Moral Hazard Heterogeneity: Genes and Health Insurance Influence Smoking after a Health Shock

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thanks to GEIGHEI team, Regina Seibel, and Pia Arce

University of Zürich

University of Connecticut
March 8th, 2021

International Women's Day

Check out Margherita's fantastic research here

Outline

Genes, health insurance, smoking choices

What:

Agenda : Use genes to assess individual level heterogeneity in economic parameters

Paper : Does reaction to a negative health shock depend on health insurance and genetic differences?

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- Identification: US adults who receive free health insurance coverage after 65 (Medicare)
- Compare high and low genetic predisposition to smoking ($G \times E$)

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Why:

- Interplay between financial and biological constraints:
  - Health insurance buffers financial consequences of health shocks
  - Genetic predispositions influence behavioral responses
- Understand **heterogeneity in moral hazard**

Preview

- Identification assumptions:
  - Probability of health shock increases with age ...
  - ... but no jump at 65
- Results:
  - Health shock when uninsured $\Rightarrow$ less smoking...
  - ... but *only* for low PGS.
  - G$\times$E effect size: 27.9 pp

Why should we care?

- Genes cannot be changed ...
- ... but **environment** can!
- Interplay between genes (bio) and environment (econ) is essentially everywhere [Rutter, 2006]

- Understand differential effects of genetic predisposition based on environment (G$\times$E)
  - shed light on pathways and mechanisms
  - provide measure of essential heterogeneity
  - revisit old econ concept with new lens

- Empirics: genes are cheaper to measure and more and more available
- Theory: biologically founded model
- Policy: understand sources of heterogeneity and discuss *fairness*
- Individual: choose individualized intervention

Previous work:

- Smoking increases diseases and health-care costs (400k deaths, $300 billion per year in US)
  [United States Department of Health and Human Services, 2014, Goodchild et al., 2017, Ma et al., 2018, Xu et al., 2015]
- Severe health shocks reduce smoking
  [Clark and Etilé, 2002, Falba, 2005, Khwaja et al., 2006, Keenan, 2009, Sundmacher, 2012]
- Health insurance plays a big role (moral hazard)
  [Richards and Marti, 2014, Marti and Richards, 2017, Einav et al., 2013, Einav and Finkelstein, 2018]
- G $\times$ E: Use molecular genetics and measures of the environment and investigate their interplay.
  See [Caspi et al., 2002, Barcellos et al., 2018, Belsky et al., 2018, Rimfeld et al., 2018, Schmitz and Conley, 2017a, Schmitz and Conley, 2017b, Rosenquist et al., 2015]
- Genoeconomics: Find genetic determinants of economic behaviors: risk aversion, time and social pref., addiction.
  See [Benjamin et al., 2007, Cesarini et al., 2009, Benjamin et al., 2016]

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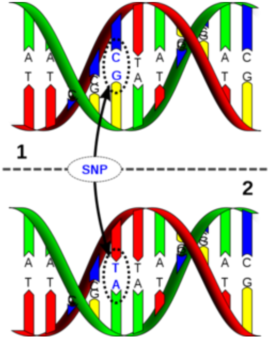
$\hookrightarrow$ **Contribution**: leverage genetic variants to measure heterogeneity in moral hazard

Outline

Genetics for social scientists

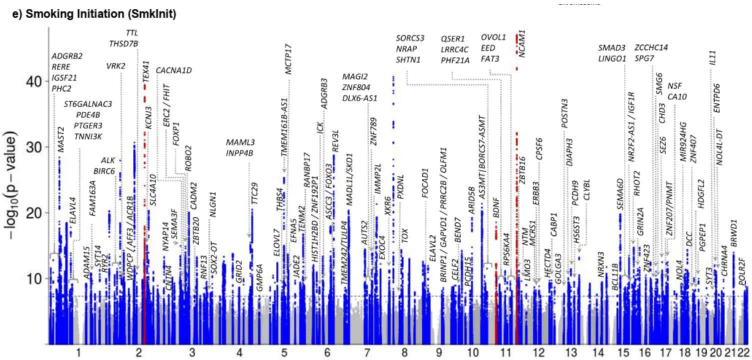
- Human genome: series of 3 billion letter pairs (A,G,T,C)
- Genetic variants: one-letter changes across individuals (single nucleotide polymorphisms, SNPs)
- About $\approx$ 10m SNPs [The 1000 Genomes Project Consortium et al., 2015]
- Genome-wide association studies (GWAS) have identified genome-wide significant relationships between specific SNPs and health behaviors
- We use SNPs identified from large, replicated GWAS to create summarized genetic scores to study gene-by-SES interplay ▸ hits



PolyGenic Scores (PGS)

Discovery stage:

GWAS
[Liu et al., 2019]



Source: Liu et al. (2019)

Prediction stage:

$$PGS_i = \sum_{j=1}^{J} W_j G_{ij},$$

where G_{ij} is the genotype for individual i at SNP j, and the weight W_j is the OLS association between SNP j and outcome. Normalized to have mean zero and standard deviation one.

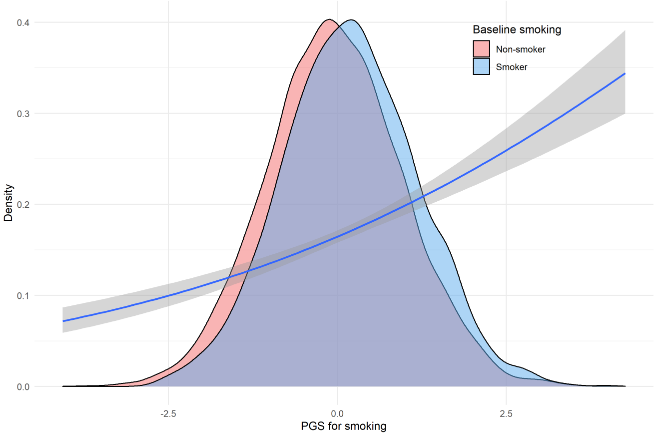
Polygenic Scores

In our setting

Data = Health and Retirement Study

Y = Pr(Smoking)

W_j = taken from [Liu et al., 2019]



Outline

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1. Research Question
2. Genes for Econ
3. Empirical Analysis
   - Data and setting
   - Regression
4. Sanity Checks
   - Confounders
   - Robustness
   - Is it really genes?
5. Conclusion
   - Limitations
   - Take home

Data

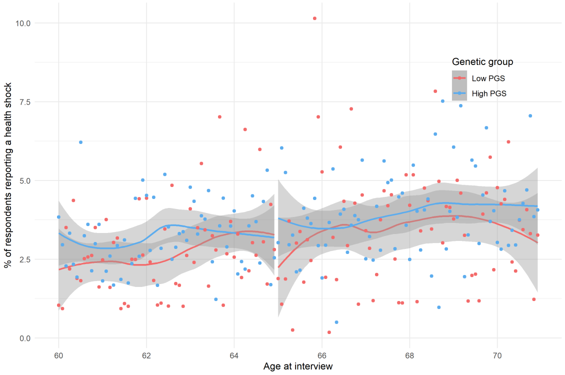
- Use HRS data: US-representative survey of 50+ (1992-2016)
- Final sample size $= 26,022$ obs from $5,854$ individuals
  - Ever smoked ≥ 100 cigarettes (at baseline)
  - Ages: 60-70
  - Observed at least 2 waves
  - European descendants
  - Non-missing smoking, PGS, insurance, health shock

Variables

- Outcome Y = current smoking status $\in \{0, 1\}$
  - Self reported
- High PGS g = above 33^{rd} in PGS for smoking initiation
  - Use [Liu et al., 2019] for weights
- Health shock = first diagnosis of acute cardiovascular condition
  - Heart problem: heart attack, coronary heart disease, angina, congestive heart failure, or other heart problems
  - or Stroke: transient ischemic attack
- Uninsured: self-reported coverage
  - Pre 65 uninsured: never report being covered by medical insurance
  - Post 65 everyone insured: eligible for Medicare
  - Who are the uninsured?

Identification

Diff in response to health shock before and after 65
Main assumption: **timing** of health shock is exogenous
[Marti and Richards, 2017, Card et al., 2009]



Summary statistics

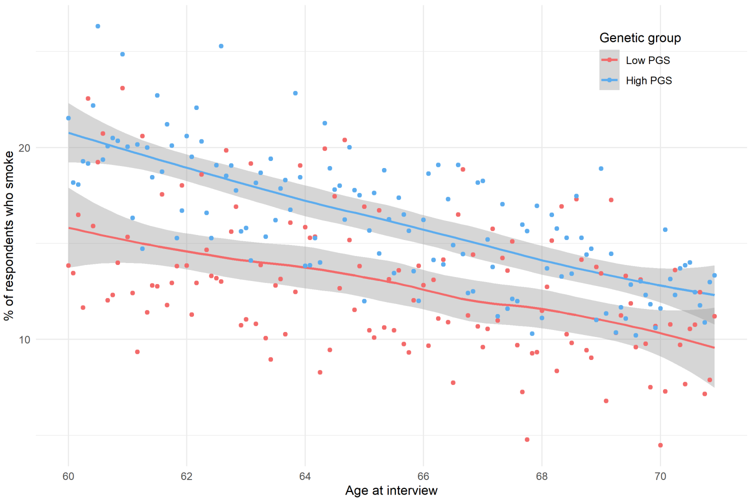
Table: Descriptive Statistics for Full Analytic Sample and Stratified by Genetic Group

	All	**Low PGS**	**High PGS**
	Mean (SD)	Mean (SD)	Mean (SD)
Age (baseline)	61.17 (1.93)	61.18 (1.96)	61.16 (1.92)
Smoking PGS	0.11 (0.99)	-0.96 (0.51)	0.64 (0.71)
No. waves present	4.44 (1.38)	4.46 (1.37)	4.43 (1.39)
	%	%	%
Female	50.42	46.97	52.14
Smoking (baseline)	29.55	27.06	30.79
Persistently uninsured	5.85	5.39	6.08
CV health shock	12.44	11.82	12.74
No. of individuals	5813	1929	3884
No. Person-year observations	25800	8602	17198

▸ Sumstats2 ▸ Uninsured

Smoking rates decrease with age

Share of smokers over different ages, split by PGS



Outline

Regression analysis

$$
\begin{aligned}
Y_{it} = {} & \beta\, shock_{it} + \gamma\, post65_{it} \\
& + \lambda_1\,(shock_{it} \times post65_{it}) \\
& + \lambda_2\,(shock_{it} \times uninsured_i) \\
& + \lambda_3\,(post65_{it} \times uninsured_i) \\
& + \lambda_4\,(shock_{it} \times g_i) \\
& + \lambda_5\,(post65_{it} \times g_i) \\
& + \delta_1\,(shock_{it} \times post65_{it} \times uninsured_i) \\
& + \delta_2\,(shock_{it} \times uninsured_i \times g_i) \\
& + \delta_3\,(shock_{it} \times post65_{it} \times g_i) \\
& + \delta_4\,(post65_{it} \times uninsured_i \times g_i) \\
& + \zeta\,(shock_{it} \times post65_{it} \times uninsured_i \times g_i) \\
& + \sum_{a=1}^{3} \phi_a\, age_{it}^{a} + \eta_i + \tau_t + \varepsilon_{it}
\end{aligned}
$$

Current smoking status (Y) regressed on the full set of interactions between the indicators for the health shock (*shock*), being uninsured pre-65 (*uninsured*), Medicare eligibility (*post*65), and high polygenic risk for smoking (g).

Controlling for age + individual and time F.E.

Effect of the shock on the outcomes

The derivative of the outcome with respect to shock is:

$$\begin{aligned}\frac{\partial Y_{it}}{\partial shock_{it}} = &\beta + \lambda_1 post65_{it} + \lambda_2 uninsured_i + \lambda_4 g_i + \delta_1(post65 \times uninsured_i) + \delta_2(uninsured_i \times g_i) \\ &+ \delta_3(post65_{it} \times g_i) + \xi(post65_{it} \times uninsured_i \times g_i)\end{aligned} \tag{1}$$

Looking at the effect for the four different types (before-after 65, high-low g):

$$E\left[\frac{\partial Y_{it}}{\partial shock_{it}} | post65_{it} = 0, g_i = 0, uninsured_i = 1\right] = \beta + \lambda_2 \tag{2}$$

$$E\left[\frac{\partial Y_{it}}{\partial shock_{it}} | post65_{it} = 1, g_i = 0, uninsured_i = 1\right] = \beta + \lambda_1 + \lambda_2 + \delta_1 \tag{3}$$

$$E\left[\frac{\partial Y_{it}}{\partial shock_{it}} | post65_{it} = 0, g_i = 1, uninsured_i = 1\right] = \beta + \lambda_2 + \lambda_4 + \delta_2 \tag{4}$$

$$E\left[\frac{\partial Y_{it}}{\partial shock_{it}} | post65_{it} = 1, g_i = 1, , uninsured_i = 1\right] = \beta + \lambda_1 + \lambda_2 + \lambda_4 + \delta_1 + \delta_2 + \delta_3 + \xi \tag{5}$$

Calculating the first two differences as above:

$$(10) - (9) = \lambda_1 + \delta_1 \tag{6}$$

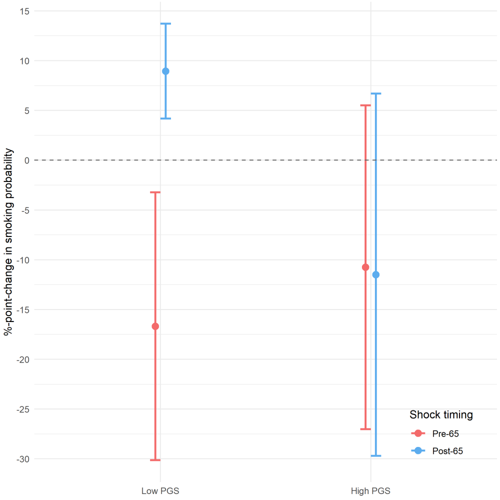
$$(12) - (11) = \lambda_1 + \delta_1 + \delta_3 + \xi \tag{7}$$

And the diff-in-diff (G×E):

$$(14) - (13) = \delta_3 + \xi \tag{8}$$

Regression results

Controlling for individual and time F.E. + age:



▸ all coefficients

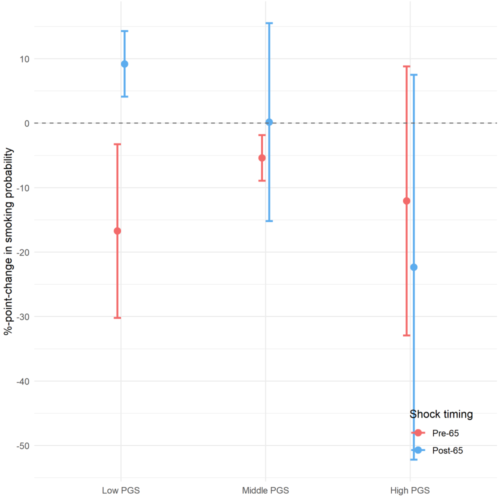
Evidence of $G \times E$

Table: Effect of the shock by timing and PGS

Effect of health shock on smoking probability		
	Low PGS	High PGS
Pre 65	-0.167**	-0.108
	(0.069)	(0.083)
Post 65	0.089***	-0.115
	(0.024)	(0.093)
Effect of health insurance on effect of health shock		
	Low PGS	High PGS
Post 65 - Pre 65	0.256***	-0.008
	(0.079)	(0.124)
Differential effect of health insurance by genetic group		
	High PGS	- low PGS
Post 65 - Pre 65	-0.264*	
	(0.146)	

Notes: Summary of the effect of the shock on smoking for those who were uninsured before 65, stratified by timing of the shock (before vs. after 65) and genetic group (high vs. low PGS)

Different PGS cutoffs



Outline

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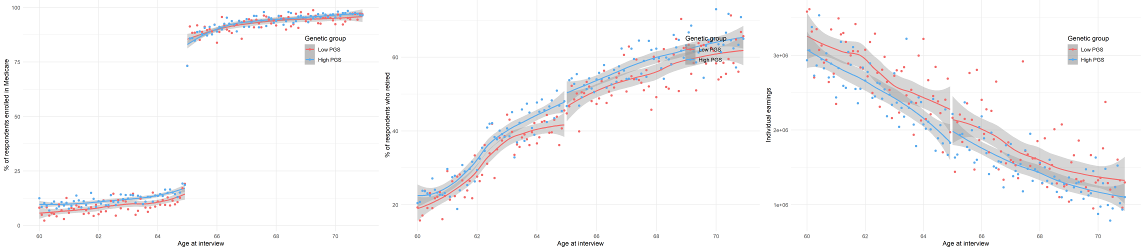
Potential interpretation problems

What else can drive this relation?

- Something that jumps at 65 (besides medicare)
  - Retirement and income: no sharp change at age 65 [Card et al., 2008, Card et al., 2009]



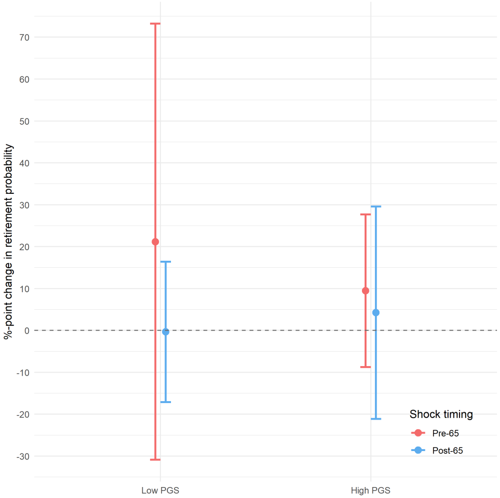
Potential Confounders

Check for differential response to shock on possible confounders [Pei et al., 2018]

- Retirement
- Individual income
- Household income
- Out of pocket med. expenditure
- Having a partner
- Partner Smoking
- Mortality 2y 5y

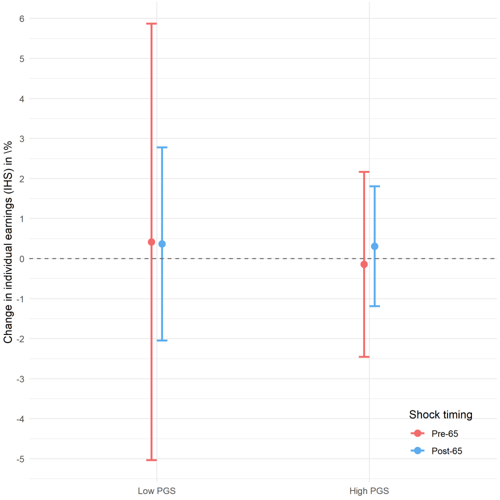
Retirement: not likely a Confounder

Coefficient plot of the effect of the shock on being retired.



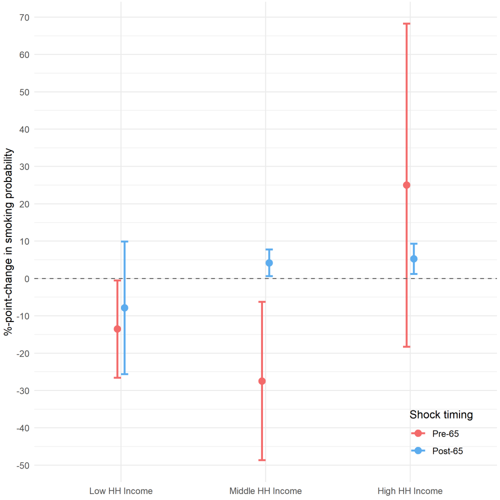
Wage: not likely a Confounder

Coefficient plot of the effect of the shock on log reported earnings.



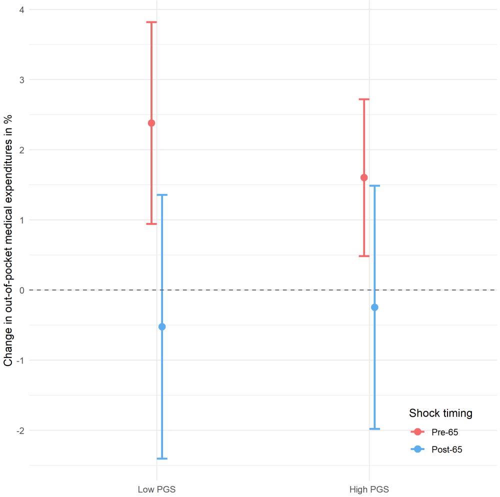
Household Income: not likely a Confounder

Coefficient plot of the effect of the shock on household income.



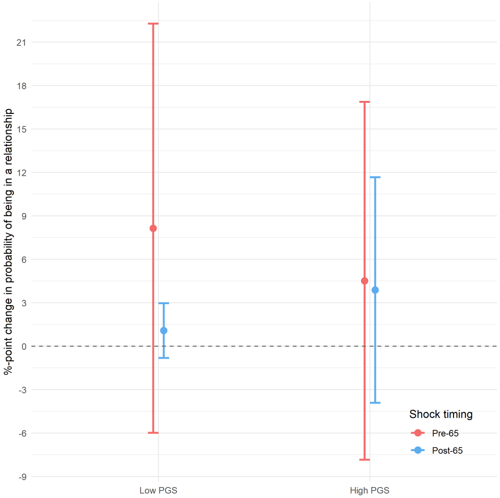
Medical expenditure: not likely a Confounder

Coefficient plot of the effect of the shock on out of poket medical enxpenditure.



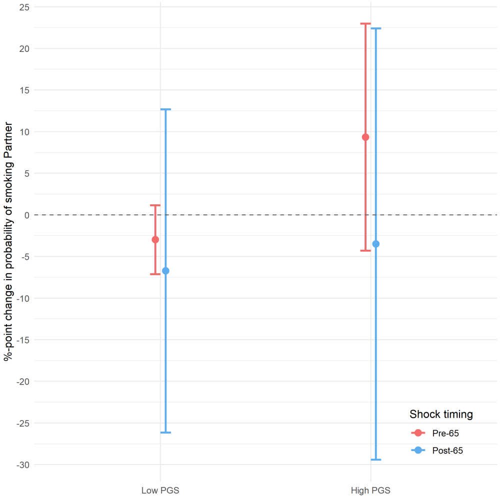
Having a partner: not likely a Confounder

Coefficient plot of the effect of the shock on having a partner.



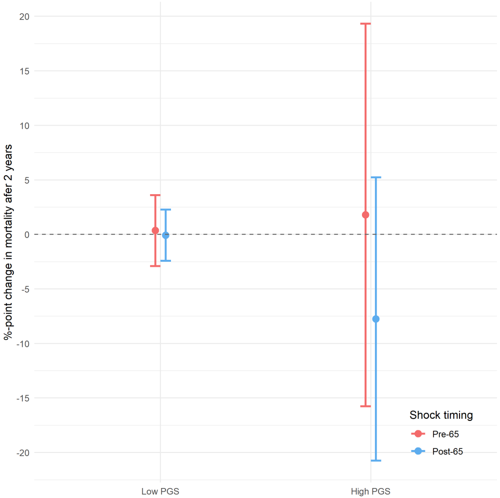
Partner smoking: not likely a Confounder

Coefficient plot of the effect of the shock on having a partner.



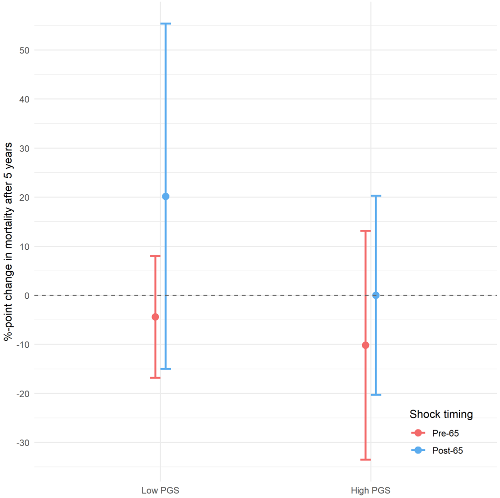
2 year mortality: not likely a Confounder

Coefficient plot of the probability of dying within 2 years of the shock.



5 year mortality: not likely a Confounder

Coefficient plot of the probability of dying within 5 years of the shock.



Outline

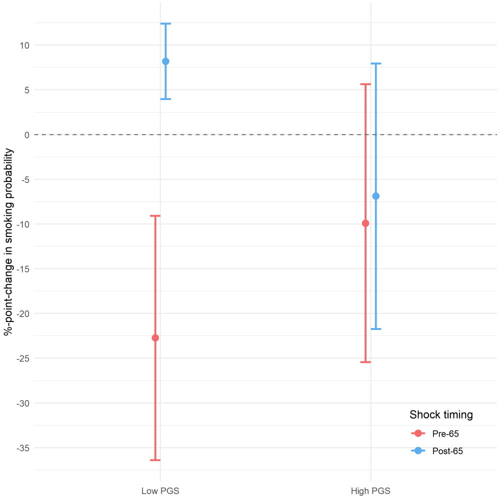
Robustness checks

Robustness checks:

- Different cutoffs for high-PGS ▸ PGS
  - Still holds for lower quartile, not for highest
  - Using continuous PGS, G$\times$E effect = -0.13 (0.11)
- Using the publicly available PGS (older GWAS from [The Tobacco and Genetics Consortium et al., 2010]) ▸ PGS
  - Similar pattern
- Different cutoffs for uninsured ▸ uninsured
  - Noisy results for uninsured only 1/3 of the times
- Different cutoffs for age ▸ age
  - Noisy results after age 72

Robustness: high PGS if above 25^{th} percentile

Coefficient plot of the main regression.



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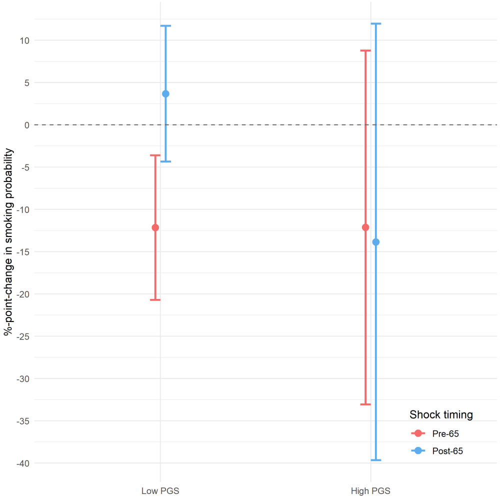
Robustness: high PGS if above 50^{th} percentile

Coefficient plot of the main regression.



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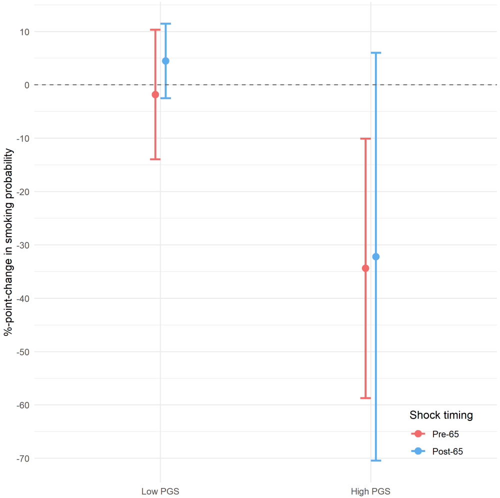
Robustness: high PGS if above 75^{th} percentile

Coefficient plot of the main regression.



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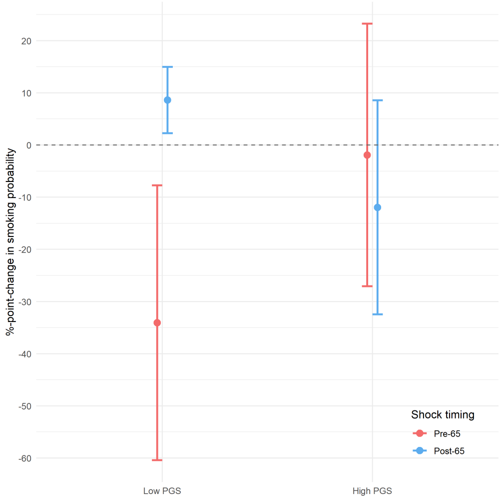
Robustness: using publicly available PGS (older GWAS)

Coefficient plot of the main regression.



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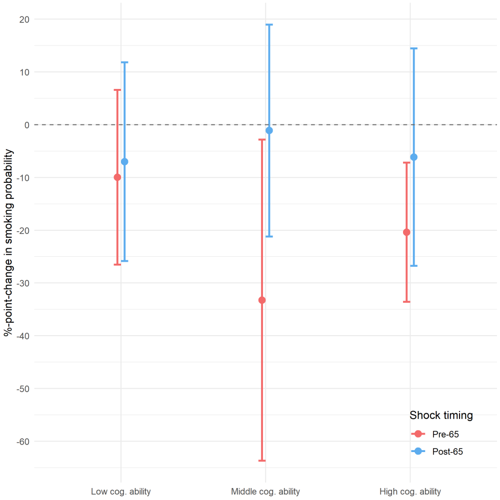
Outline

Is it really genes?

Are there other characteristics that might be driving this relationship?

- Try to cut the data according to other dimensions:
  - Cognitive skills
  - Conscientiousness
  - Risk aversion
  - Gender
  - Education
  - Income
- Or according to other PGS:
  - Cognition PGS
  - Risk aversion PGS

Split by cognitive ability



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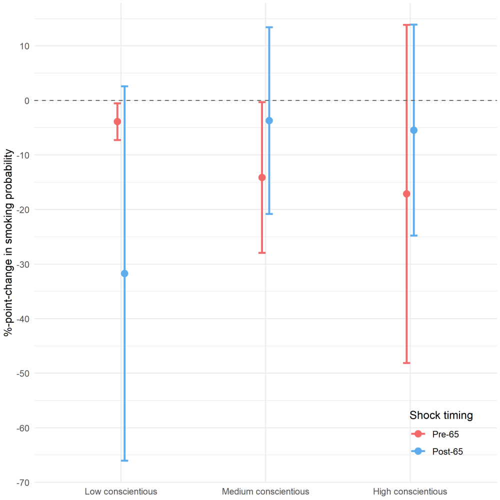
Split by conscientiousness



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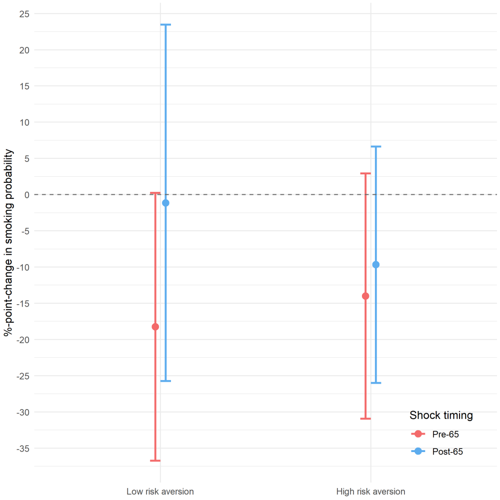
Split by risk aversion



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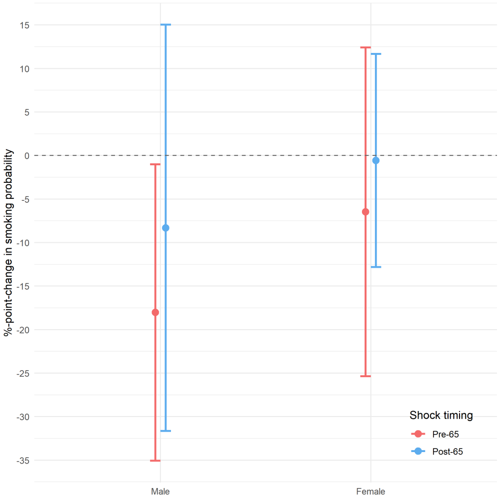
Split by gender



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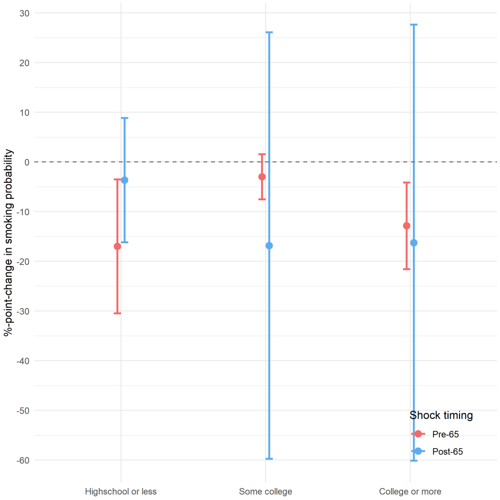
Split by education



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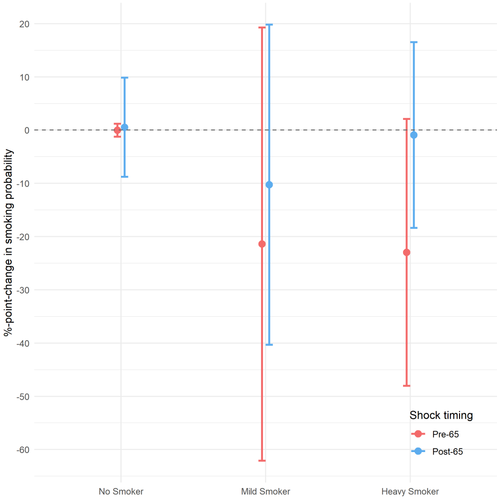
Split by former smoking behaviour



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Limitations

Limitations:

- Small sample size of those hit by a shock (replication needed) ▸ Sumstats2
- Short-run smoking response
- Self-reported information
- Unobserved selection into DNA-sample

- External validity:
  - U.S. insurance system
  - Results only for old, uninsured people ▸ sumstats

Outline

Summary of Results

- Health shock when uninsured ⇒ less smoking...
- ... but *only* for low PGS.
- Effect size is quite sizable (27.9 pp)

- Interaction between financial and "biological" constraints:
  - Health insurance buffers financial consequences of health shocks
  - Genetic predisposition to smoking mutes this effect (lower elasticity)

- Biological foundation of heterogeneity in **moral hazard** [Einav et al., 2013]

Conclusions

What does this tell us?

- Environment <u>and</u> genes jointly influence healthy behaviors
- Biological predispositions can tell a story about choices and economic fundamentals

Thank you

Outline

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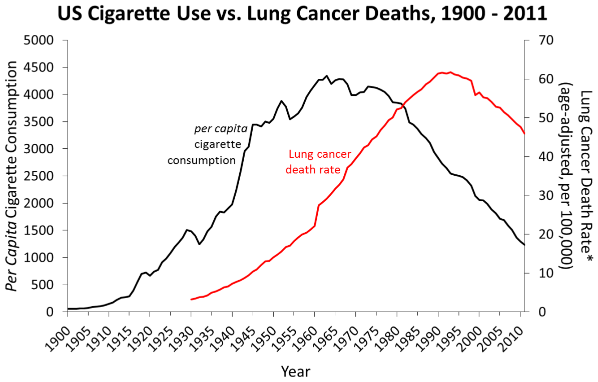
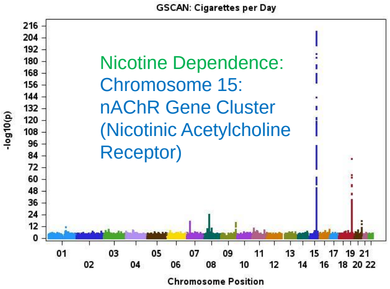
Smoking and lung cancer have same genetic hits

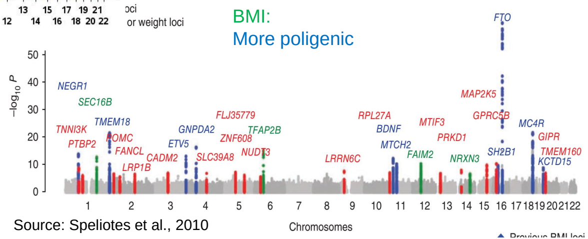


Death rates sources: Public-use data files, National Vital Statistics System, National Center for Health Statistics, Centers for Disease Control and Prevention; and Jemal et al., CA Cancer J Clin, 2010. Cigarette consumption sources: Tobacco Outlook Report, Economic Research Service, US Department of Agriculture; and Alcohol and Tobacco Trade and Tax Bureau, US Department of Treasury.

Smoking and Obesity Manhattan Plots



Source: GSCAN (2019)



Source: Speliotes et al., 2010

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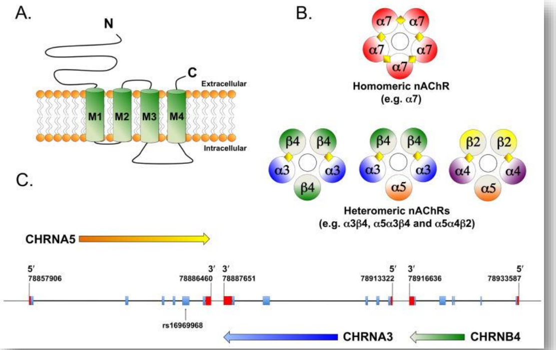
The biological pathways of the nicotine receptor gene

15q25: nAChR Gene Cluster

Nicotinic Acetylcholine Receptor



Improgo, et al., *Prog Neurobiol.* 2010 Oct;92(2):212-26

Outline

Summary statistics, by health shock timing

	Low PGS	**High PGS**	**P value**
Shock at ages 60-64			
	Mean (SD)	Mean (SD)	
Age (baseline)	60.49 (0.57)	60.47 (0.64)	0.78
Smoking PGS	-0.97 (0.54)	0.63 (0.68)	0.00
Years of education	12.2 (3.41)	12.11 (3.17)	0.81
Income (nominal $ 1000)	19.79 (27.82)	18.95 (30.14)	0.79
No. waves present	4.65 (1.32)	4.59 (1.32)	0.65
	%	%	
Female	48.7	45.05	0.51
Smoking (baseline)	31.3	37	0.28
Persistently uninsured	4.35	6.59	0.36
Avg. cessation rate (baseline smokers)	12.05	12.17	0.97
No. of individuals	115	273	
No. of Person-year individuals	535	1252	
Shock at ages 67-70			
	Mean (SD)	Mean (SD)	
Age (baseline)	61.33 (2.15)	61.04 (1.4)	0.19
Smoking PGS	-0.94 (0.48)	0.75 (0.79)	0.00
Years of education	12.68 (3.13)	12.41 (3.09)	0.46
Income (nominal $ 1000)	17.81 (27.44)	15.74 (20.15)	0.48
No. waves present	5.06 (1.15)	5.12 (0.84)	0.65
	%	%	
Female	40.71	49.1	0.14
Smoking (baseline)	30.09	35.59	0.31
Persistently uninsured	8.85	6.31	0.42
Avg. cessation rate (baseline smokers)	10.92	11.03	0.97
No. of individuals	113	222	
No. of Person-year individuals	572	1136	

back limitations

Who are the uninsured?

Table: Descriptive Statistics for Full Analytic Sample Stratified by Insurance Status

	All	**Uninsured**	**Insured**	**P value**
	Mean (SD)	Mean (SD)	Mean (SD)	
Age (baseline)	61.17 (1.93)	60.85 (0.94)	61.19 (1.97)	0.00
Smoking PGS	0.11 (0.99)	0.19 (0.92)	0.1 (1)	0.07
Years of education	12.48 (3.1)	10.44 (3.55)	12.61 (3.02)	0.00
Income (nominal $ 1000)	20.37 (34.95)	8.66 (13.29)	21.1 (35.74)	0.00
No. waves present	4.44 (1.38)	4.36 (1.28)	4.44 (1.39)	0.26
	%	%	%	
Female	50.42	57.06	50.01	0.01
Smoking (baseline)	29.55	46.76	28.49	0.00
Persistently uninsured	5.85	100	0	-
CV health shock	12.44	13.82	12.35	0.45
Avg. cessation rate (baseline smokers)	10.35	8.54	10.53	0.08
No. of individuals	5813	340	5473	
No. of person-year individuals	25800	24317	1483	

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Outline

Regression results

Coefficients from Estimating the Linear Probability Model in Equation (2) Using OLS

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	Dependent variable:				
	Smoking status				
	(1)	(2)	(3)	(4)	(5)
Health Shock	−0.026	−0.026	−0.026	-0.050^{**}	-0.050^{**}
	(0.040)	(0.040)	(0.040)	(0.023)	(0.023)
Post-65	-0.066^{***}	-0.021^{*}	-0.021^{*}	−0.011	−0.011
	(0.008)	(0.013)	(0.013)	(0.008)	(0.008)
Uninsured	0.171^{***}	0.171^{***}	0.171^{***}		
	(0.027)	(0.027)	(0.027)		
High PGS	0.032^{**}	0.032^{**}	0.032^{**}		
	(0.012)	(0.013)	(0.013)		
Shock × Post-65	0.014	0.023	0.022	0.022	0.022
	(0.055)	(0.056)	(0.056)	(0.032)	(0.032)
Shock × Uninsured	−0.198	−0.192	−0.193	−0.115	−0.117
	(0.184)	(0.184)	(0.184)	(0.073)	(0.073)
Post-65 × Uninsured	0.067	0.065	0.065	-0.052^{*}	-0.053^{*}
	(0.048)	(0.048)	(0.048)	(0.032)	(0.032)
Shock × High PGS	0.024	0.024	0.022	0.020	0.020
	(0.049)	(0.049)	(0.049)	(0.028)	(0.029)
Post-65 × High PGS	0.001	0.001	0.001	−0.003	−0.003
	(0.010)	(0.010)	(0.010)	(0.008)	(0.008)
Shock × Post-65 x Uninsured	0.286	0.280	0.280	0.233^{***}	0.235^{***}
	(0.250)	(0.251)	(0.250)	(0.086)	(0.085)
Shock × Uninsured × High PGS	0.189	0.188	0.189	0.037	0.039
	(0.219)	(0.220)	(0.219)	(0.112)	(0.111)
Shock × Post-65 × High PGS	−0.048	−0.048	−0.046	-0.077^{*}	-0.076^{*}
	(0.068)	(0.068)	(0.068)	(0.042)	(0.042)
Post-65 × Uninsured × High PGS	-0.117^{*}	-0.117^{*}	-0.117^{*}	0.043	0.043
	(0.062)	(0.062)	(0.062)	(0.037)	(0.037)
Shock × Post-65 × Uninsured × High PGS	−0.151	−0.153	−0.154	−0.185	−0.188
	(0.309)	(0.310)	(0.309)	(0.153)	(0.152)
Age		*Yes*	*Yes*	*Yes*	*Yes*
Year FE			*Yes*		*Yes*
Individual FE				*Yes*	*Yes*
Observations	25,800	25,800	25,800	25,800	25,800

Meaning of OLS coefficients

From estimating equation 1 we get the following: back

$$E\left[Y_{it}|post65_{it}=0, g_i=0, shock_{it}=1, uninsured_i=1\right]=\beta+\lambda_2 \tag{9}$$

$$\begin{aligned}E\left[Y_{it}|post65_{it}=1, g_i=0, shock_{it}=1, uninsured_i=1\right]&=\beta+\gamma+\lambda_1+\lambda_2\\&+\lambda_3+\delta_1\end{aligned} \tag{10}$$

$$E\left[Y_{it}|post65_{it}=0, g_i=1, shock_{it}=1, uninsured_i=1\right]=\beta+\lambda_2+\lambda_4+\delta_2 \tag{11}$$

$$\begin{aligned}E\left[Y_{it}|post65_{it}=1, g_i=1, shock_{it}=1, uninsured_i=1\right]&=\beta+\gamma+\lambda_1+\lambda_2\\&+\lambda_3+\lambda_4+\lambda_5+\delta_1+\delta_2\\&+\delta_3+\delta_4+\xi\end{aligned} \tag{12}$$

Then the first two differences yield:

$$(2)-(1)=\gamma+\lambda_1+\lambda_3+\delta_1 \tag{13}$$

$$(4)-(3)=\gamma+\lambda_1+\lambda_3+\lambda_5+\delta_1+\delta_3+\delta_4+\xi \tag{14}$$

And finally the diff-in-diff (G$\times$E) is identified by:

$$(6)-(5)=\lambda_5+\delta_3+\delta_4+\xi \tag{15}$$

Effect of the shock on the outcomes

The derivative of the outcome with respect to shock is: back

$$\begin{aligned}\frac{\partial Y_{it}}{\partial shock_{it}} &= \beta + \lambda_1 post65_{it} + \lambda_2 uninsured_i + \lambda_4 g_i \\ &+ \delta_1 (post65 \times uninsured_i) + \delta_2 (uninsured_i \times g_i) + \delta_3 (post65_{it} \times g_i) \\ &+ \xi (post65_{it} \times uninsured_i \times g_i)\end{aligned} \tag{16}$$

Again, we can look at the decomposition:

$$E\left[\frac{\partial Y_{it}}{\partial shock_{it}} | post65_{it} = 0, g_i = 0, uninsured_i = 1\right] = \beta + \lambda_2 \tag{17}$$

$$E\left[\frac{\partial Y_{it}}{\partial shock_{it}} | post65_{it} = 1, g_i = 0, uninsured_i = 1\right] = \beta + \lambda_1 + \lambda_2 + \delta_1 \tag{18}$$

$$E\left[\frac{\partial Y_{it}}{\partial shock_{it}} | post65_{it} = 0, g_i = 1, uninsured_i = 1\right] = \beta + \lambda_2 + \lambda_4 + \delta_2 \tag{19}$$

$$\begin{aligned}E\left[\frac{\partial Y_{it}}{\partial shock_{it}} | post65_{it} = 1, g_i = 1, , uninsured_i = 1\right] &= \beta + \lambda_1 + \lambda_2 + \lambda_4 \\ &+ \delta_1 + \delta_2 + \delta_3 + \xi\end{aligned} \tag{20}$$

Calculating the first two differences as above:

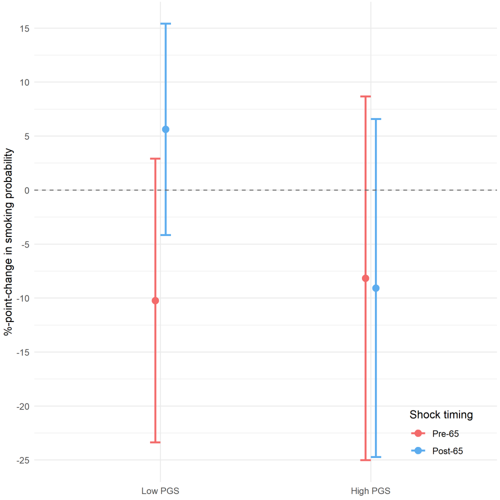
$$(10) - (9) = \lambda_1 + \delta_1 \tag{21}$$

$$(12) - (11) = \lambda_1 + \delta_1 + \delta_3 + \xi \tag{22}$$

Outline

Robustness: age range 59-71

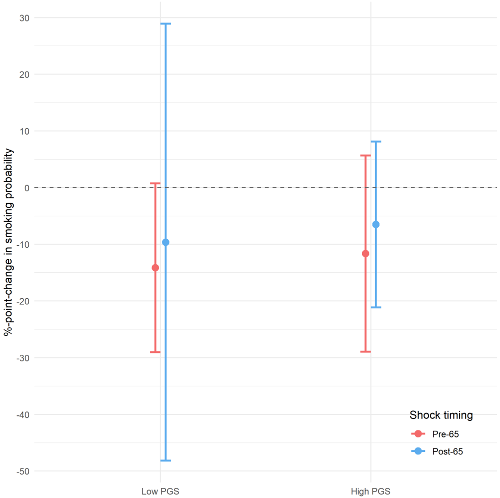
Coefficient plot of the main regression.



back

Robustness: age range 58-72

Coefficient plot of the main regression.



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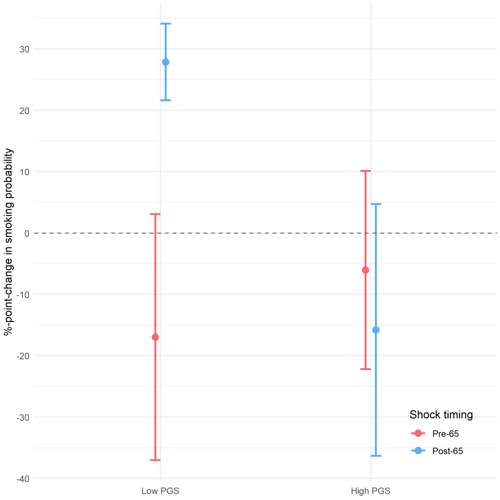
Robustness: age range 55-70

Coefficient plot of the main regression.



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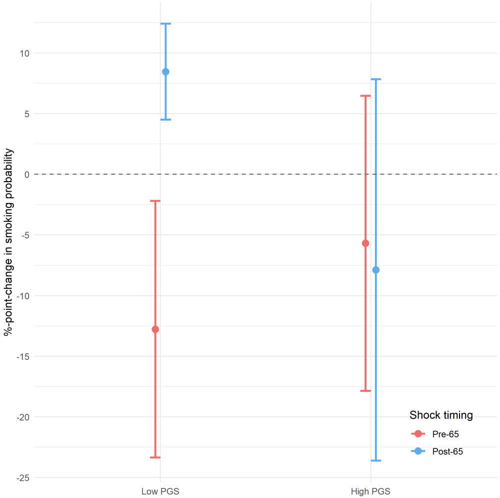
Robustness: uninsured only 2/3 of the time

Coefficient plot of the main regression.



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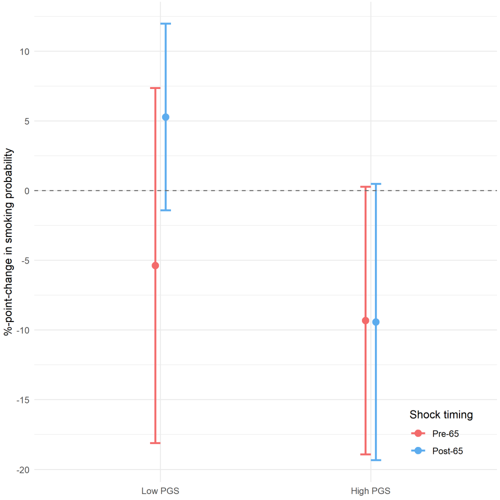
Robustness: uninsured only 1/3 of the time

Coefficient plot of the main regression.



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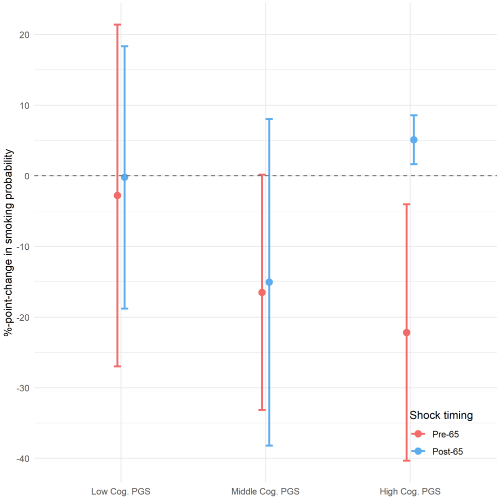
Split by cognitive ability PGS



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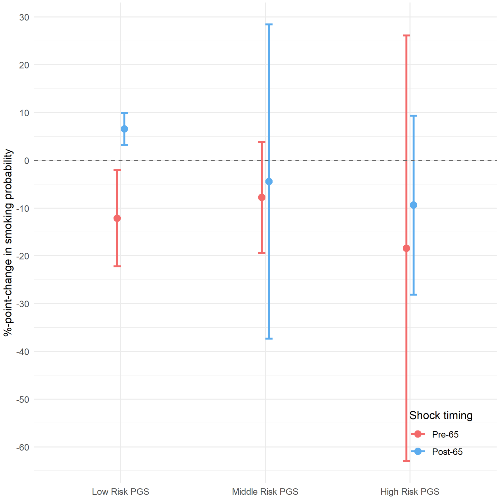
Split by risk-seeking PGS



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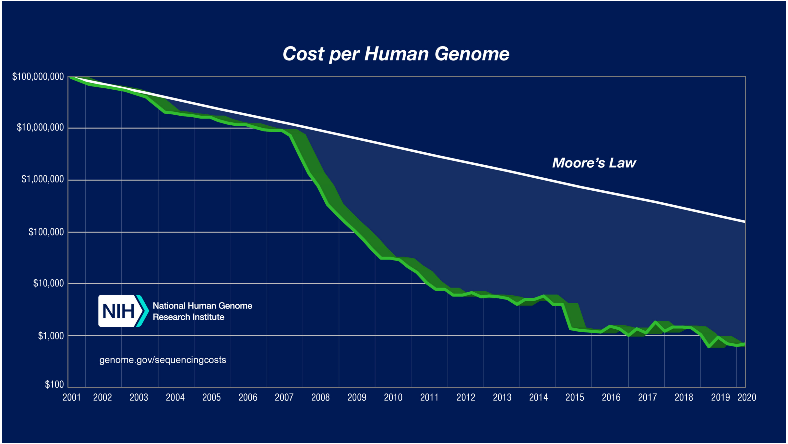
DNA Sequencing Cost

Cost of sequencing the DNA has been falling rapidly (NIH)



Cost per participant: $\approx$ 50 \$ (with SNP imputation)

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