{i,t} + \alpha_1 y_{i,t-1} + \alpha_2 y_{i,t-2} + \delta \mathbf{Z}_{i,t} + \varepsilon_{i,t}$$

using Blundell-Bond System GMM estimator



 $y_{i,t}$ is log of earnings (or hours, or wages)

 $Z_{i,t}$ is vector of exogenous controls: marital status, marital status×gender, # of kids, # of kids×gender, cubic in age, and year dummies.

Empirical Analysis: Question

- What is the impact of adding one more deficit on earnings?
- We estimate the following regression

$$y_{i,t} = b_i + \gamma f_{i,t} + \alpha_1 y_{i,t-1} + \alpha_2 y_{i,t-2} + \delta \mathbf{Z}_{i,t} + \varepsilon_{i,t}$$

using Blundell-Bond System GMM estimator



 $y_{i,t}$ is log of earnings (or hours, or wages)

 $Z_{i,t}$ is vector of exogenous controls: marital status, marital status×gender, # of kids, # of kids×gender, cubic in age, and year dummies.

• Report $\gamma/27$: response of earnings/hours to one more deficit.

Why dynamic panel?

- Want fixed effects to control for unobserved heterogeneity
- Earnings and frailty are both highly persistent variables
- Concerns of endogeneity/simultaneity

		Everyone			Workers		
	(1)	(2)	(3)	(4)	(5)	(6)	
$\log(earnings_{t-1})$	0.283 (0.364)					
$\log(earnings_{t-2})$	0.396 (0.298)					
$frailty_t$	-0.199 (0.061	***					

frailty \uparrow by 1 deficit \Downarrow earnings \downarrow 19.9%

AR(1) test (p-value)	0.455	0.104	
AR(2) test (p-value)	0.380	0.949	
Hansen test (<i>p</i> -value)	0.796	0.752	
Diff-in-Hansen test (p-value)	0.652	0.464	

Note:

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

	Everyone				Worke	rs
	(1)	(2)	(3)	(4)	(5)	(6)
$\log(earnings_{t-1})$	0.283 (0.364)	0.628** (0.291)				
$\log(earnings_{t-2})$	0.396 (0.298)	0.115 (0.239)				
frailty _t	-0.199*** (0.061)					
$frailty_t \times Young \; (age \leq 45)$		-0.185*** (0.066)				
$frailty_t \times Old \; (age > 45)$		-0.149*** (0.049)				

similar effect for young and old

AR(1) test (p-value)	0.455	0.104	
AR(2) test (p-value)	0.380	0.949	
Hansen test (<i>p</i> -value)	0.796	0.752	
Diff-in-Hansen test (p-value)	0.652	0.464	

Note:

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

	Everyone			Workers		
	(1)	(2)	(3)	(4)	(5)	(6)
$\log(earnings_{t-1})$	0.283 (0.364)	0.370 (0.319)	0.220 (0.362)	1.474*** (0.509)	1.371*** (0.400)	1.293*** (0.410)
$\log(earnings_{t-2})$	0.396 (0.298)	0.318 (0.259)	0.444 (0.297)	-0.640 (0.454)	-0.569 (0.356)	-0.498 (0.377)
frailty _t	-0.199^{***} (0.061)			-0.036**		
$frailty_t \times HSD$		-0.232** (0.066)			-0.068** (0.030)	
$frailty_t \times HSG$		-0.207*** (0.058)			-0.046*** (0.002)	
$frailty_t\timesCG$		-0.093* (0.052)			-0.021 (0.018)	
$frailty_t \times Bad Health$			-0.193*** (0.065)			-0.036** (0.017)
$frailty_t \times Good \; Health$			-0.071 (0.178)			-0.065 (0.066)
AR(1) test (p-value)	0.455	0.319	0.497	0.030	0.010	0.021
AR(2) test (p-value)	0.380	0.474	0.298	0.130	0.082	0.138
Hansen test (p-value)	0.796	0.132	0.826	0.434	0.826	0.543
Diff-in-mansen test (p-value)	0.052	0.300	0.027	0.255	0.404	0.259

concentrated in less educated and those in bad health

Note:

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

	Everyone				Workers	
	(1)	(2)	(3)	(4)	(5)	(6)
$log(earnings_{t-1})$	0.283 (0.364)	0.370 (0.319)	0.220 (0.362)	1.474*** (0.509)	1.371*** (0.400)	1.293*** (0.410)
$\log(earnings_{t-2})$	0.396 (0.298)	0.318 (0.259)	0.444 (0.297)	-0.640 (0.454)	-0.569 (0.356)	-0.498 (0.377)
frailty _t	-0.199*** (0.061)			-0.036**		
$frailty_t \times HSD$		-0.232** (0.066)			-0.068** (0.030)	
$frailty_t \times HSG$		-0.207*** (0.058)			-0.046*** (0.002)	
$frailty_t \times CG$		-0.093* (0.052)			-0.021 (0.018)	
$frailty_t imes Bad Health$			-0.193*** (0.065)			-0.036** (0.017)
$frailty_t \times Good \; Health$			-0.071 (0.178)			-0.065 (0.066)
AR(1) test (p-value)	0.455	0.319	0.497	0.030	0.010	0.021
AR(2) test (p-value)	0.380	0.474	0.298	0.130	0.082	0.138
Hansen test (p-value)	0.796	0.132	0.826	0.434	0.826	0.543
Diff-in-Hansen test (p-value)	0.652	0.360	0.827	0.255	0.484	0.259

primarily due to extensive margin

Note:

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

Effect of Frailty on Hours

	Everyone			Workers			
	(1)	(2)	(3)	(4)	(5)	(6)	
$\log(hours_{t-1})$	0.399 (0.322)	0.383 (0.319)	0.386 (0.317)	0.003 (0.345)	0.074 (0.313)	0.040 (0.311)	
$\log(hours_{t-2})$	0.263 (0.257)	0.269 (0.253)	0.272 (0.253)	0.304 (0.218)	0.168 (0.221)	0.282 (0.219)	
frailty _t	-0.144*** (0.044)			0.003 (0.009)			
$frailty_t \times HSD$		-0.177*** (0.049)			-0.02 (0.013)		
$frailty_t \times HSG$		-0.159*** (0.045)			0.001 (0.010)		
$frailty_t \times CG$		-0.082** (0.041)			0.009 (0.009)		
$frailty_t \times Bad Health$			-0.137*** (0.046)			0.001 (0.010)	
$frailty_t \times Good \; Health$			-0.082 (0.128)			-0.002 (0.034)	
AR(1) test (p-value)	0.287	0.290	0.289	0.409	0.286	0.335	
AR(2) test (p-value)	0.596	0.569	0.565	0.273	0.572	0.312	
Hansen test (<i>p</i> -value)	0.971	0.317	0.838	0.060	0.166	0.174	
Diff-in-Hansen test (p-value)	0.944	0.597	0.713	0.080	0.062	0.108	
Note:				* <i>p</i> < 0.1;	** <i>p</i> < 0.05;	**** p < 0.01	

Similar findings for hours

Hosseini, Kopecky & Zhao

How Important is Health Inequality for Lifetime Earnings Inequality?



• Other Results

Effect of Frailty on Wages of Workers

	Everyone			Workers			
	(1)	(2)	(3)	(4)	(5)	(6)	
$\log(wage_{t-1})$				0.212 (0.541)	0.122 (0.368)	0.303 (0.449)	
$\log(wage_{t-2})$				0.532 (0.489)	0.600* (0.328)	0.461 (0.419)	
frailty _t				-0.023** (0.010)			
$frailty_t \times HSD$					-0.069*** (0.023)		
$frailty_t \times HSG$					-0.033^{***} (0.011)		
$frailty_t\timesCG$					-0.008 (0.011)		
$frailty_t \times Bad \; Health$						-0.022* (0.012)	
$frailty_t \times Good \; Health$						0.013 (0.062)	
AR(1) test (p-value)	0.651	0.518	0.552				
AR(2) test (p-value)	0.454	0.189	0.474				
Hansen test (p-value)	0.085	0.374	0.207				
Diff-in-Hansen test (p-value)	0.044	0.145	0.082				
Note:	*p < 0.1:	**p < 0.05:	***p < 0.01				

Average effect of frailty on wages is small

Significant negative effect for less educated workers



Effect of Earnings on Frailty

	(1)	(2)	(3)	(4)
frailty _{t-1}	0.445 (0.463)	0.334 (0.435)	-0.152 (0.528)	-0.456 (0.400)
frailty _{t-2}	0.602 (0.447)	0.661 (0.443)	1.124** (0.495)	1.446*** (0.404)
$log(earnings_t)$	0.004* (0.002)			
$log(earnings_t) \times HSD$		0.003 (0.002)		
$log(earnings_t) \times HS$		-0.008 (0.039)		
$\log(earnings_t) \times CL$		0.000 (0.001)		
$log(earnings_t) \times Bad \; Health$			0.002 (0.002)	
$log(earnings_t) \times Good \; Health$			0.000 (0.003)	
$log(earnings_t) \times Young$				-0.000 (0.001)
$log(earnings_t) \times Old$				-0.000 (0.002)
AR(1) test (p-value)	0.531	0.573	0.501	0.001
AR(2) test (p-value)	0.333	0.260	0.061	0.002
Hansen test (p-value)	0.269	0.842	0.621	0.129
Diff-in-Hansen test (p-value)	0.450	0.852	0.894	0.132
Note:	*p < 0.1	: ** p < 0.0	5: ***p < 0.01	

No statistically significant effect of earnings on frailty

Empirical Findings — Summary

- Increases in frailty reduce earnings and hours
- The effect is
 - primarily driven by employment margin
 - concentrated in less educated and less healthy individuals
- These findings suggest that
 - health inequality may be an important source of lifetime earnings inequality
 - social insurance may play an important role.

Empirical Findings — Summary

- Increases in frailty reduce earnings and hours
- The effect is
 - primarily driven by employment margin
 - concentrated in less educated and less healthy individuals
- These findings suggest that
 - health inequality may be an important source of lifetime earnings inequality
 - social insurance may play an important role.
- Next we develop a structural model to quantify these

Structural Mode

- J period, OLG, GE model
- Individuals are subject to exogenous shocks:
 - frailty, productivity, and separation
- If separated, can choose to pay a one-time wage cost and go back to work

- J period, OLG, GE model
- Individuals are subject to exogenous shocks:
 - frailty, productivity, and separation
- If separated, can choose to pay a one-time wage cost and go back to work
- Frailty impacts an individual's
 - Labor productivity
 - Mortality
 - OOP medical expenditures
 - Disutility of working
 - Probability of becoming DI beneficiary

- Individuals:
 - Employed:

If young: can choose to switch to non-employment If old: can choose to retire

- Non-employed:

Become a DI beneficiary with some probability

Can choose to go to employed state

- DI beneficiaries: Collect DI benefits until retirement at age R
- Retirees: Collect social security benefits and do not work

- Individuals:
 - Employed:

If young: can choose to switch to non-employment If old: can choose to retire

- Non-employed:

Become a DI beneficiary with some probability

Can choose to go to employed state

- DI beneficiaries: Collect DI benefits until retirement at age R
- Retirees: Collect social security benefits and do not work
- Government collects taxes (capital, income, payroll)
 - Pays out SS, DI, and means-tested transfers $+ \mbox{ exogenous government purchases}$

Problem of Young Employed Individual

Employed individual with j < R - 1 solves

$$V^{E}(x, i_{s}) = \max_{c, a' \ge 0} u(c, v(f)) + \sigma \beta p(j, f, s) E\left[\max\left\{V^{E}(x', 1), V^{N}(x', 0)\right\}\right] + (1 - \sigma) \beta p(j, f, s) E\left[\max\left\{V^{E}(x', 0), V^{N}(x', 0)\right\}\right]$$

subject to ...

individual state variable $x = (j, a, s, f, \epsilon, \overline{e})$

- j: age
- a: assets
- s: education
- f: frailty $\equiv \psi(j, s, \varepsilon_f)$ where ε_f : frailty shocks and fixed effect
- $\epsilon:$ productivity shock and fixed effect
- ē: average past earnings

Problem of Young Employed Individual

Employed individual with j < R - 1 solves

$$V^{E}(x, i_{s}) = \max_{c, a' \ge 0} u(c, v(f)) + \sigma \beta p(j, f, s) E\left[\max\left\{V^{E}(x', 1), V^{N}(x', 0)\right\}\right] + (1 - \sigma)\beta p(j, f, s) E\left[\max\left\{V^{E}(x', 0), V^{N}(x', 0)\right\}\right]$$

subject to

$$\frac{a'}{1+r} + c + m^{\mathcal{E}}(j, f, s) = a + w\eta (j, f, s, \epsilon) - T(w\eta) - \chi(w\eta)i_{s} + Tr(x, i_{s}),$$
$$\bar{e}' = [(j-1)\bar{e} + w\eta]/j$$

i_s: indicates the worker is coming from separation

Hosseini, Kopecky & Zhao

Problem of Young Employed Individual

Employed individual with j < R - 1 solves

$$V^{E}(x, i_{s}) = \max_{c, a' \ge 0} u(c, v(f)) + \sigma \beta p(j, f, s) E\left[\max\left\{V^{E}(x', 1), V^{N}(x', 0)\right\}\right] + (1 - \sigma) \beta p(j, f, s) E\left[\max\left\{V^{E}(x', 0), V^{N}(x', 0)\right\}\right]$$

Utility function is

$$u(c,v(f)) = rac{\left(c^{\mu}(1-v(f))^{1-\mu}\right)^{1-\gamma}}{1-\gamma},$$

where
$$v\left(f
ight)=\phi_{0}\left(1+\phi_{1}f^{\phi_{2}}
ight), \hspace{0.5cm} \phi_{0}\geq0, \hspace{0.1cm} \phi_{1}\geq0, \hspace{0.1cm}$$
 and $\phi_{2}\geq0.$

Problem of Old Employed Individual

Employed individual with j > R - 1 solves

$$V^{E}(x, i_{s}) = \max_{c, a' \ge 0} u(c, v(f)) + \sigma p(j, f, s) E\left[\max\left\{V^{E}(x', 1), V^{R}(x')\right\}\right] + (1 - \sigma) \beta p(j, f, s) E\left[\max\left\{V^{E}(x', 0), V^{R}(x')\right\}\right]$$

subject to

$$\frac{a'}{1+r} + c + m^{R}(j, f, s) = a + w\eta(j, f, s, \epsilon) + SS(\overline{e}) - T(w\eta)$$
$$-\chi(w\eta)i_{s} + Tr(x, i_{s}),$$

$$ar{e}' = ar{e}$$

Problem of Young Nonemployed Individual

Nonemployed individual with j < R - 1 solves

$$V^{N}(x, n_{a}) = \max_{c, a' \ge 0} u(c) + \theta(f, n_{a})\beta p(j, f, s) E\left[V^{D}(x', 0)\right] \\ + \left[1 - \theta(f, n_{a})\right]\beta p(j, f, s) E\left[\max\left\{V^{E}(x', 1), V^{N}(x', n_{a} + 1)\right\}\right]$$

subject to

$$\frac{a'}{1+r} + c + m^N(j, f, s) = a + Tr(x, n_a)$$

- *n_a*: number of periods in non-employment
- Probability of successful DI application: $\theta(f, n_a) = \min\{1, \kappa_0 f^{\kappa_1} n_a^{\kappa_2}\}$
Problem of Young Nonemployed Individual at R-1

• Nonemployed individual with j = R - 1 solves

$$V^{N}(x, n_{a}) = \max_{c, a' \geq 0} u(c) + \beta p(j, f, s) E\left[\max\left\{V^{E}(x', 1), V^{R}(x')\right\}\right]$$

subject to

$$\frac{a'}{1+r} + c + m^N(j, f, s) = a + Tr(x, n_a)$$

Problem of a DI Beneficiary

• DI beneficiary with j < R - 1 solves

$$V^{D}(x, n_{d}) = \max_{c, a' \geq 0} u(c) + \beta p(j, f, s) E\left[V^{D}(x', n_{d} + 1)\right]$$

subject to

$$\frac{a'}{1+r} + c + m^{D}(j, f, s, n_d) = a + SS(\bar{e}) + Tr(x, n_d)$$

 n_d : number of periods on DI.

Hosseini, Kopecky & Zhao

Problem of a DI Beneficiary

• DI beneficiary with j < R - 1 solves

$$V^{D}(x, n_{d}) = \max_{c, a' \geq 0} u(c) + \beta p(j, f, s) E\left[V^{D}(x', n_{d} + 1)\right]$$

$$\frac{a'}{1+r}+c+m^{D}\left(j,f,s,n_{d}\right)=a+SS\left(\bar{e}\right)+Tr(x,n_{d}).$$

• When j = R - 1 solves

$$V^{D}(x, n_{d}) = \max_{c, a' \ge 0} u(c) + \beta p(j, f, s) E\left[V^{R}(x')\right]$$

subject to similar BC.

 n_d : number of periods on DI.

Problem of a Retiree

• Retiree solves

$$V^{R}(x) = \max_{c,a' \geq 0} u(c) + \beta p(j, f, s) E\left[V^{R}(x')\right]$$

subject to

$$\frac{a'}{1+r} + c + m^{R}(j, f, s) = a + SS(\bar{e}) + Tr(x)$$

Parametrization: Tax and Transfers

- Taxes includes
 - Proportional capital tax τ_K paid by firm
 - Federal income tax HSV tax function
 - SS retirement & disability payroll tax statutory tax formula
 - Medicare payroll tax

$$T(e) = e - \lambda e^{1-\tau} + \tau_{ss} \min\{e, 2.47\bar{e}_a\} + \tau_{med}e$$

- Transfers include
 - SS retirement & disability benefit statutory benefit formula
 - Welfare programs to guarantee minimum consumption floor \underline{c}

Equilibrium

- Return on assets, r, is exogenously given (small open economy)
- There is an aggregate production function

 $Y = AK^{\alpha}L^{1-\alpha}$

where *L* is aggregate labor input = sum of hours×productivity

- Wage per efficient unit of labor = marginal product
- Consolidated government budget holds with exog. purchases g
- All measures are stationary usual definition

Calibration

Calibration: Overview of Strategy

- Model period is 1 year
- Agents live from j = 1 (age 25) to a maximum J = 70 (age 94)
- Frailty affects earnings through five channels:
- 1. Survival rate
- 2. Out of pocket medical expenditures
- 3. Labor productivity proxied by hourly wages
- 4. Probability of successful DI application
- 5. Preferences disutility of work

> estimated outside model

calibrated using model

Details 1

Details

Stochastic process for frailty

- Estimate separate frailty process for each education group.
- To account for selection due to mortality, estimation is done using
 - auxiliary simulation model
 - simulated method of moments
- Assume positive fraction of people with zero frailty at age 25.
- Frailty remains zero w/ prob. P(age), becomes positive o/w
- If positive, log frailty is sum of
 - deterministic component: age poly
 - stochastic component: fixed effect, transitory shock, and AR(1) shock



Stochastic frailty process for high school graduates





Stochastic frailty process for high school graduates





Stochastic process for productivity

- By education, log productivity (wage) is sum of
 - deterministic component: age poly and linear frailty effect
 - stochastic component: fixed effect and AR(1) shock
- Frailty effects are estimated using dynamic panel system GMM estimator
- We correct for selection bias using procedure recommended by Al-Saddoon et al. (2019)
- Effect of an additional deficit on wage:

	HSD	HSG	COL
Before correction	-4.2%	-2.5%	none
After correction	-4.4%	-2.7%	none



Disutility of Work vs DI Probabilities: Identification Strategy

- DI probability and disutility of work parameters calibrated using the model
- Calibration targets:
 - DI recipiency rates by age and frailty for ages 25 to 64
 - Labor force participation by age and frailty for ages 25 to 74
 - DI acceptance rate by year since initial application.
- Idea: DI process does not directly affect labor supply after age 65
 - Dispersion in LFPR's by frailty after age 65 pin down frailty effect on work disutility

DI and LFP by Age and Frailty: Model vs Data



DI and LFP by Age and Frailty: Model vs Data



DI acceptance rate: Model vs. Data



• Data source: French and Song (2014)

Hosseini, Kopecky & Zhao

Parameter	Description	Value
κ_0	level	50
κ_1	elasticity w.r.t. frailty	5.0
κ_2	elasticity w.r.t. 'number of attempts'	0.1
ϕ_0	level	1.59
ϕ_1	frailty level effect	1.2
ϕ_2	elasticity w.r.t frailty	3.0

• DI prob. $\theta(f, n_a) = \min\{1, \kappa_0 f^{\kappa_1} n_a^{\kappa_2}\} \uparrow \text{ in frailty and } \downarrow \text{ in } \# \text{ of attempts.}$

• Disutility from work $v(f) = \phi_0 \left(1 + \phi_1 f^{\phi_2} \right)$ is increasing and convex in frailty.

Assessment: DI and LFP by Education Groups

	HS Dropout	HS Graduates	Col Graduates
Data	9.6	5.0	1.4
Model	10.3	5.8	1.0

Table: DI recipiency rate (%), ages 25–64

Table: LFPR (%), ages 25-64

	HS Dropout	HS Graduates	Col Graduates
Data	78	87	93
Model	77	86	94

The model matches levels and patterns of DI recipiency and LFP by education.

Hosseini, Kopecky & Zhao

Assessment: % on DI by Frailty and Age





Assessment: % on DI by Frailty and Age





Assessment: LFP by Frailty and Age





Hosseini, Kopecky & Zhao

How Important is Health Inequality for Lifetime Earnings Inequality?

Assessment: LFP by Frailty and Age





How Important is Health Inequality for Lifetime Earnings Inequality?

Quantitative Exercise

Quantitative Exercise

- We use the model to run the following counterfactual experiment
- Give everyone the same (average) frailty profile
- What is the impact on lifetime earnings inequality?
- Lifetime earnings at each age = sum of all earnings up to that age

Lifetime earnings inequality by age: Variance of log





Lifetime earnings inequality by age: Variance decomposition

	Age 45	Age 55	Age 65	Age 75
Benchmark	0.384	0.438	0.437	0.405
No frailty heterogeneity $ riangle \downarrow 12.9\%$	0.335 26.8%	0.321 28.9%	0.311 21.1%	0.320
No frailty fixed effect $\bigtriangleup \downarrow$	0.343 10.7%	0.349 20.4%	0.349 20.1 %	0.369 8.8%
No frailty shock $\bigtriangleup \downarrow$	0.355 7.7%	0.394 10.0%	0.382 12.5%	0.379 6.4%

- ex ante heterogeneity in frailty dominates at younger ages
- frailty shocks dominates at older ages

Lifetime earnings inequality by age: Ratios



Impact is concentrated in the bottom of the lifetime earnings distribution

Quantitative Model Results: Decomposition

- How important are each of the 5 channels through which health affects individuals?
 - 1. Probability of getting DI
 - 2. Labor productivity
 - 3. Disutility
 - 4. Medical expenses
 - 5. Survival probability
- To assess the importance of each channel:
 - Run 5 counterfactuals
 - Counterfactual 1: Equivalent to baseline except probability of DI is determined by average frailty profile.
 - And so on...

Computational Experiments: Decomposition

Table: Effect of removing frailty variation in each channel on the variance of log lifetime earnings

	age 45	age 55	age 65	age 75
1. DI channel	$\uparrow 5.1\%$	$\downarrow 8.1\%$	$\downarrow 15.5\%$	$\downarrow 14.9\%$
2. Labor prod channel	↓ 5.6%	↓ 7.5%	↓ 8.3%	↓ 4.9%
3. Disutility channel	$\downarrow 1.6\%$	$\downarrow 1.9\%$	↓ 2.3	$\downarrow 1.6\%$
4. Med exp channel	↓ 0.4%	$\downarrow 0.1\%$	↓ 0.3%	$\downarrow 0.1\%$
5. Surv prob channel	$\downarrow 2.1\%$	$\downarrow 1.0\%$	\uparrow 7.9%	\uparrow 7.0%

• These three channels are least important.

Computational Experiments: Decomposition

Table: Effect of removing frailty variation in each channel on the variance of log lifetime earnings

	age 45	age 55	age 65	age 75
1. DI channel	$\uparrow 5.1\%$	$\downarrow 8.1\%$	$\downarrow 15.5\%$	$\downarrow 14.9\%$
2. Labor prod channel	↓ 5.6%	↓ 7.5%	↓ 8.3%	↓ 4.9%
3. Disutility channel	$\downarrow 1.6\%$	$\downarrow 1.9\%$	↓ 2.3	$\downarrow 1.6\%$
4. Med exp channel	↓ 0.4%	$\downarrow 0.1\%$	$\downarrow 0.3\%$	$\downarrow 0.1\%$
5. Surv prob channel	$\downarrow 2.1\%$	$\downarrow 1.0\%$	\uparrow 7.9%	\uparrow 7.0%

• Removing DI channel increases inequality at younger ages and decreases it at older ages

Table: Effect of removing frailty variation in each channel on the variance of log lifetime earnings

	age 45	age 55	age 65	age 75
1. DI channel	$\uparrow 5.1\%$	$\downarrow 8.1\%$	$\downarrow 15.5\%$	$\downarrow 14.9\%$
2. Labor prod channel	↓ 5.6%	↓ 7.5%	↓ 8.3%	↓ 4.9%
3. Disutility channel	$\downarrow 1.6\%$	$\downarrow 1.9\%$	↓ 2.3	$\downarrow 1.6\%$
4. Med exp channel	↓0.4%	$\downarrow 0.1\%$	↓ 0.3%	$\downarrow 0.1\%$
5. Surv prob channel	$\downarrow 2.1\%$	$\downarrow 1.0\%$	\uparrow 7.9%	\uparrow 7.0%

- Removing DI channel increases inequality at younger ages and decreases it at older ages
- Removing productivity channel reduces lifetime earnings inequality at all ages

LFP of Highly Frail in Counterfactural Economies



• Without DI channel:

- Frail individuals won't qualify for SSDI w/ high prob \Rightarrow Highly frail old's LFP \uparrow
- Less incentive to work w/ young to accumulate SSDI credits \Rightarrow Highly frail young's LFP \downarrow

LFP of Highly Frail in Counterfactural Economies



• Without productivity channel:

- Wages of highly frail non-college $\uparrow \Rightarrow$ Highly frail LFP \uparrow at all ages



Inequality in lifetime disposable income: Variance of log



	Age 45	Age 55	Age 65	Age 75
Benchmark	0.275	0.306	0.303	0.304
No frailty heterogeneity	0.244	0.256	0.259	0.254
$\bigtriangleup \downarrow$	11.5%	16.1 %	14.7%	16.5%

Alternative Inequality Measure

Inequality in lifetime disposable income by age: Variance of Log

	Age 45	Age 55	Age 65	Age 75
Benchmark	0.275	0.306	0.303	0.304
No frailty heterogeneity	0.244	0.256	0.259	0.254
$\bigtriangleup \downarrow$	11.5%	16.1 %	14.7%	16.5%
No frailty shock	0.263	0.286	0.288	0.293
$\bigtriangleup \downarrow$	4.5%	6.4%	4.9%	3.7%
No frailty fixed effect	0.269	0.296	0.292	0.294
$\bigtriangleup \downarrow$	2.3%	3.1%	3.8%	3.4%

• Effect is mainly due to frailty shocks after age 45

Welfare effects of eliminating the SSDI program

• SSDI contributes to \uparrow inequality. Should we eliminate it?
Welfare effects of eliminating the SSDI program

- SSDI contributes to \uparrow inequality. Should we eliminate it?
- No, removing DI program reduces ex-ante welfare.

	Average	HSD	HSG	COL
No DI program (PE)	-0.46%	-1.55%	-0.83%	0.63%
no benefits or DI payroll taxes				
No DI program (GE),	-0.73%	-1.79%	-1.10%	0.34%
prop. increase in income taxes				
No DI program (GE),	-0.98%	-2.55%	-1.36%	0.32%
reduction of consumption floor				

Table: Ex-ante welfare changes (% of lifetime consumption)

Conclusion

- Document empirically:
 - large response of earnings to incremental changes in frailty: mostly driven by participation
 - wage effects for less educated workers
- Results from structural model:
 - health inequality accounts for approximately 29% of lifetime earnings inequality at age 75
 - increased access to SSDI when health is poor plays an important role
- Work in progress:
 - welfare implications of expanding/contracting SSDI

Back Up Slides

LFP in Counterfactural Economies



- LFP effects of removing frailty inequality are small in healthy half of distribution
- Without DI channel: LFP is lower at young ages and higher at older ages
- Without productivity channel: LFP of highly frail is higher at all ages



Computational Experiments: Aggregate Effects

	NFH in	NFH in	NFH in	NFH in	NFH in	NFH in
	model	SSDI	Disutility	Labor prod.	Med. Exp.	Mortality
		%	change rela	ative to benchr	mark	
GDP	2.03	1.06	1.12	0.33	0.14	-0.56
Consumption	0.95	0.50	0.90	0.10	0.10	-1.41
Capital	2.03	1.06	1.12	0.33	0.14	-0.56
Labor input	2.03	1.06	1.12	0.33	0.14	-0.56
Hours	3.61	0.98	1.41	0.81	0.19	-0.32
GDP per Hour	-1.53	0.08	-0.29	-0.47	-0.05	-0.24

Note: NFH: no frailty heterogeneity.

- Removing frailty heterogeneity increases GDP per capita
- Effect of higher LFP larger than effect of lower mortality

Frailty-Earnings Correlation by Age





Frailty Correlations by Age





Gerontology Literature

- Mitnitski et al. (2001); Mitnitski et al. (2002)
- Mitnitski et al. (2005); Goggins et al. (2005)
- Searle et al. (2008); Yang and Lee (2010)
- Woo et al. (2005); Rockwood and Mitnitski (2007)
- Rockwood et al. (2007); Mitnitski et al. (2004)
- Kulminski et al. (2007a); Kulminksi et al. (2007b)



Frailty and SRHS over the Life Cycle



- Area shows share reporting each SRHS at each age.
- We partition frailty distribution at each age.
- Choose cutoffs to match dist. of SRHS at 25-29.
- Hold cutoffs fixed.

Health declines faster after age 50 when measured by frailty

▶ Go Bacl

Frailty and SRHS over the Life Cycle





Probit: Becoming a DI recipient (HRS)

			Panel A	. Everyone			Panel B. Po	Panel B. Poor health in $t-1$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)		
$frailty_{t-1}$			7.937***	7.886***	6.456***	6.549*** (0.301)	5.375***	5.573***		
$frailty_{t-1}^2$			-5.571*** (0.395)	-5.628*** (0.404)	-4.820*** (0.415)	-4.953*** (0.423)	-3.350*** (0.525)	-3.602*** (0.534)		
very $good_{t-1}$	0.087 (0.051)	0.082 (0.052)	(****)		-0.081 (0.054)	-0.071 (0.055)		(****)		
$good_{t-1}$	0.473*** (0.047)	0.438*** (0.048)			0.052 (0.052)	0.042 (0.053)				
$fair_{t-1}$	1.060*** (0.046)	0.994*** (0.048)			0.348*** (0.054)	0.324*** (0.055)				
poor _{t-1}	1.722*** (0.050)	1.635*** (0.051)			0.647*** (0.060)	0.609*** (0.061)				
Controls	NO	YES	NO	YES	NO	YES	NO	YES		
Observations	69,438	69,438	69,438	69,438	69,438	69,438	14,450	14,450		
Pseudo R ²	0.162	0.181	0.222	0.239	0.239	0.254	0.108	0.123		



Probit: Becoming a DI recipient (PSID)

			Panel A	. Everyone			Panel B. P	oor health in $t-1$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$frailty_{t-1}$			6.880*** (0.347)	6.103*** (0.364)	4.844*** (0.375)	4.366*** (0.389)	3.948*** (0.537)	3.600*** (0.555)
$frailty_{t-1}^2$			-5.807*** (0.62)	-5.055*** (0.637)	-4.548*** (0.661)	-4.006*** (0.673)	-2.673** (0.878)	-2.245* (0.894)
very $good_{t-1}$	0.146* (0.074)	0.112 (0.076)			0.061 (0.077)	0.052 (0.078)		
$good_{t-1}$	0.621*** (0.068)	0.525*** (0.071)			0.436*** (0.071)	0.386*** (0.073)		
$fair_{t-1}$	1.220*** (0.07)	1.059*** (0.072)			0.876*** (0.074)	0.788*** (0.076)		
$poor_{t-1}$	1.903*** (0.078)	1.689*** (0.081)			1.365*** (0.085)	1.247*** (0.087)		
Controls	NO	YES	NO	YES	NO	YES	NO	YES
Observations	44,837	44,837	44,837	44,837	44,837	44,837	5,915	5,915
Pseudo R ²	0.165	0.192	0.143	0.173	0.211	0.226	0.067	0.082



Probit: Becoming a DI recipient - under 45 only (PSID)

			Panel A.	Everyone			Panel B. P	oor health in $t-1$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$frailty_{t-1}$			6.486*** (0.579)	6.066*** (0.599)	4.784*** (0.617)	4.637*** (0.632)	3.652*** (0.954)	3.921*** (0.981)
$frailty_{t-1}^2$			-4.483*** (1.076)	-4.101*** (1.097)	-3.375** (1.12)	-3.250** (1.136)	-1.231 (1.593)	-1.57 (1.617)
very $good_{t-1}$	0.093 (0.097)	0.079 (0.1)			0.006 (0.1)	0.008 (0.102)		
$good_{t-1}$	0.413*** (0.091)	0.335*** (0.095)			0.226* (0.096)	0.18 (0.098)		
$fair_{t-1}$	1.125*** (0.093)	1.006*** (0.097)			0.770*** (0.101)	0.697*** (0.103)		
$poor_{t-1}$	1.614*** (0.123)	1.494*** (0.126)			0.989*** (0.137)	0.917*** (0.139)		
Controls	NO	YES	NO	YES	NO	YES	NO	YES
Observations	24,304	24,304	24,304	24,304	24,304	24,304	2,440	2,440
Pseudo R ²	0.133	0.156	0.145	0.17	0.193	0.209	0.094	0.109

			Panel A	. Everyone			Panel B. P	oor health in $t-1$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$frailty_{t-1}$			4.096***	3.213***	3.443***	2.278***	0.780***	0.820***
$frailty_{t-1}^2$			(0.110) -2.383*** (0.152)	(0.122) -1.676*** (0.164)	(0.121) -1.881*** (0.159)	(0.132) -1.055*** (0.171)	(0.167) 0.677** (0.209)	(0.181) 0.516* (0.223)
$very\;good_{t-1}$	0.151*** (0.023)	0.097*** (0.026)	(0.132)	(0.104)	0.045	(0.040) (0.026)	(0.209)	(0.225)
$good_{t-1}$	0.405***	(0.020) 0.308^{***} (0.025)			0.150*** (0.023)	(0.020) 0.164^{***} (0.026)		
$fair_{t-1}$	0.698***	(0.025)			0.226***	0.298***		
$poor_{t-1}$	1.004*** (0.024)	(0.027) (0.027)			0.282*** (0.028)	0.463*** (0.030)		
Controls	NO	YES	NO	YES	NO	YES	NO	YES
Observations	167,851	167,851	167,851	167,851	167,851	167,851	49,105	49,105
Pseudo R ²	0.049	0.180	0.088	0.191	0.090	0.196	0.024	0.130



Probit: Entering Nursing Home

			Panel A	. Everyone			Panel B. P	oor health in $t-1$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$frailty_{t-1}$			4.588***	3.458***	5.019***	3.374***	1.604***	1.125***
$frailty_{t-1}^2$			(0.212) -2.710*** (0.278)	(0.245) -1.497*** (0.311)	(0.232) -3.007*** (0.292)	(0.262) -1.522*** (0.322)	(0.298) 0.103 (0.361)	(0.341) 0.667 (0.403)
very $good_{t-1}$	0.130**	0.077	(0.270)	(0.511)	-0.030	-0.011	(0.001)	(0.400)
$good_{t-1}$	(0.042) 0.298***	(0.050) 0.198***			(0.045) -0.085	(0.052) -0.027		
$fair_{t-1}$	(0.040) 0.535***	(0.048) 0.421***			(0.045) -0.151**	(0.051) 0.001		
	(0.040) 0.800***	(0.048) 0.742***			(0.047) -0.196***	(0.054) 0.088		
poor t-1	(0.043)	(0.051)			(0.052)	(0.058)		
Controls	NO	YES	NO	YES	NO	YES	NO	YES
Observations	149,230	149,230	149,230	149,230	149,230	149,230	43,478	43,478
Pseudo R ²	0.035	0.222	0.120	0.261	0.121	0.262	0.046	0.197
► Go Back								

Why use frailty index?



Lots of action in the tails: need for finer grid.



Summary Statistics for PSID Sample

	2002	2004	2006	2008	2010	2012	2014	2016	Pooled 2002-2016
Panel A: Mean (median) [standard	deviation] of :	sample charact	teristics						
Age	44.33	44.28	44.34	44.58	44.74	45.02	45.4	45.54	44.65
	(43)	(43)	(43)	(43)	(43)	(43)	(43)	(42)	(43)
	[15.24]	[15.53]	[15.67]	[15.8]	[16.01]	[16.08]	[16.04]	[15.99]	[15.71]
Frailty	0.1	0.1	0.11	0.11	0.12	0.12	0.12	0.12	0.11
	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.1)	(0.07)	(0.07)
	[0.1]	[0.11]	[0.11]	[0.11]	[0.12]	[0.12]	[0.12]	[0.12]	[0.12]
Annual Earnings	\$35,623.31	\$35,992.43	\$36,313.91	\$36,712.28	\$33,658.89	\$34,072.19	\$33,635.38	\$35,303.67	\$35,095.34
	(27,231.43)	(27,247.63)	(27,474.38)	(26,544.91)	(22,987.3)	(23,000)	(23,339.49)	(24,978.14)	(25,564.01)
	[68,179.23]	[63,875.82]	[62,243.45]	[74,320.19]	[57,064.71]	[87,518.92]	[65,135.22]	[51,803.91]	[64,377.99]
Annual Hours	1,531.6	1,528.01	1,517.57	1,448.99	1,377.42	1,411.74	1,434.46	1,471.19	1,476.92
	(1,888)	(1,880)	(1,880)	(1,813.5)	(1,700)	(1,783)	(1,814)	(1,872)	(1,840.5)
	[1,035.63]	[1,049.47]	[1,042.58]	[991.18]	[1,033.49]	[1,045.86]	[1,057.89]	[1,059.13]	[1,037.86]
Hourly Wage	\$23.43	\$24.31	\$24.35	\$24.76	\$24.14	\$23.59	\$23.11	\$24.03	\$23.78
	(17.67)	(17.77)	(17.67)	(18.74)	(17.76)	(17)	(17.23)	(18)	(17.68)
	[37.64]	[57.69]	[61.27]	[36.63]	[29.94]	[40.69]	[31.39]	[28.38]	[40.52]
Panel B: Fraction of sample by cha	racteristics								
$ \begin{array}{c} Male \\ +\Delta \ Frailty \\ -\Delta \ Frailty \\ Observations \ (N) \\ \# \ of Individuals \ (n) \\ Average \ \# \ of Years \ Observed \ (T) \end{array} $	0.46 - - 11,777	0.46 0.3 0.13 12,210	0.46 0.33 0.13 12,727	0.46 0.32 0.13 13,177	0.46 0.3 0.14 13,473	0.46 0.29 0.14 13,524	0.46 0.28 0.14 13,294	0.46 0.29 0.14 14,092	0.46 0.3 0.14 104,274 21,024 4.86



Summary Statistics for PSID Sample

D	device in all of											
Panel A: Mean (median) [standard deviation] of sample characteristics												
Age	44.33	44.28	44.34	44.58	44.74	45.02	45.4	45.54	44.65			
	[15.24]	[15.53]	[15.67]	[15.8]	[16.01]	[16.08]	[16.04]	[15.99]	[15.71]			
Frailty	0.1	0.1	0.11	0.11	0.12	0.12	0.12	0.12	0.11			
	[0.1]	[0.11]	[0.11]	[0.11]	[0.12]	[0.12]	[0.12]	[0.12]	[0.12]			
Annual Earnings	\$35,623.31	\$35,992.43	\$36,313.91	\$36,712.28	\$33,658.89	\$34,072.19	\$33,635.38	\$35,303.67	\$35,095.34			
	[68,179.23]	[63,875.82]	[62,243.45]	[74,320.19]	[57,064.71]	[87,518.92]	[65,135.22]	[51,803.91]	[64,377.99]			
Annual Hours	1,531.6	1,528.01	1,517.57	1,448.99	1,377.42	1,411.74	1,434.46	1,471.19	1,476.92			
	[1,035.63]	[1,049.47]	[1,042.58]	[991.18]	[1,033.49]	[1,045.86]	[1,057.89]	[1,059.13]	[1,037.86]			
Hourly Wage	\$23.43	\$24.31	\$24.35	\$24.76	\$24.14	\$23.59	\$23.11	\$24.03	\$23.78			
	[37.64]	[57.69]	[61.27]	[36.63]	[29.94]	[40.69]	[31.39]	[28.38]	[40.52]			
Panel B: Fraction of sample by cha	racteristics											
High School Dropouts (HSD) High School Graduates (HS) College Graduates (CL) +∆ Frailty −∆ Frailty Observations (N) # of Individuals (n)	0.46 15.16 55.76 29.08 - - 11,777	0.46 14.92 55.19 29.89 0.3 0.13 12,210	0.46 14.28 55.04 30.68 0.33 0.13 12,727	0.46 13.96 54.89 31.15 0.32 0.13 13,177	0.46 13.9 54.43 31.67 0.3 0.14 13,473	0.46 13.91 54.09 32 0.29 0.14 13,524	0.46 13.61 54.32 32.07 0.28 0.14 13,294	0.46 13.89 53.7 32.41 0.29 0.14 14,092	0.46 14.58 54.88 30.55 0.3 0.14 104,274 21,024			



Hosseini, Kopecky & Zhao

Summary Statistics for Dynamic Panel Sample

	2002	2004	2006	2008	2010	2012	2014	2016	Pooled 2002-2016
Panel A: Mean (median) [standard	deviation] of	sample charac	teristics						
Age	40.75	41.2	41.73	42.36	42.97	43.77	45.64	47.53	42.65
	(41)	(42)	(42)	(42)	(42)	(42)	(44)	(46)	(42)
	[11.11]	[11.77]	[12.33]	[12.85]	[13.34]	[13.7]	[13.7]	[13.69]	[12.72]
Frailty	0.08	0.09	0.10	0.10	0.11	0.11	0.12	0.13	0.11
	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.10)	(0.10)	(0.07)
	[0.09]	[0.09]	[0.1]	[0.1]	[0.11]	[0.11]	[0.12]	[0.12]	[0.11]
Annual Earnings	\$39,913.5	\$39,951.17	\$39,779.58	\$39,670.04	\$36,294.58	\$36,659.7	\$36,554.79	\$38,088.25	\$38,526.71
	(30,944.81)	(30,446.27)	(30,277.88)	(29,730.3)	(26,121.94)	(25,100)	(26,256.93)	(27,860.24)	(29,174.36)
	[73,161.16]	[68,148.32]	[65,088.35]	[77,401.9]	[58,809.46]	[92,687.86]	[70,310.25]	[56,168.13]	[68,482.15]
Annual Hours	1,698.71	1,675.51	1,647.33	1,550.34	1,466.27	1,492.25	1,495.81	1,482.53	1,590.6
	(1,960)	(1,960)	(1,944)	(1,880)	(1,820)	(1,856)	(1,872)	(1,888)	(1,920)
	[965.19]	[990.17]	[989.62]	[949.76]	[1,011.75]	[1,030.75]	[1,051.32]	[1,064.97]	[999.24]
Hourly Wage	\$22.84	\$23.27	\$23.03	\$24.38	\$24.01	\$23.27	\$23.67	\$25.27	\$23.50
	(17.84)	(17.94)	(17.74)	(18.96)	(18.09)	(17.56)	(18.04)	(18.89)	(18.06)
	[25.85]	[28.3]	[23.46]	[27.15]	[26.59]	[25.73]	[23.07]	[26.81]	[25.37]
Panel B: Fraction of sample by cha	racteristics								
Male High School Dropouts (HSD) High School Graduates (HS) College Graduates (CL) +∆ Frailty —∆ Frailty Observations (N) # of Individuals (n)	0.45 13.47 55.62 30.91 - 9,665	0.45 13.31 55.06 31.63 0.28 0.13 10,100	0.45 13.06 54.56 32.39 0.32 0.13 10,647	0.45 13.02 54.33 32.66 0.3 0.13 11,174	0.45 13.04 53.97 32.99 0.28 0.13 11,536	0.45 13.04 53.47 33.48 0.28 0.13 11,663	0.44 13.12 53.49 33.39 0.27 0.14 10,809	0.44 12.86 53.42 33.72 0.27 0.14 10,206	0.45 13.21 54.51 32.28 0.13 85,800 14,269

→ Go Back

Summary Statistics for Dynamic Panel Sample, Workers

	2002	2004	2006	2008	2010	2012	2014	2016	Pooled 2002-2016
Panel A: Mean (median) [standard	deviation] of	sample charac	teristics						
Age	38.69	38.95	39.39	39.77	40.14	40.66	42.42	44.34	40.10
	(39)	(39)	(39)	(39)	(39)	(39)	(40)	(42)	(39)
	[9.61]	[10.26]	[10.79]	[11.33]	[11.83]	[12.13]	[12.1]	[12.14]	[11.19]
Frailty	0.06	0.06	0.07	0.07	0.08	0.08	0.09	0.09	0.08
	(0.04)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)
	[0.06]	[0.06]	[0.06]	[0.07]	[0.07]	[0.07]	[0.08]	[0.08]	[0.07]
Annual Earnings	51,857.65	53,167	53876.26	54,826.77	52,899.68	54,881.27	55,503.18	58,201.99	53,757.76
	(39609.35)	(41,463.79)	(41,491.91)	(42,471.86)	(41,585.08)	(40,000)	(42,789.07)	(45,152.8)	(41,463.79)
	[84,044.28]	[64,951.95]	[59,016.86]	[63,531.05]	[64,581.51]	[120,948.31]	[87,450.06]	[64,377.8]	[75,912]
Annual Hours	2124.32	2140.36	2122.89	2034.56	2037.7	2081.94	2106.28	2096.56	2095.49
	(2065.5)	(2080)	(2064)	(2000)	(2024)	(2040)	(2050)	(2056)	(2040)
	[654.65]	[671.24]	[649.82]	[593.82]	[637.21]	[642.07]	[634.54]	[645.84]	[639.66]
Hourly Wage	23.9	24.72	24.72	26.35	25.57	25.31	26.02	27.78	25.29
	(19.06)	(19.35)	(19.42)	(20.42)	(19.8)	(19.32)	(19.98)	(21.52)	(19.67)
	[22.37]	[27.64]	[22.21]	[27.6]	[25.85]	[27.99]	[24.33]	[26.21]	[25.09]
Panel B: Fraction of sample by cha	aracteristics								
Male High School Dropouts (HSD) High School Graduates (HS) College Graduates (CL) +∆ Frailty	0.54 8.82 50.35 40.82	0.54 8.02 49.77 42.21 0.24	0.54 7.28 49.47 43.25 0.28	0.54 6.84 49.27 43.89 0.26	0.54 6.68 49.46 43.86 0.23	0.54 6.59 48.99 44.42 0.24	0.53 6.64 48.89 44.48 0.23	0.53 6.5 48.87 44.63 0.23	0.54 7.4 49.61 42.99 0.24
−∆ Frailty Observations (N) # of Individuals (n) _Average # of Years Observed (T)	- 4794	0.11 4937	0.10 5237	0.10 5557	0.11 5869	0.11 6119	0.10 5742	0.11 5355	0.10 43610 7,539 5.78

• Go Back

Blundell-Bond System GMM Estimation

- In short panels, fixed effect estimator biases can be large (Nickell (1981 ECTA))
- Follow Blundell-Bond (1998, JoEtrics), we estimate the following using GMM

$$\begin{bmatrix} y_{i,t} \\ \Delta y_{i,t} \end{bmatrix} = \gamma \begin{bmatrix} f_{i,t} \\ \Delta f_{i,t} \end{bmatrix} + \alpha_1 \begin{bmatrix} y_{i,t-1} \\ \Delta y_{i,t-1} \end{bmatrix} + \alpha_2 \begin{bmatrix} y_{i,t-2} \\ \Delta y_{i,t-2} \end{bmatrix} \\ + \delta \begin{bmatrix} \mathbf{Z}_{i,t} \\ \Delta \mathbf{Z}_{i,t} \end{bmatrix} + \begin{bmatrix} \varepsilon_{i,t} \\ \Delta \varepsilon_{i,t} \end{bmatrix}$$

- Full sample:
 - Use $f_{i,t-k}$, $y_{i,t-k}$, k = 4, 5, 6 as instruments for differences
 - Use $\Delta f_{i,t-k}$, $\Delta y_{i,t-k}$, k = 4, 5, 6 as instruments for levels
- Workers k = 5, 6, 7 and frailty (reverse causality) k = 6, 7, 8
- Use system estimator because earnings and frailty are close to random walk 🔽 Go Back

Blundell-Bond System GMM Estimation

- For our instruments to be valid is must be that:
 - lagged levels are uncorrelated with current error term.
 - correlation between endogenous variables and the unobserved (fixed) effect is constant over time.
- To check these assumptions we run the following tests:
 - AR(1) test for no ser corr in error terms (of diff eqn): this should be rejected (by construction)
 - AR(2) test for no second-order ser corr in error terms (of diff eqn): this should not be rejected
 - Hansen test for validity of level instruments: this should not be rejected
 - Diff-in-Hansen test for validity of diff instruments: this should not be rejected
- Also do additional robustness checks.



Dynamic Panel Additional Robustness Checks

- Perform Diff-in-Hansen test on y-lag set only.
- Check that estimates lie in expected range based on OLS and FE.
- Run F-tests of instrument power.
- Conduct robustness tests to instrument set.

Effect of Frailty on Earnings Full Set of Diagnostic Tests

		Ev	eryone			Workers				
	(1)	(2) By Educ	(3) By Health	(4) By Age	(5)	(6) By Educ	(7) By Health	(8) By Age		
AR(1) test (p-value)	0.455	0.319	0.497	0.104	0.030	0.010	0.021	0.008		
AR(2) test (p-value)	0.380	0.474	0.298	0.949	0.130	0.082	0.138	0.160		
Hansen test (<i>p</i> -value)	0.796	0.132	0.826	0.752	0.434	0.826	0.543	0.465		
Diff-in-Hansen test (p-value)	0.652	0.360	0.827	0.464	0.255	0.484	0.259	0.214		
Diff-in-Hansen test (p-value), Y-lag set	0.796	0.516	0.960	0.479	0.434	0.388	0.283	0.249		
Starting IV Lag t-k (k=)	4	4	4	4	5	5	5	5		
Ending IV Lag t-k $(k=)$	5	5	5	5	6	6	6	6		



Dynamic Panel Additional Robustness Checks

- Perform Diff-in-Hansen test on y-lag set only.
- Check that estimates lie in expected range based on OLS and FE.
- Run F-tests of instrument power.
- Conduct robustness tests to instrument set.

Effect of Frailty on Earnings

		Everyone			Workers			
	OLS	FE	SYS-GMM	OLS	FE	SYS-GMM		
$\log(earnings_{t-1})$	0.564***	0.206***	0.283	0.555***	0.098***	1.474***		
	(0.006)	(0.004)	(0.364)	(0.013)	(0.006)	(0.509)		
$\log(earnings_{t-2})$	0.188***	-0.021***	0.396	0.240***	-0.031***	-0.640		
	(0.006)	(0.005)	(0.298)	(0.012)	(0.006)	(0.454)		
$frailty_t$	-4.973***	-8.818***	-5.374***	-0.519***	-0.471***	-0.978**		
	(0.138)	(0.235)	(1.653)	(0.044)	(0.084)	(0.447)		
Observations R^2	64,965 0.580	64,965 0.432	64,965	34,274 0.601	34,274 0.080	34,274		



Effect of Frailty on Earnings – Young vs Old

		Everyone			Workers	
	OLS	FE	SYS-GMM	OLS	FE	SYS-GMM
$\log(earnings_{t-1})$	0.564***	0.206***	0.628**	0.555***	0.098***	1.127***
	(0.006)	(0.004)	(0.291)	(0.013)	(0.006)	(0.302)
$\log(earnings_{t-2})$	0.188***	-0.021***	0.115	0.241***	-0.031***	-0.308
	(0.006)	(0.005)	(0.239)	(0.012)	(0.006)	(0.273)
$frailty_t \times Young$	-4.870***	-8.547***	-4.992***	-0.660***	-0.483***	-1.650**
	(0.202)	(0.297)	(1.784)	(0.061)	(0.099)	(0.673)
$frailty_t \times Old$	-5.034***	-8.943***	-4.030***	-0.376***	-0.463***	-0.293
	(0.161)	(0.249)	(1.317)	(0.054)	(0.091)	(0.365)
Observations R^2	64,965 0.580	64,965 0.433	64,965	34,274 0.601	34,274 0.080	34,274

Effect of Frailty on Earnings – Education

		Lveryone		Workers			
	OLS	FE	SYS-GMM	OLS	FE	SYS-GMM	
$\log(earnings_{t-1})$	0.560***	0.206***	0.370	0.544***	0.097***	1.371***	
	(0.006)	(0.004)	(0.319)	(0.013)	(0.006)	(0.400)	
$\log(earnings_{t-2})$	0.183***	-0.022***	0.318	0.233***	-0.031***	-0.569	
	(0.006)	(0.005)	(0.259)	(0.011)	(0.006)	(0.356)	
$frailty_t \times HSD$	-6.143***	-8.533***	-6.269***	-1.340***	-0.742***	-1.846**	
	(0.213)	(0.526)	(1.777)	(0.111)	(0.254)	(0.807)	
$frailty_t \times HS$	-5.215***	-9.586***	-5.591***	-0.762***	-0.712***	-1.239***	
	(0.155)	(0.289)	(1.574)	(0.052)	(0.107)	(0.460)	
$frailty_t \times CL$	-3.003***	-6.900***	-2.519*	0.053	-0.014	-0.558	
	(0.209)	(0.457)	(1.402)	(0.053)	(0.132)	(0.484)	
Observations R ²	64,965 0.581	64,965 0.435	64,965	34,274 0.605	34,274 0.089	34,274	

Hosseini, Kopecky & Zhao

Effect of Frailty on Earnings – Good Health vs Bad Health

		Everyone			Workers	
	OLS	FE	SYS-GMM	OLS	FE	SYS-GMM
$\log(earnings_{t-1})$	0.564***	0.206***	0.220	0.555***	0.097***	1.293***
	(0.006)	(0.004)	(0.362)	(0.013)	(0.006)	(0.410)
$\log(earnings_{t-2})$	0.188***	-0.021***	0.444	0.240***	-0.031***	-0.498
	(0.006)	(0.005)	(0.297)	(0.012)	(0.006)	(0.377)
$frailty_t \times Good Health$	-3.076***	-6.816***	-1.930	-0.610***	-0.230*	-1.765
	(0.305)	(0.499)	(4.816)	(0.082)	(0.135)	(1.775)
$frailty_t \times Bad \; Health$	-4.818***	-8.607***	-5.207***	-0.522***	-0.446***	-0.963**
	(0.137)	(0.239)	(1.745)	(0.044)	(0.085)	(0.469)
Observations R ²	64,965 0.580	64,965 0.433	64,965	34,274 0.601	34,274 0.079	34,274

		Everyone			Workers			
	OLS	FE	SYS-GMM	OLS	FE	SYS-GMM		
$\log(hours_{t-1})$	0.554***	0.200***	0.399	0.332***	-0.027***	0.003		
	(0.006)	(0.004)	(0.322)	(0.008)	(0.006)	(0.345)		
$\log(hours_{t-2})$	0.180***	-0.028***	0.263	0.157***	-0.090***	0.304		
	(0.006)	(0.004)	(0.257)	(0.007)	(0.006)	(0.218)		
$frailty_t$	-3.626***	-6.655***	-3.887***	-0.175***	-0.442***	0.070		
	(0.100)	(0.172)	(1.188)	(0.028)	(0.056)	(0.246)		
Observations R^2	64,965 0.556	64,965 0.400	64,965	34,274 0.234	34,274 0.001	34,274		



Effect of Frailty on Hours – Young vs Old

		Everyone			Workers	
	OLS	FE	SYS-GMM	OLS	FE	SYS-GMM
$\log(hours_{t-1})$	0.554***	0.200***	0.669***	0.332***	-0.027***	0.382
	(0.006)	(0.004)	(0.257)	(0.008)	(0.006)	(0.318)
$\log(hours_{t-2})$	0.180***	-0.028***	0.048	0.157***	-0.090***	0.254
	(0.006)	(0.004)	(0.206)	(0.007)	(0.006)	(0.246)
$frailty_t \times Young$	-3.457***	-6.411***	-3.564***	-0.200***	-0.484***	-0.286
	(0.149)	(0.217)	(1.325)	(0.039)	(0.066)	(0.387)
$frailty_t \times Old$	-3.726***	-6.767***	-3.131***	-0.151***	-0.414***	0.144
	(0.116)	(0.182)	(0.936)	(0.036)	(0.060)	(0.259)
Observations R^2	64,965 0.556	64,965 0.401	64,965	34,274 0.234	34,274 0.001	34,274

Effect of Frailty on Hours – Education

		Everyone			Workers			
	OLS	FE	SYS-GMM	OLS	FE	SYS-GMM		
$\log(hours_{t-1})$	0.550***	0.200***	0.383	0.331***	-0.027***	0.074		
	(0.006)	(0.004)	(0.319)	(0.008)	(0.006)	(0.313)		
$\log(hours_{t-2})$	0.176***	-0.028***	0.269	0.156***	-0.091***	0.168		
	(0.006)	(0.004)	(0.253)	(0.007)	(0.006)	(0.221)		
$frailty_t \times HSD$	-4.433***	-6.526***	-4.770***	-0.403***	-0.942***	-0.533		
	(0.157)	(0.385)	(1.320)	(0.078)	(0.169)	(0.356)		
$frailty_t \times HS$	-3.732***	-7.241***	-4.303***	-0.189***	-0.440***	-0.033		
	(0.112)	(0.211)	(1.224)	(0.032)	(0.071)	(0.281)		
$frailty_t \times CL$	-2.380***	-5.119***	-2.219**	-0.092***	-0.311***	0.248		
	(0.150)	(0.334)	(1.118)	(0.035)	(0.088)	(0.254)		
Observations R^2	64,965 0.557	64,965 0.402	64,965	34,274 0.234	34,274 0.001	34,274		

Hosseini, Kopecky & Zhao

How Important is Health Inequality for Lifetime Earnings Inequality?

Effect of Frailty on Hours – Good Health vs Bad Health

		Everyone			Workers	
	OLS	FE	SYS-GMM	OLS	FE	SYS-GMM
$\log(hours_{t-1})$	0.553***	0.200***	0.386	0.332***	-0.027***	0.040
	(0.006)	(0.004)	(0.317)	(0.008)	(0.006)	(0.311)
$\log(hours_{t-2})$	0.180***	-0.028***	0.272	0.157***	-0.091***	0.282
	(0.006)	(0.004)	(0.253)	(0.007)	(0.006)	(0.219)
$frailty_t \times Good Health$	-1.957***	-5.137***	-2.216	-0.046	-0.292***	-0.060
	(0.222)	(0.365)	(3.455)	(0.049)	(0.090)	(0.910)
$frailty_t \times Bad \; Health$	-3.491***	-6.494***	-3.707***	-0.171***	-0.426***	0.026
	(0.099)	(0.175)	(1.242)	(0.028)	(0.056)	(0.258)
Observations R^2	64,965 0.556	64,965 0.402	64,965	34,274 0.234	34,274 0.001	34,274



		Eve	ryone		Workers			
	OLS	FE	SYS-GMM	OLS	FE	SYS-GMM		
$\log(wage_{t-1})$				0.525*** (0.010)	0.067*** (0.006)	0.212 (0.541)		
$\log(wage_{t-2})$				0.288*** (0.009)	-0.028*** (0.006)	0.532 (0.489)		
$frailty_t$				-0.378*** (0.037)	-0.028 (0.073)	-0.623** (0.263)		
Observations R^2*				34,170 0.592	34,170 0.056	34,170		



Hosseini, Kopecky & Zhao

How Important is Health Inequality for Lifetime Earnings Inequality?

	015	Eve FF	ryone SYS-GMM	015	Workers FF	SYS-GMM
$\log(wage_{t-1})$	010			0.525*** (0.010)	0.067*** (0.006)	0.511 (0.399)
$\log(wage_{t-2})$				0.289*** (0.009)	-0.029*** (0.006)	0.272 (0.359)
$frailty_t \times Young$				-0.481*** (0.050)	0.028 (0.086)	-1.106** (0.463)
$frailty_t \times Old$				-0.274*** (0.045)	-0.064 (0.079)	-0.414 (0.295)
Observations $R^{2}*$				34,170 0.592	34,170 0.055	34,170



Wage regression – Education

		Eve	ryone		Workers				
	OLS	FE	SYS-GMM	OLS	FE	SYS-GMM			
$\log(wage_{t-1})$				0.514*** (0.010)	0.067*** (0.006)	0.122 (0.368)			
$\log(wage_{t-2})$				0.279*** (0.009)	-0.029*** (0.006)	0.600* (0.328)			
$frailty_t \times HSD$				-1.040*** (0.102)	0.191 (0.222)	-1.854*** (0.616)			
$frailty_t \times HS$				-0.602*** (0.043)	-0.268*** (0.094)	-0.889*** (0.307)			
$frailty_t \times CL$				0.123*** (0.046)	0.298*** (0.116)	-0.216 (0.309)			
Observations R^2*				34,170 0.596	34,170 0.063	34,170			


Wage regression – Good Health vs Bad Health

	Everyone				Workers			
	OLS	FE	SYS-GMM	OLS	FE	SYS-GMM		
$log(wage_{t-1})$				0.525*** (0.010)	0.067*** (0.006)	0.303 (0.449)		
$\log(wage_{t-2})$				0.288*** (0.009)	-0.028*** (0.006)	0.461 (0.419)		
$frailty_t \times Good Health$				-0.561*** (0.071)	0.061 (0.118)	0.348 (1.685)		
$frailty_t \times Bad \ Health$				-0.384*** (0.037)	-0.019 (0.074)	-0.581* (0.332)		
Observations R ² *				34,170 0.592	34,170 0.055	34,170		



Hosseini, Kopecky & Zhao

How Important is Health Inequality for Lifetime Earnings Inequality?

Dynamic Panel Additional Robustness Checks

- Check that estimates lie in expected range based on OLS and FE.
- Run F-tests of instrument power.
- Conduct robustness tests to instrument set.

▶ Go Back

Effect of Frailty on Earnings – Education

Robustness to instrument set

	Everyone	Everyone	Everyone
$\log(earnings_{t-1})$	0.676*** (0.110)	0.370 (0.319)	0.055 (0.264)
$\log(earnings_{t-2})$	0.050 (0.046)	0.318 (0.259)	0.632*** (0.210)
$frailty_t \times HSD$	-5.133*** (1.809)	-6.269*** (1.777)	-5.772*** (2.050)
$frailty_t \times HS$	-5.009*** (1.610)	-5.591*** (1.574)	-6.532*** (1.876)
$frailty_t \times CL$	-3.237** (1.313)	-2.519* (1.402)	-3.125* (1.743)
AR(2) test (p-value)	0.156	0.474	0.024
Hansen test (p-value)	0.022	0.132	0.116
Diff-in-Hansen test (p-value)	0.015	0.360	0.151
Diff-in-Hansen test (p-value), Y-lag set	0.053	0.516	0.516
Starting IV Lag t-k (k=)	3	4	5
Ending IV Lag t-k (k=)	4	5	6



Effect of Frailty on Hours - Young v. Old

	Everyone		Wa	rkers
	(1)	(2)	(3)	(4)
$\log(hours_{t-1})$	0.399 (0.322)	0.669*** (0.257)	0.003 (0.345)	0.382 (0.318)
$\log(hours_{t-2})$	0.263 (0.257)	0.048 (0.206)	0.304 (0.218)	0.254 (0.246)
$frailty_t$	-1.144*** (1.044)		0.003 (0.009)	
$frailty_t \times Young \; (age \leq 45)$		-0.061*** (0.025)		-0.132** (0.049)
$frailty_t \times Old \; (age > 45)$		$egin{array}{c} -0.011^{***} \ (0.014) \end{array}$		-0.116 (0.035)
AR(1) test (p-value)	0.287	0.043	0.409	0.180
AR(2) test (<i>p</i> -value)	0.596	0.706	0.273	0.642
Hansen test (<i>p</i> -value)	0.971	0.811	0.060	0.051
Diff-in-Hansen test (p-value)	0.944	0.545	0.080	0.037
Note:		*p < 0.1;	** <i>p</i> < 0.05;	**** <i>p</i> < 0.01



Effect of Frailty on Wages of Workers - Young v. Old

	Workers		
	(1)	(2)	
$\log(wages_{t-1})$	0.212 (0.541)	0.511 (0.399)	
$\log(wages_{t-2})$	0.532 (0.489)	0.272 (0.359)	
frailty _t	-0.023** (0.010)		
$frailty_t \times Young$		-0.041** (0.017)	
$frailty_t \times Old$		-0.015 (0.011)	
AR(1) test (<i>p</i> -value)	0.651	0.362	
AR(2) test (<i>p</i> -value)	0.454	0.734	
Hansen test (<i>p</i> -value)	0.085	0.170	
Diff-in-Hansen test (p-value)	0.044	0.104	
Note:	*p < 0.1; **	p < 0.05; ***p < 0.01	



Estimation of Frailty Process: Deterministic Component

$$Prob(f_{i,t} = 0) = Probit(quad(t) + \nu_{i,t})$$

$$\begin{aligned} &\ln f_{i,t} = quartic(t) + R_{i,t}, \\ &R_{ij,} = \alpha_i + z_{ij} + u_{i,t}, \\ &z_{i,t} = \rho z_{i,t-1} + \varepsilon_{i,t}, \end{aligned}$$

- Run OLS to remove time effects
- Estimate zero frailty probit
- Estimate deterministic component of log frailty via SMM
- Calculate cohort-adjusted vars/covars of R_{i,t}
- Estimate process for $R_{i,t}$ using SMM
- Separate estimation for each educ group



Estimation of Frailty Process: Deterministic Component

	HS Dropout	HS Graduates	Col Graduates
age	1.26	0.988	0.999
	(0.095)	(0.030)	(0.064)
age^2	2.19	1.40	2.04
	(0.492)	(0.146)	(0.305)
age^3	-0.607	-1.39	-0.838
	(0.951)	(0.380)	(0.585)
age^4	3.03	8.77	3.05
	(0.636)	(0.307)	(0.403)
const.	-2.50	-2.57	-2.83
	(0.006)	(0.003)	(0.004)

Note: age is scaled so that age = (age-25)/100.



Estimation of Frailty Process: Stochastic Component

results of estimating the shock process

	HS Dropout	HS Graduates	Col Graduates
ρ	0.979	1.001	0.9690
	(0.002)	(0.001)	(0.002)
σ_{α}^2	0.2232	0.1542	0.1270
	(0.0107)	(0.005)	(0.0050)
σ_u^2	0.0368	0.0506	0.0357
	(0.0039)	(0.002)	(0.0023)
σ_{ε}^2	0.0286	0.0162	0.0250
	(0.0018)	(0.001)	(0.0012)



Stochastic frailty process for high school dropouts



• Mortality has little impact on the fraction at zero by age.



Stochastic frailty process for high school dropouts



- Deterministic age polynomial targets mean frailty by age in data.
- Stochastic component targets variance-covariance profile of frailty residuals.



Stochastic frailty process for high school dropouts



• Effects of mortality on mean and variance of frailty are large at older age.

▶ Go Back

Stochastic frailty process for college graduates



• Mortality has little impact on the fraction at zero by age.



Stochastic frailty process for college graduates



• Deterministic age polynomial targets mean frailty by age in data.

• Stochastic component targets variance-covariance profile of frailty residuals.



Stochastic frailty process for college graduates



• Effects of mortality on mean and variance of frailty are large at older age.

▶ Go Back

Calibration: What is done outside the model

- Utility parameters : γ and μ
- Technology parameters: capital share α , depreciation δ
- Job separation rate σ , return on asset r, pop. growth ν
- Tax progressivity τ , payroll tax rates (τ_{ss} , τ_{med}), capital tax τ_K
- SS and DI benefits, and minimum consumption \underline{c}
- The following processes
 - Stochastic processes for frailty and labor productivity
 - Out of pocket medical expenditures
 - Survival rates

Hosseini, Kopecky & Zhao

How Important is Health Inequality for Lifetime Earnings Inequality?







Calibration: Predetermined Parameters

D	D	N/ 1 /		
Parameter	Description	Values/source		
Demographics				
J	maximum age	70 (94 y/o)		
R	retirement age	41 (66 y/o)		
ν	population growth rate	0.02		
Preferences				
γ	curvature of utility function	2		
μ	weight on consumption	0.5		
	(implies CRRA of 1.5)			
Job Separation				
σ	annual layoffs/separations in JOLTS	0.15		
Technology				
α , δ , r	capital share, depreciation, return on assets	0.33, 0.07, 0.04		
Government	t policies			
au	tax progressivity (Guner et al (2014))	0.036		
$ au_{K}$	captial tax (Gomme and Rupert (2007)	0.3		
τ_{ss}, τ_{med}	payroll tax rates	0.124, 0.029		
<u>c</u>	minimum consumption (% of ave. earning)	11		
G	government purchases (% of GDP)	17.5		



Parametrization: Survival and OOP Med. Expenditure

• For survival: estimate (probit) - using HRS

 $s_{ij} =$ quad. poly. on age + quad. poly. on frailty + edu + gender

• For out of pocket medical expenditures: estimate - using MEPS

 $oop_{ii} = cubic poly.$ on age + cubic poly. on frailty

separate for each edu. & labor market status

• Education: HSD, HSG, CG

Labor market status: employed, non-employed and on Medicare, non-employed and not on Medicare

Step 1: exclusion restriction

- Following Low & Pistaferri (2014) assume "potential" government transfers have different work disincentives for people w/ different health levels.
 - These effects are captured by interactions
- We regress participation on
 - log wage (1 and 2 lags), lag of frailty interacted educ., poly. on age, year dummies
 - interaction term: state \times # of kids \times marital status \times frailty
 - fixed effect
- We use estimated fixed effects in step 2

Step 2: bias correction

- Follow: Al-Saddoon, Jimenez-Martin, & Labeaga (2019)
- Run log wage on
 - 2 lags of log wage
 - lag of frailty (treated exogenous given our earlier findings)
 - poly. on age + year dummies
 - edu. interaction w/ frailty
 - fixed effects estimated in step 1



Estimation of frailty effect

	w/o correction	w/ correction
$\log(wage_t - 1)$	1.044***	1.034***
	(0.298)	(0.295)
$\log(wage_t - 2)$	-0.263	-0.262
	(0.270)	(0.262)
$frailty_t \times HSD$	-0.042**	-0.044**
	(0.017)	(0.017)
$frailty_t \times HS$	-0.025***	-0.027***
	(0.009)	(0.009)
frailty $_t \times CL$	0.002	0.001
	(0.004)	(0.004)
selection term		0.076**
		(0.035)
Observations	23,874	23,755
AR(2) test (p-value)	0.182	0.163
Hansen test (p-value)	0.107	0.096
Diff-in-Hansen test (p-value)	0.307	0.417

▶ Go Back

Steps 3 and 4: estimating shock process

- Using results in step 2, remove effect of frailty
- Run the remainder (separate for college and non-college) on
 - poly. on age
 - year dummies
- Back out residuals
- Estimate a RIP process for residuals using GMM
- Sample: 25-74 year-old men in PSID



Step 3: Deterministic component estimates

	Non-college	Col Graduates
age	0.0535	0.181
	(0.0194)	(0.0323)
age^2	-0.0005	-0.0027
	(0.0004)	(0.0007)
age^3	5.25e-7	1.19e-5
	(3.0e-6)	(4.9e-6)
constant	1.830	-0.0334
	(0.286)	(0.4808)



Step 4: Shock process estimates

	Non-college	Col Graduates
var. of transitory shock	0.0824	0.1033
	(0.0115)	(0.0180)
var. of permanent shock	0.0165	0.0181
	(0.0049)	(0.0070)
var. of fixed effect	0.0920	0.0636
	(0.0145)	(0.0291)
persistence	0.9218	0.9805
	(0.0231)	(0.0125)



Comparison with Low & Pistaferri (2014)

- Low & Pistaferri (2014) estimate the effect of disability on wages
- They have three disability groups d = 0, 1, 2
 - d = 0: those with no work limitation
 - d = 2: those with severe work limitation
 - d = 1: the rest
- We calculate mean frailty for each of these categories in our sample
 - d = 0 has mean frailty of 0.068
 - d = 1 has mean frailty of 0.177
 - d = 2 has mean frailty of 0.285
- Now we can compute effects that are comparable to Low & Pistaferri (2014)

Table: Effect of disability on wages

	Low & Pistaferri (2014)	Our estimation
d = 1	-0.057	-0.110
d = 2	-0.177	-0.219

- Note Low and Pistaferri's estimates are based on non-college sample only.
- Our estimates are based on average effect for all education groups.

▶ Go Back

Robustness to Exogenous Frailty

Estimation of frailty effect (men only)

	ENDOGENOUS No Correction	ENDOGENOUS stateXkidsXmar	ENDOGENOUS +Xfrail	EXOGENOUS No Correction	EXOGENOUS stateXkidsXmar	EXOGENOUS +Xfrail
$\log(wage_t - 1)$	0.863*** (0.172)	0.859*** (0.170)	0.853*** (0.170)	1.044*** (0.298)	1.043*** (0.296)	1.034*** (0.295)
$\log(wage_t - 2)$	-0.093 (0.158)	-0.091 (0.161)	-0.088 (0.159)	-0.263 (0.270)	-0.274 (0.264)	-0.262 (0.262)
frail_hsd	-0.037 (0.024)	-0.039 (0.024)	-0.039 (0.024)	-0.042** (0.017)	-0.044** (0.017)	-0.044** (0.017)
frail_hsgp	-0.019 (0.018)	-0.026 (0.020)	-0.026 (0.019)	-0.025*** (0.009)	-0.027*** (0.009)	-0.027*** (0.009)
frail_col	0.000 (0.021)	-0.003 (0.022)	-0.002 (0.021)	0.002 (0.004)	0.001 (0.005)	0.001 (0.004)
eta		0.038 (0.152)	0.059 (0.141)		0.046 (0.032)	0.076** (0.035)
Controls	YES	YES	YES	YES	YES	YES
Observations	23,874	23,755	23,755	23,874	23,755	23,755
AR(1) test (p-value)	0.000	0.000	0.000	0.010	0.008	0.009
AR(2) test (p-value)	0.195	0.183	0.189	0.182	0.152	0.163
Hansen test (p-value)	0.228	0.169	0.172	0.107	0.096	0.096
Diff-in-Hansen test (p-value)	0.370	0.324	0.356	0.307	0.385	0.417
Diff-in-Hansen test (p-value), Y-lag set	0.122	0.070	0.079			
Starting IV Lag t-k (k=)	5	5	5	5	5	5
Ending IV Lag t-k (k=)	7	7	7	7	7	7

* pj.1, ** pj.05, *** pj.01



Frailty: Model vs Data



• Adjust the fixed effect grid to matches mean frailty by age in each pctile group **COB**ack

Calibration: What is Chosen to Match Targets

- Prob. of DI acceptance parameters: $\theta(f, n_a) = \min \{1, \kappa_0 f^{\kappa_1} n_a^{\kappa_2}\}$
 - Targets:

SSDI enrollment by frailty percentiles and 5-year age group (ages 25–64) Rate of decline in DI acceptance by year since initial application (French and Song, 2014)

- Disutility of work parameters: $v(f) = \phi_0 \left(1 + \phi_1 f^{\phi_2}\right)$
 - Targets: LFP by frailty percentiles for age group 25 to 74.
- Discount factor β
 - Target: wealth to output ratio of 3.2.
- Average tax parameter λ
 - Target: federal income tax as % of GDP = 8%



Calibration: Parameters Chosen using the Model

Table: Additional Parameters and Targets: Values

Parameter	Description		Value
β	discount factor		0.982
λ	HSV tax parameter		0.119
Moment		Target	Model
Wealth-output ratio		3.2	3.2
Federal Inc. Tax (% of GDP)		8.0	8.0



Quantitative Model Results

Lifetime earnings inequality by age: Gini





High School Dropouts: Model vs Data



High School Dropouts: Model vs Data



High School Graduates: Model vs Data



High School Graduates: Model vs Data



College Graduates: Model vs Data





College Graduates: Model vs Data





Hosseini, Kopecky & Zhao
High School Dropouts: Model vs Data



High School Dropouts: Model vs Data



High School Graduates: Model vs Data



High School Graduates: Model vs Data



College Graduates: Model vs Data





College Graduates: Model vs Data





Sample Details

- Use PSID 2003-2017 (years 2002-2016)
 - Cannot construct frailty index in earlier waves.
- Sample consists of household heads and spouses aged 25–64 with non-missing labor earnings.
- Workers are defined as follows:
 - $LF_t = 1$ if hours \geq 260 AND wages > \$3/hour
 - Worker = 1 if $LF_t = 1$ for all time periods observed
 - Wages = Annual labor earnings/Annual hours worked
 - Annual hours worked = (52 weeks unemployed) \times average weekly hours
- Good/Bad health: frailty below/above 75th percentile

▶ Go Bac

Fraction at zero: Model vs Data



• Removing frailty heterogeneity reduces the fraction with zero lifetime earnings.

Hosseini, Kopecky & Zhao

69 of 71

► Go Back

Stochastic frailty process for high school dropouts





How Important is Health Inequality for Lifetime Earnings Inequality?

Stochastic frailty process for high school dropouts





Stochastic frailty process for college graduates





How Important is Health Inequality for Lifetime Earnings Inequality?

Stochastic frailty process for college graduates





How Important is Health Inequality for Lifetime Earnings Inequality?