The Impact of Social Insurance on Household Debt

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Q: How does social insurance affect household debt?

- \rightarrow Theoretically ambiguous effect
- Direct insurance channel ⇒ less debt
 - Negative shocks have lower impact on household resources
- Credit demand channel ⇒ more debt
 - Weakens precautionary savings motive
- Credit supply channel ⇒ more debt
 - $\blacktriangleright \ \ {\sf Reduces \ default \ risk} \to {\sf improves \ borrowing \ terms}$

1. Empirical analysis

2. Theoretical analysis

This Paper

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- Study impact of expanding Medicaid eligibility on household debt
- ► Two approaches exploit variation in states' timing and & heterogeneity in impact
 - Medicaid expansion led to 2.2% increase in credit card debt and a 1.4% increase in HH debt
- 2. Theoretical analysis

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1. Empirical analysis

- Study impact of expanding Medicaid eligibility on household debt
- ▶ Two approaches exploit variation in states' timing and & heterogeneity in impact
 - Medicaid expansion led to 2.2% increase in credit card debt and a 1.4% increase in HH debt

2. Theoretical analysis

- Heterogeneous-agents model with delinquency option
- Study the impact of Medicaid expansion on borrowing
- Decompose the effect into direct, credit demand, and credit supply channels
 - Credit-supply is fully responsible for increase in debt
 - Credit-supply accounts for 17% of welfare gain

• Distributional impact of social insurance

Kotlikoff (1986), Hubbard et al. (1995), Gruber and Yelowitz (1999), Engen and Gruber (2001)

- → Introduce role for credit supply
- Models of unsecured household debt

Chatterjee et al. (2007), Livshits et al. (2007), Chatterjee and Gordon (2012), Mitman (2016), Nakajima and Rios-Rull (2019) → Study impact of changes to availability of insurance

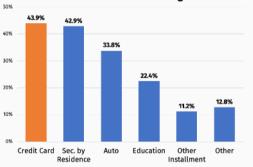
• Relationship between household debt and the macroeconomy

Jordá et al. (2015), Mian et al. (2017), Gomes et al. (2019), Mian et al. (2020)

→ Higher debt due to better social insurance may be a sign of financial resilience

Health insurance weakens reliance on debt and default to cope with illness
 Gross and Notowidigdo (2011), Finkelstein et al. (2012), Mahoney (2015), Barcellos and Jacobson (2015), Allen et al. (2017), Brevoort et al. (2017), Hu et al. (2018), Miller et al. (2018), Gallagher et al. (2019), Goldsmith-Pinkham et al. (2021) → New focus on general equilibrium channels

Empirical Analysis: Credit Card Debt and Medicaid



Percent of Households Holding Debt

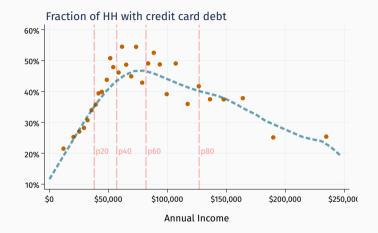
• US households held **\$927 bil.** in credit card balances in 2019 (\$7,210 per household)

• Commercial banks earned \$90 bil. in CC interest income in 2019

• The average APR is 14%, the legal max is 36%

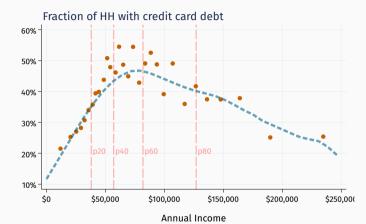
Source: 2016 SCF

Credit Card Debt along the Income Distribution



By Age Group

Credit Card Debt along the Income Distribution



→ At odds with standard incomplete-market models (Aiyagari, Bewley, Imrohoroglu, Hugget)

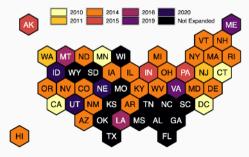
→ Credit supply is first order → endogenous credit supply (Chatterjee et al., Livshits et al.)

Medicaid Expansions

- Medicaid: gov't program providing health insurance to low-income households
- 64.7 million Americans received health insurance through Medicaid in 2019
- ACA provided federal funds for state expansions of Medicaid eligibility in 2014
 - ▶ But 2012 NFIB v. Sebelius Supreme Court ruling made take-up optional

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 - ▶ But 2012 NFIB v. Sebelius Supreme Court ruling made take-up optional
- Staggered expansion across states ensued:



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- Strategy 1: IV exploiting staggered timing of expansions

• Strategy 2: Recentered simulated IV (RSIV, Borusyak and Hull, 2021)

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 - Pros: can be used to study credit card outcomes (from NYFed CCP)
 - Cons: state-level variation
 - Identifying assumption: random timing of expansions conditional on state and year
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 - ▶ Pros: county-level variation, large estimator efficiency gains (Borusyak and Hull, 2021)
 - Cons: only measure HH debt-to-income (DTI), which includes mortgages and auto loans
 - ▶ Identifying assumption: random *path* of eligibility polices within Dem/Rep states

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- Soon: ZIP-level RSIV with CC borrowing and rich array of debt outcomes (Experian)

State-Level: Health Insurance and CC Debt

	TSLS		OLS	
	(1)	(2)	(3)	(4)
Insured _{s,t}	1.34**	1.41***	0.01	0.06
	(0.43)	(0.35)	(0.11)	(0.09)
	First Stage			
$1[Adopted]_{s,t}$	1.44***	1.56***		
	(0.19)	(0.19)		
Controls		\checkmark		\checkmark
Stage 1 F	55.7	65.8		
Obs.	765	765	765	765

$$\begin{split} \textit{In}(\mathsf{cc}_{s,t}) &= \mathsf{Insured}_{s,t}\beta + X_{s,t}\gamma + \theta_s + \tau_t + \varepsilon_{s,t} \\ & \mathbb{1}[\mathsf{Adopted}]_{s,t} \xrightarrow{\mathsf{IV}} \mathsf{Insured}_{s,t} \end{split}$$

Notes: Each regression includes state and year fixed effects and robust standard errors. Control variables include the unemployment rate, log(population), log(house prices), house price growth, and state-level GDP growth. Statistical significance: 5%*, 1%**, and 0.1%***. • CC Debt

State-Level: Health Insurance and CC Debt

	TS (1)	GLS (2)	(3)	LS (4)	$In(cc_{s,t}) = Insured_{s,t}\beta + X_{s,t}\gamma + \theta_s + \tau_t + \varepsilon_{s,t}$
Insured _{s,t}	1.34** (0.43)	1.41*** (0.35)	0.01 (0.11)	0.06 (0.09)	$\mathbb{1}[Adopted]_{s,t} \xrightarrow{IV} Insured_{s,t}$
1[Adopted] _{s,t}	First 1.44***	Stage 1.56***			
Controls	(0.19)	(0.19)			Expanding Medicaid $\rightarrow \uparrow$ cc debt 2.2%
Stage 1 F Obs.	55.7 765	65.8 765	765	765	→ ↑ \$20.4 bil

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County-Level: Recentered Simulated IV (RSIV)

- Goal: estimate causal effect of an increase in pop. Medicaid eligibility on DTI
- Challenge: non-random exposure to Medicaid expansion (low-inc., non-parents, ...)
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 - Assume states' history of Medicaid eligibility rules is drawn from known distribution
 - Step 1: simulate/calculate permutations of a person's eligibility under diff. state policies
 - Step 2: calculate their *propensity* to be eligible for Medicaid over time μ_{it}
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 - Step 3: construct RSIV as (eligibility_{*it*} μ_{it}), or control for μ_{it}
- The μ_{it} term accounts for a person's propensity to be exposed to higher eligibility
- Instrument (eligibility_{*it*} μ_{it}) is "excess" eligibility due to state's realized policy

County-Level Estimation of Effect of Eligibility on Debt-to-Income (DTI)

• Estimate the county-level equation below using TSLS:

 $\mathsf{DTI}_{it} = \beta_1 \mathsf{Elig}_{it} + \beta_2 \left(1 [\mathsf{Low \, Inc}_{it}] \times \mathsf{Elig}_{it} \right) + X_{it} \gamma + \varepsilon_{it}$

- DTI_{it} is the DTI ratio in county i at year t
- Elig_{it} is the % of county i's population that's eligible for Medicaid at t
- ▶ 1[Low Inc]_{it} indicates county i's income is the below median in year t
- Instrument for Elig and its interaction with $\widetilde{\mathsf{Elig}}_{it} = \mathsf{Elig}_{it} \mu_{it}$
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- Alternatively, we can control for predicted eligibility μ_{it} in an OLS regression

 $DTI_{it} = \beta_1 \text{Elig}_{it} + \beta_2 \left(1[\text{Low Inc.}] \times \text{Elig}_{it}\right) + \alpha_1 \mu_{it} + \alpha_2 \left(1[\text{Low Inc.}] \times \mu_{it}\right) + X_{it}\gamma + \nu_{it}$

RSIV First Stage

	Outcome = Elig	Outcome = Elig \times 1[Low. Inc]
Elig	0.978*** (0.021)	0.010 (0.024)
$\widetilde{\text{Elig}}{\times}1[\text{Low Inc.}]$	-0.015 (0.011)	0.906*** (0.055)
1[Low Inc.]	0.008*** (0.001)	0.235*** (0.007)
log(Avg. Inc.)	-0.092*** (0.006)	-0.026*** (0.006)
log(#HHs)	0.002*** (0.001)	1.00e-04 (0.001)
Obs R2	15,513 0.900	15,513 0.946
Stage 1 F Dem x Year FE:	1,112	281.4 ✓

Notes: All columns include state and year fixed effects. Standard errors clustered by state. p < 0.1, ** p < 0.05, *** p < 0.01.¹¹

The Effect of Eligibility on DTI: RSIV Estimation Results

	(1)	(2)	(3)
Elig%	0.337 (0.507)	0.243 (0.395)	0.230 (0.405)
Elig% × 1[Low Inc.]	1.096* (0.555)	0.980* (0.507)	0.989* (0.507)
1[Low Inc.]	-0.536*** (0.167)	-0.324** (0.154)	-0.325** (0.154)
log(Avg. Inc.)		0.742*** (0.141)	0.742*** (0.140)
log(# HHs)		-0.058 (0.055)	-0.058 (0.055)
Obs. R2 Dem x Year FE:	15,513 0.095	15,513 0.104	15,513 0.104 √

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The Effect of Eligibility on DTI: Control Estimation Results

	(1)	(2)	(3)
Elig	0.031	0.010	-0.038
	(0.273)	(0.279)	(0.286)
Elig $ imes$ 1[Low Inc.]	0.786**	0.795**	0.806**
	(0.380)	(0.384)	(0.383)
μ	-9.218***	-10.749***	-11.749***
	(1.624)	(2.477)	(2.577)
$\mu imes$ 1[Low Inc.]	0.057	0.374	0.210
	(1.396)	(1.362)	(1.387)
1[Low Inc.]	-0.160	-0.283	-0.235
	(0.307)	(0.317)	(0.323)
log(Avg. Inc.)		-0.267	-0.361
		(0.221)	(0.236)
log(# Inc.)		-0.034	-0.032
		(0.049)	(0.049)
Obs.	15,513	15,513	15,513
R2	0.121	0.122	0.125
Dem x Year FE:			\checkmark

Notes: All columns include state and year fixed effects. Standard errors clustered by state. p < 0.1, ** p < 0.05, *** p < 0.01.¹³

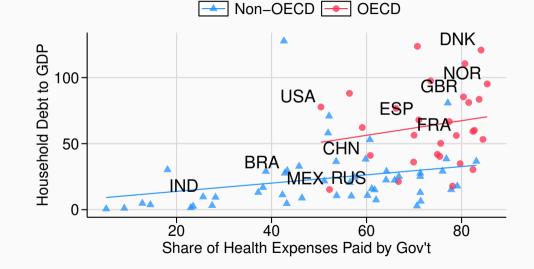
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Expanding Medicaid →
↑ Elig. 6.3%
\uparrow DTI 5.1 pps for bottom 50% inc. group
↑ agg. HH debt 1.4% (avg. DTI = 187%)

Notes: All columns include state and year fixed effects. Standard errors clustered by state. p < 0.1, ** p < 0.05, *** p < 0.01.¹³

Across Countries: Household Debt and Public Health Insurance



Model

Households

Income shocks

• Income:

Expenditure shocks

$$\ln y_{it} = \begin{cases} \rho \ln y_{it-1} + \epsilon_{it}^{y}, & \text{w.p. } \lambda_{y} \\ \ln y_{it-1}, & \text{w.p. } 1 - \lambda_{y} \end{cases}$$

- Medical expenditure:
- Insurance by income:

$$X_{it} \sim \ln \mathcal{N}(\mu_x, \sigma_x^2)$$

$$M_{it} = oop(y_{it})X_{it}$$

Debt

- Borrow (or save) using one-period debt securities: *b_{it}*
 - Can choose to go delinquent on debt (suffer utility cost)
 - Pay endogenous interest rate $r(y_{it}, b_{it+1}) = \frac{1}{q(y_{it}, b_{it+1})}$

Households with delinquent debt:

- Cannot save or borrow
- Medical expenditure piles up on debt
- With some probability, stochastic fraction of debt is forgiven

Credit supply

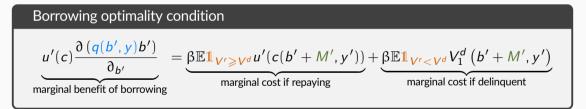
- Perfect competition among lenders
- Hybrid of short-term and long-term debt

● Insurance raises disposable resources ⇒ less debt

Indirect channels

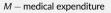
M- medical expenditure

- b' debt obligations
- $q(\cdot) \mathsf{price} \text{ of debt}$
- V^r value of repayment
- V^d value of delinquency

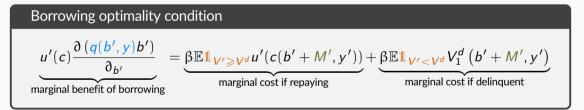


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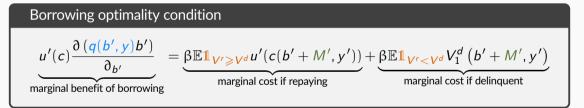
Precautionary savings motive: var(M') ↓ reduces mc of borrowing ⇒ more debt

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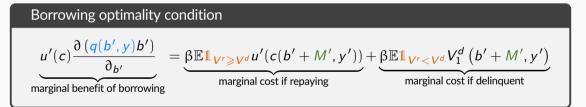
- Precautionary savings motive: var(M') ↓ reduces mc of borrowing ⇒ more debt
- Debt aversion motive: $\mathbb{E}\mathbb{1}_{V' \ge V^d} \uparrow$ increases mc of borrowing \Rightarrow less debt

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Indirect channels

M – medical expenditure

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- Precautionary savings motive: var(M') ↓ reduces mc of borrowing ⇒ more debt
- Debt aversion motive:
- Credit supply channel:

 $\mathbb{E} \mathbb{1}_{V^r \ge V^d} \uparrow \text{ increases mc of borrowing} \Rightarrow \text{less debt}$ $q(b', y) \uparrow \text{ increases mb of borrowing} \Rightarrow \text{more debt}$

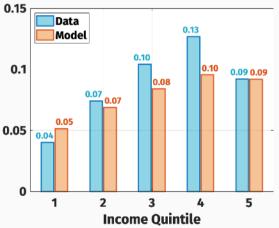
Calibration

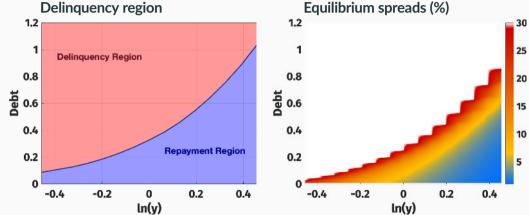
Medical Expenditure Panel Survey

- Distribution of medical expenditure
- Joint distribution of insurance type and income
- Out-of-pocket (OOP) expenses by insurance type

Panel Study of Income Dynamics

Credit card debt (% of median income)





Equilibrium spreads (%)

Expansion of Medicaid

Experiment: raise Medicaid coverage by 1.6 pp

Decomposition \rightarrow three channels

- Direct insurance channel: medical shocks less costly
- Credit demand channel: precautionary savings and debt aversion
- Credit supply channel: lower delinquency risk → better credit terms

Results:		Medicaid Expansion Impact	Direct Effect	CD	CS
	Credit debt level	+1.33%	-1.14%	-1.43%	+3.90%
	Welfare	+0.18%	+0.15%	+0.0001%	+0.03%

Conclusion

Conclusion

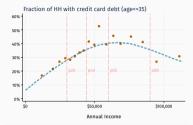
Q: How does social insurance affect household debt?

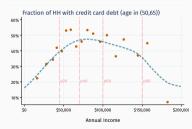
- We focus on expansion of health insurance through Medicaid
- Empirical evidence estimates
 - ► Medicaid expansion → 1.6 pp reduction in uninsured population
 - ▶ Medicaid expansion → 2.2% increase in credit card debt
 - ▶ Medicaid expansion → 1.4% increase in household debt
- Quantitative model
 - Credit supply channel drives the rise in debt
 - Credit supply response leads to first order welfare gains
- Social insurance can crowd in private insurance (credit access) with large welfare gains

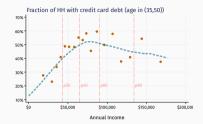
Thank You!

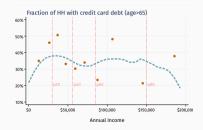
Empirical Appendix

Credit card debt versus income across age groups

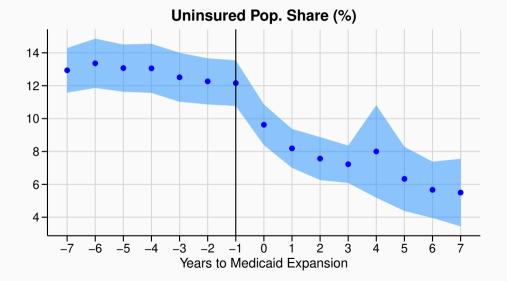








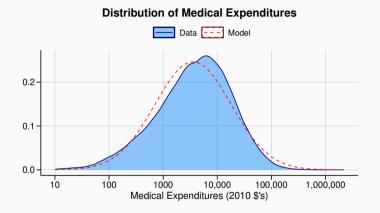
Uninsured rates fell after Medicaid expansion



Model Appendix

Utility $egin{aligned} eta &= 0.92 \ \gamma &= 3 \ \xi &= 0.35 \ r_f &= 2\% \end{aligned}$	Income Process $\lambda_y = 0.42$ $\rho_y = 0.88$ $\sigma_y = 0.07$	Haircut Process $\lambda_d=0.94$ $eta_1^d=1.7$ $eta_2^d=9$
Medical Shocks $\mu_e=0.08$ $\sigma_e=1.6$	Insurance $P_m = 0.1 - 0.15 \ln y$ $P_i = 0.78 + 0.21 \ln y$ $P_u = 1 - P_m - P_i$	Out of Pocket $OOP = P_m O_m + P_i O_i + P_u O_u$ $O_m = 7\%$ $O_i = 27\%$ $O_u = 63\%$

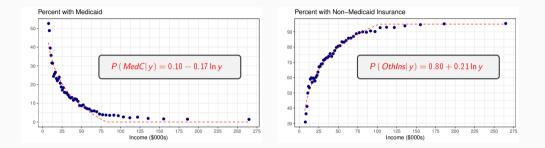
Distribution of expenditure shocks



 $X_{it} \sim \ln \mathcal{N} \left(\ln(0.08), 2.62 \right)$

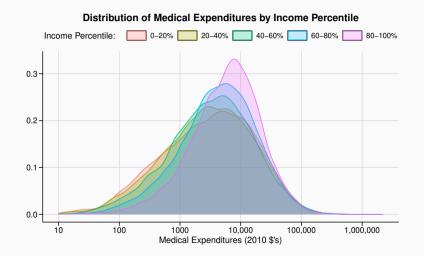
- Median expenditure shock = 8% annual income
- \blacktriangleright 1 s d above median = 40% annual income

Out-of-pocket expenditure by income

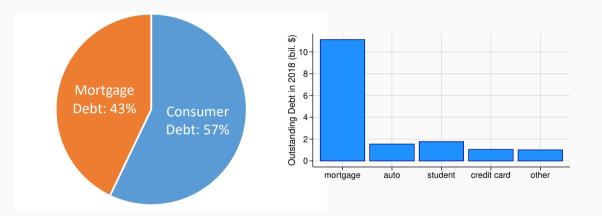


 $oop(y) = P(MedC|y) \times 6.8\% + P(OthIns|y) \times 27.5\% + P(NoIns|y) \times 62.7\%$

Medical expenditure distribution by income



Share of Debt Service Payments (2018)



◀ Go Back

Large uninsured pop. in some states

Pop % w/o Health Insurance (2007)

