THE CHILD PENALTY ATLAS

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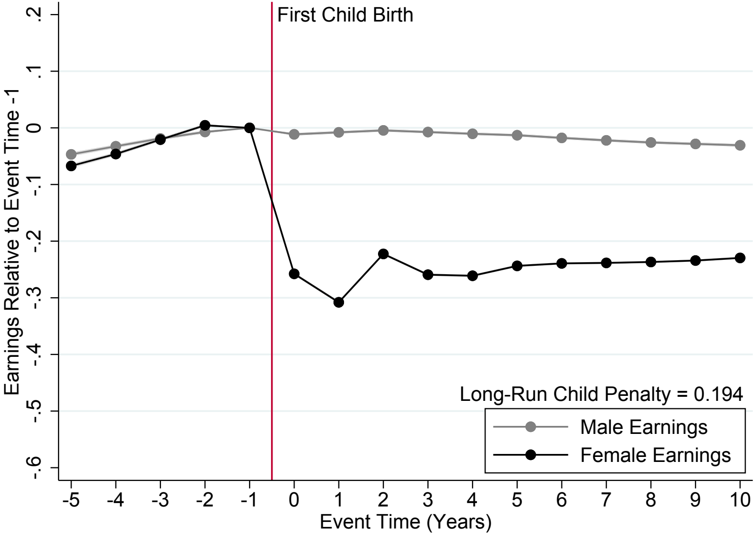
MOTIVATION

- Significant differences between men and women's earnings, wages and employment exist in virtually all countries (Kleven and Landais, 2017)
- Increasingly large share of gender inequality can be explained by the **child penalty**: the causal impact of having children on outcomes of women relative to men
- In Denmark (Kleven et al., 2019b):
  - Share of earnings inequality associated with penalty rose from 40% in 1980 to 80% in 2013
  - First child associated with long-term reduction of 20% in earnings and 13% in employment for mothers relative to fathers
- Current event-study methodology requires extensive panel data with detailed labour market information, only available for a handful of highly developed countries (Kleven et al., 2019a)

Evidence from Denmark (Kleven et al., 2019b)

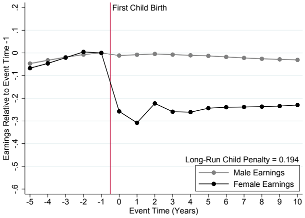
Child penalty in earnings



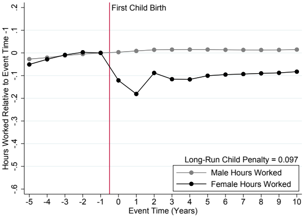
EVIDENCE FROM DENMARK (KLEVEN ET AL., 2019B)

CHILD PENALTY IN DIFFERENT DIMENSIONS

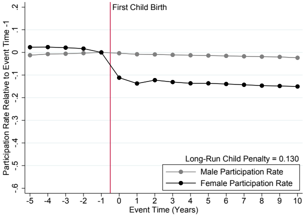
Earnings



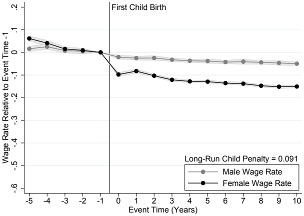
Hours Worked



Employment



Wage Rates



THIS PROJECT

We bridge current limitations in literature with two main contributions:

1. Methodological innovation: create **pseudo-event studies** around child birth using cross-sectional data
   - Validate the approach comparing with panel when possible
   - Expanding set of countries where child penalty can be calculated (no need for large panels)
2. Data collection: harmonise individual-level data for 120 countries from various underlying sources

Parents are positively selected, so a naive cross-sectional approach does not work well

	Men		Women	
	Child	No Child	Child	No Child
Employment	0.89	0.79	0.71	0.80
Earnings	54,001	28,650	24,136	24,943
Fraction College	0.30	0.25	0.28	0.34
Fraction Married	0.87	0.25	0.72	0.34
Fraction White	0.72	0.67	0.67	0.70
Age	38.64	32.55	37.30	32.90

Methodology

Pseudo-Event Study

- Denote event-time relative to the first childbirth by t
  - For those with children, we observe event times $t \leq 0$
  - For those without children, we don't observe event times $t < 0$

- Idea: create a synthetic population of "future parents" who are very similar to observed parents

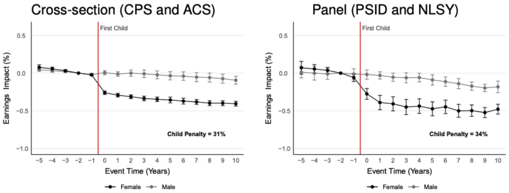
- Consider parent i observed at event-time $t = 0$, at age a in with characteristics X_i

- Parent i is exactly matched to:
  - A non-parent j observed in year y with age $a - s$ and characteristics $X_j = X_i \Rightarrow$ observation for $t = -s$
  - X_i includes gender, marital status, education and urban/rural

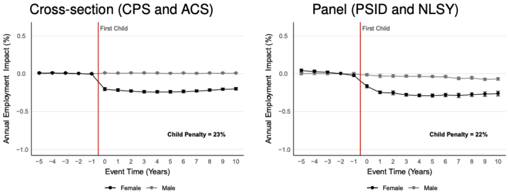
Methodology

Pseudo-Event Study - Validation using US data UK

Earnings



Employment

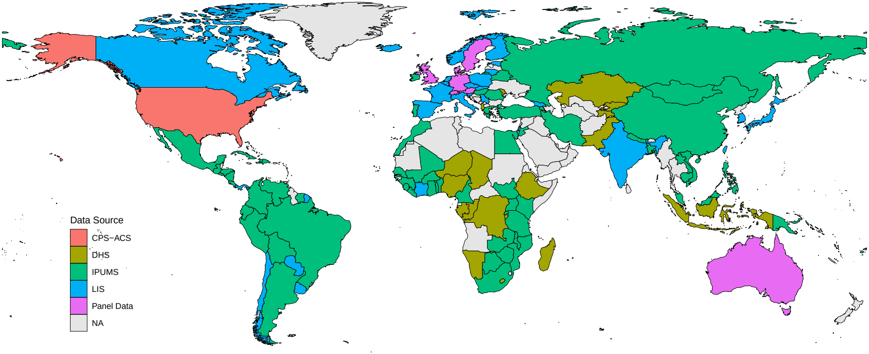


Data sources

We combine sources for 120 different countries to build a world atlas

- Panel data
  - Administrative data: Austria, Denmark, Sweden, Switzerland
  - Survey data: Australia (HILDA), Germany (GSOEP), UK (BHPS)
- Cross-sectional data
  - IPUMS (63 countries): large sample from census harmonised via GJD
  - DHS (22 countries): household survey harmonised via GJD
  - LIS (28 countries): cross-national initiative harmonising national surveys, mostly from developed countries
  - Country-specific household survey: United States (CPS/ACS)

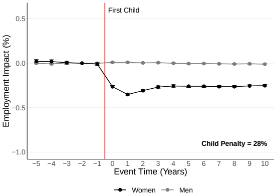
Data sources



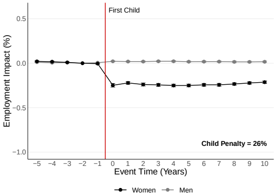
The Child Penalty Atlas

Event-studies by continent

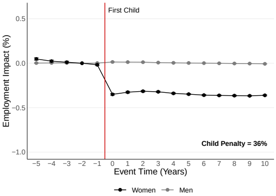
Europe



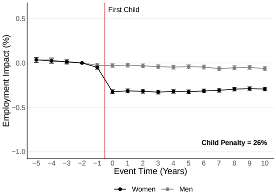
North America



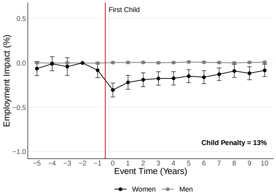
Latin America



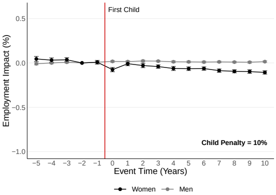
Oceania



Asia



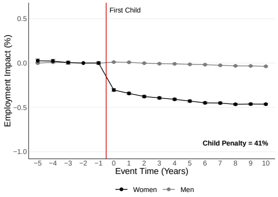
Africa



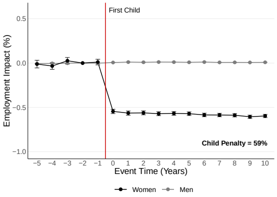
The Child Penalty Atlas

Event-studies by country (1/2)

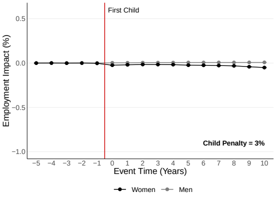
Argentina



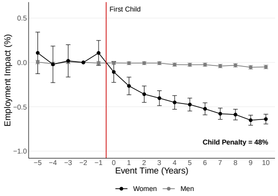
Bangladesh



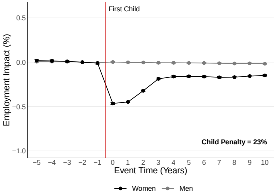
China



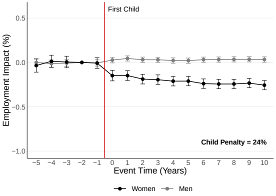
Jordan



Russia

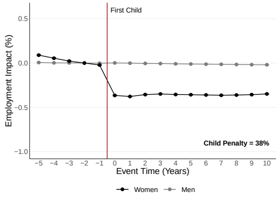


France

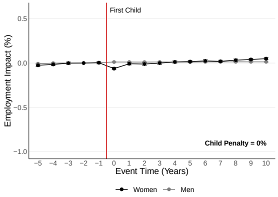


THE CHILD PENALTY ATLAS
EVENT-STUDIES BY COUNTRY (2/2)

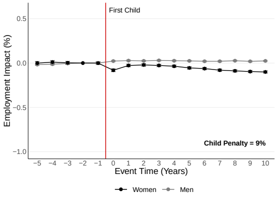
Brazil



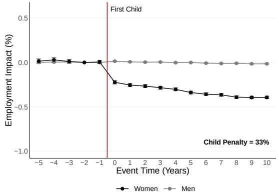
Cambodia



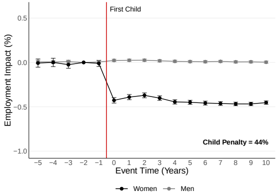
Ghana



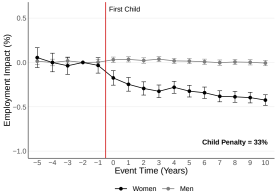
Greece



Mexico

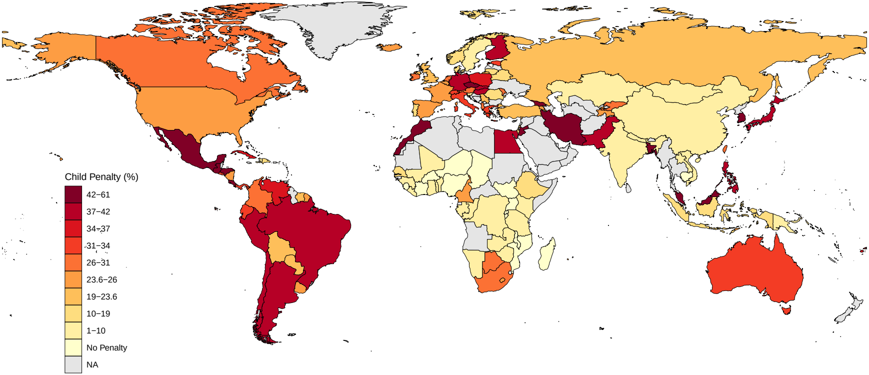


Italy



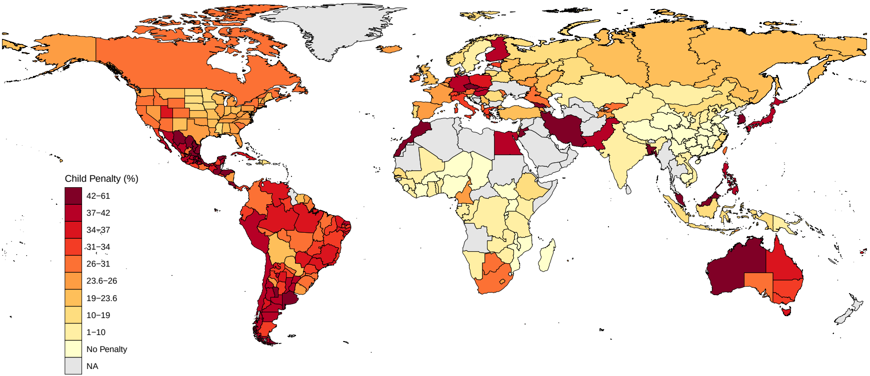
The Child Penalty Atlas

Employment



The Child Penalty Atlas

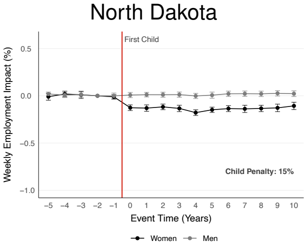
Large samples from IPUMS allow us to go at the regional level in some countries

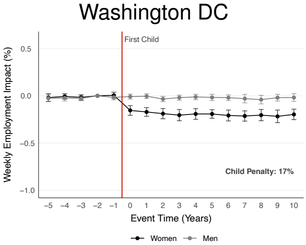


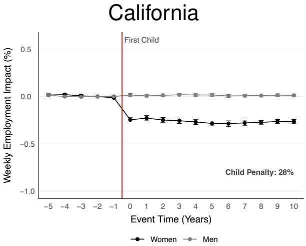
Europe Latin America China & Russia

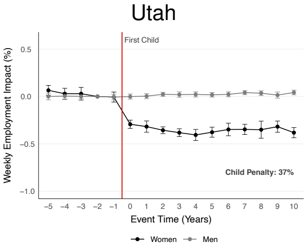
The Child Penalty Atlas

Employment Penalty: Event-studies US States





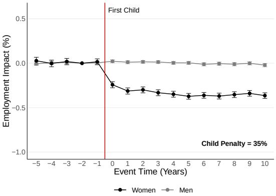




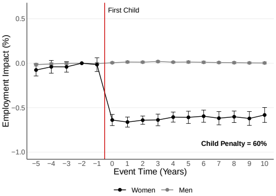
The Child Penalty Atlas

Event-studies in large cities (1/2)

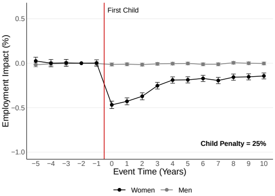
Buenos Aires



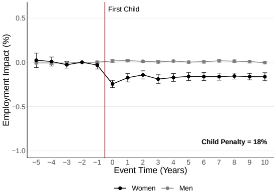
Dhaka



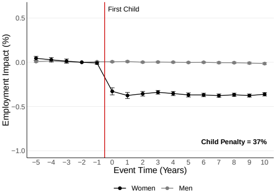
Moscow



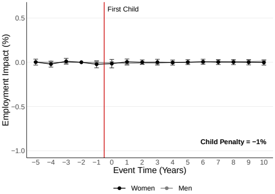
Nairobi



São Paulo



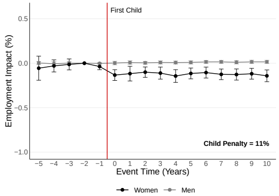
Shanghai



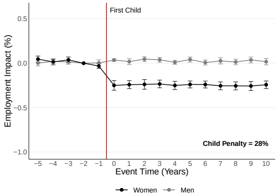
THE CHILD PENALTY ATLAS

EVENT-STUDIES IN LARGE CITIES (2/2)

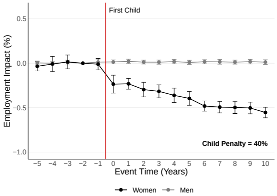
Beijing



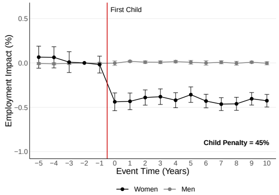
Cape Town



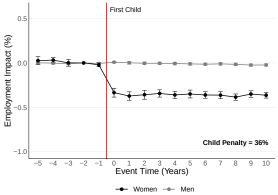
Kuala Lumpur



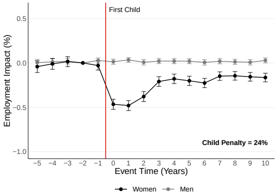
Mexico City



Rio de Janeiro



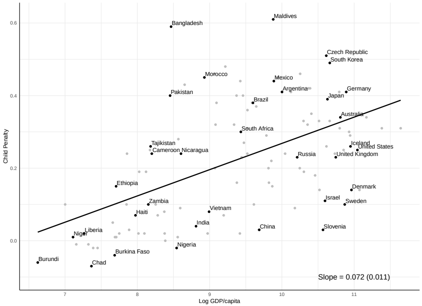
St. Petersburg



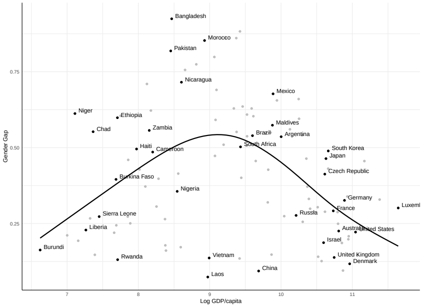
Gender Inequality and Development

- As GDP per capita increases:
  - Child penalty increases
  - Gender gap in employment follows a inverted-U shape

Child Penalty vs GDP/capita

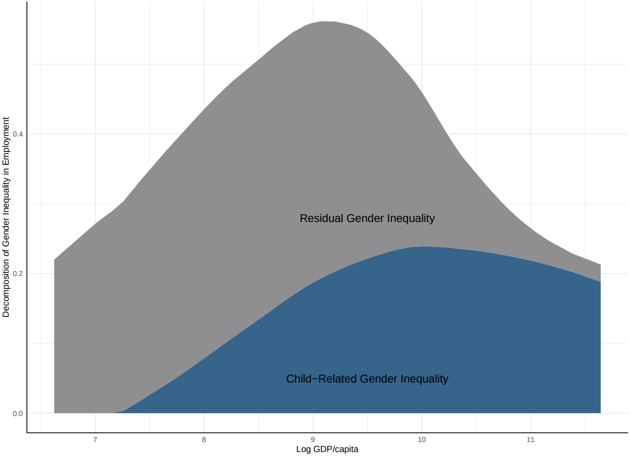


Employment Gap vs GDP/capita



Gender Inequality and Development

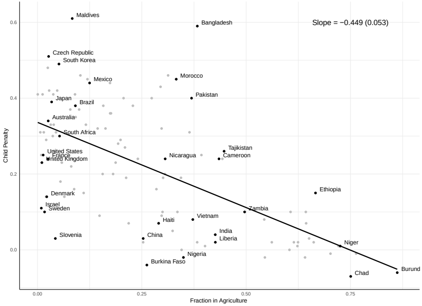
- As GDP per capita increases:
  - Child penalty accounts for an increasingly large share of the total gender gap



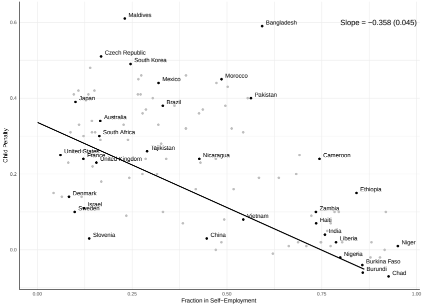
Correlates of Child Penalty

- Child penalty is highest in countries with lower share in agriculture and self-employment

Agriculture

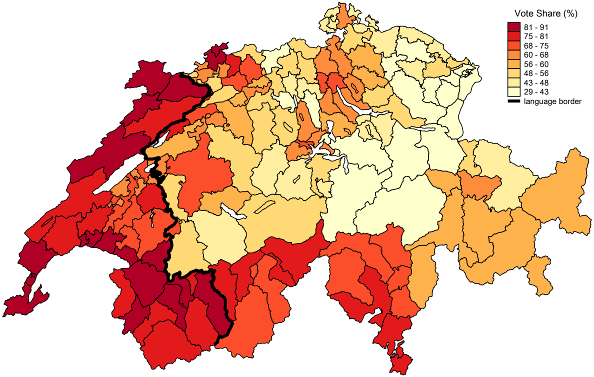


Self-Employment



The Role of Norms

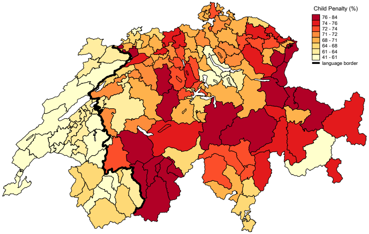
Switzerland: Fraction Voting Yes To Female Suffrage Referendum 1971



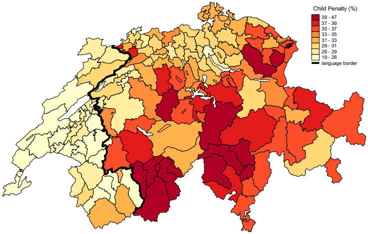
The Role of Norms

Switzerland: Child Penalties By Canton

Earnings Penalties

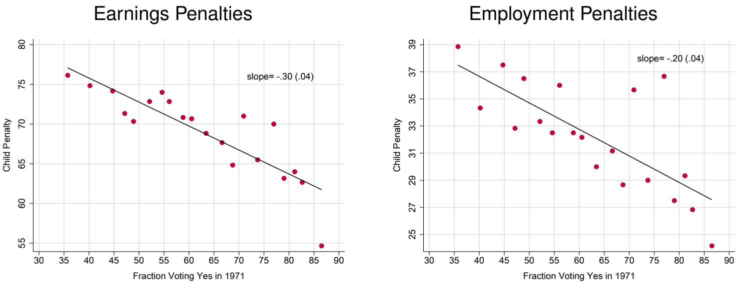


Employment Penalties



The Role of Norms

Switzerland: Correlation Btw Child Penalties & Norms By Canton



NEXT STEPS

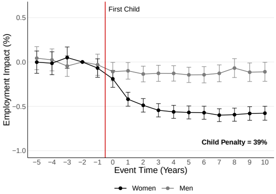
- Study potential underlying drivers of child penalty
  - Gender norms
  - Public policy (parental leave, welfare support, etc.)
  - Path dependence
- Look at child penalty in different outcomes
  - Time use
  - Welfare
  - Values and norms
- Continue gathering data for the remaining ~70 countries

Thank you!

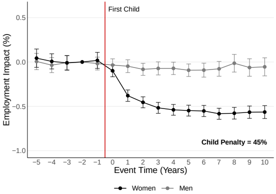
Methodology

Pseudo-Event Study - Validation (UK)

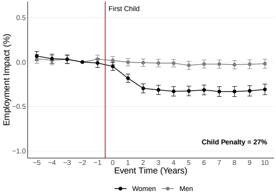
Earnings - cross-secion



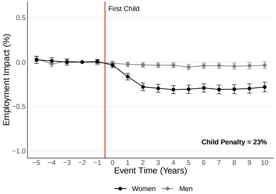
Earnings - panel



Employment - cross-section



Employment - panel



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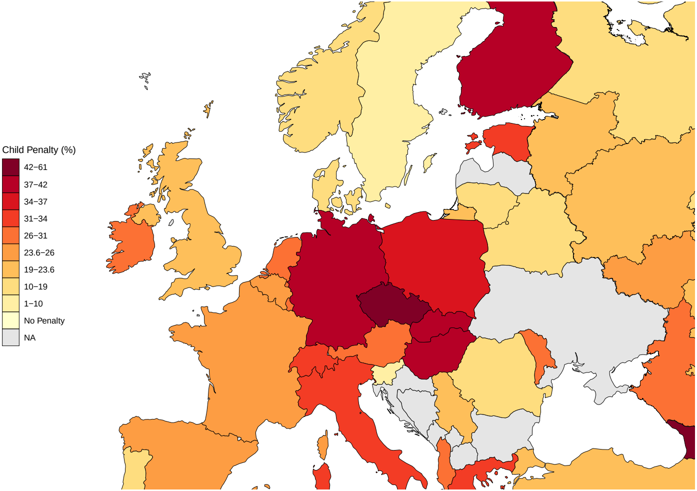
The Child Penalty Atlas - Europe



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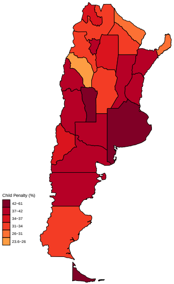
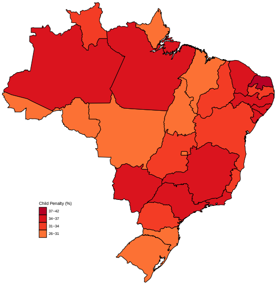
The Child Penalty Atlas - Latin America

Back

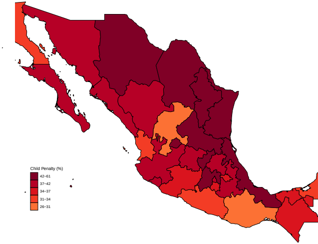
Argentina



Brazil



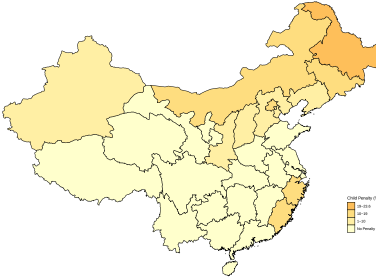
Mexico



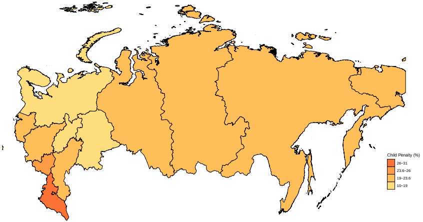
The Child Penalty Atlas - China and Russia

Back

China



Russia



Inequality and Creative Destruction

New Evidence from New Data

Xavier Jaravel, *London School of Economics*

October 27, 2021

From Inequality to Creative Destruction

- Recent work leverages new data to characterize how “inequality” shapes the rate and direction of creative destruction
- Three main channels investigated in recent work:
  1. Creative destruction responds endogenously to **market size effects**, which amplifies income inequality through the direction of innovation in the product market
  2. **Unequal acess to careers in entrepreneurship and innovation**, which affects both the rate and direction of innovation
  3. The role of **financial incentives/top income taxes** to induce innovation

[1/3] From Market Size to Creative Destruction

(Jaravel 2019)

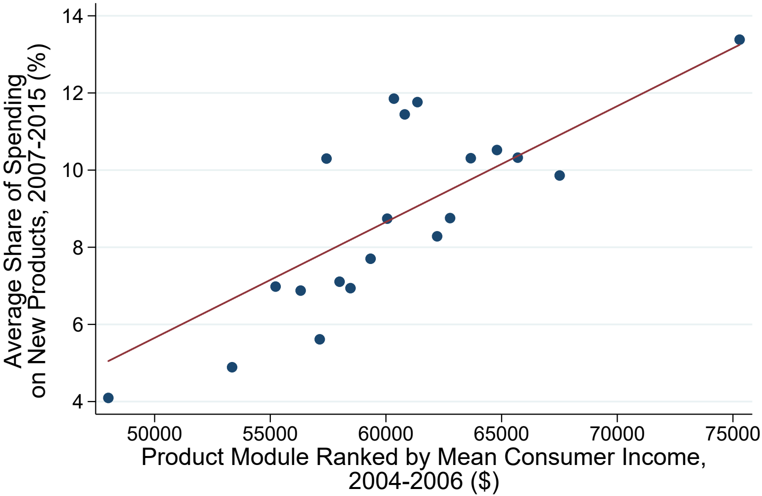
- Theory:

  Shifts in income distribution $\Rightarrow$ Increased demand for premium products

  $\Rightarrow$ Shift in direction of product innovations

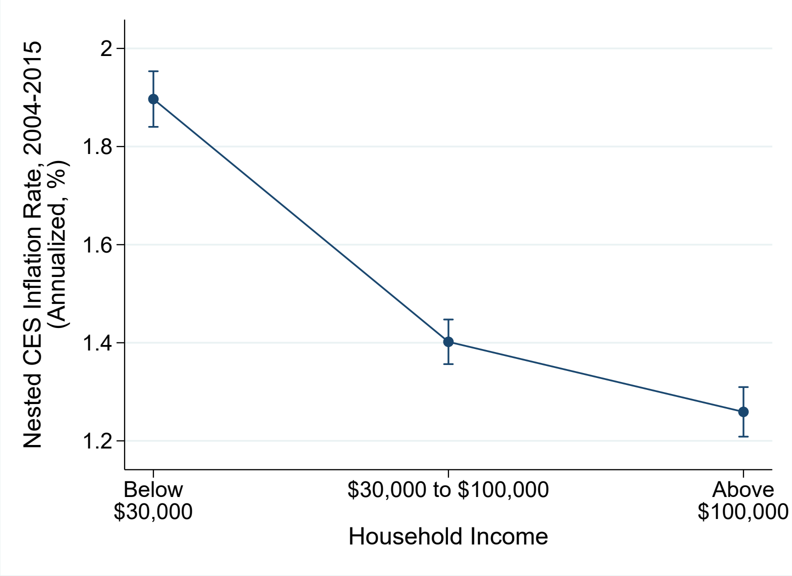
  $\Rightarrow$ Increase in purchasing-power inequality

New Products Benefit Higher-Income Consumers More



Coeff. 3.004*** s.e. (1.103)
Standard errors clustered at the level of 1014 product modules

Lower Inflation for Higher-Income Consumers



The Endogenous Response of Creative Destruction to Market Size

- Research design in two steps:
  - Identify effect of demand on supply using changes in age and income distributions over time as demand shifters (shift-share) $\Rightarrow$ find that increase in demand leads to a fall in prices
  - Apply point estimates to changes in demand induced by shifts in US income distribution

Policy Implications

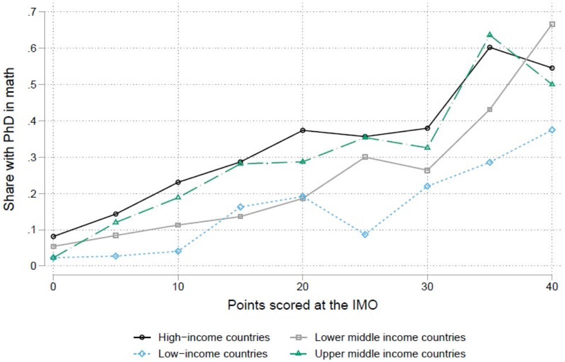
1. Measurement of poverty and eligibility/indexation of government transfers
   - Food stamps
   - Medicaid
2. Cost-benefit analysis of redistributive policies
   - Amplification through the direction of creative destruction
   - Implications for optimal taxation

[2/3] From Social Background to Creative Destruction

- There is mounting evidence that social background (parent income, parent occupation, neighbourhoods, peers, etc.) matters significantly for the decision of entering an inventor's career
  - Similar evidence in many countries and time periods

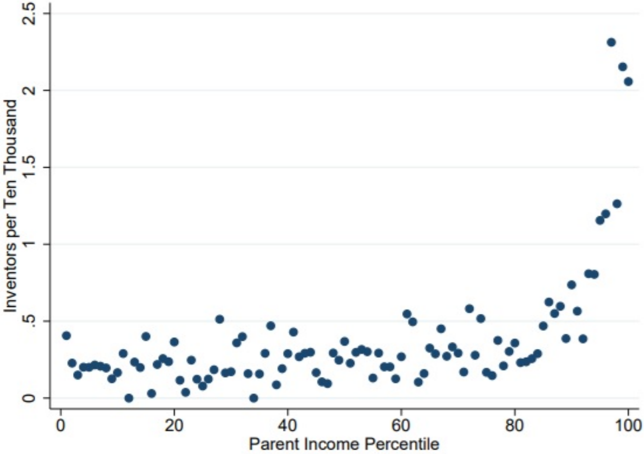
Developing countries (Agarwal and Gaule, 2020)

Figure 6: Share getting a PhD in mathematics across country income groups



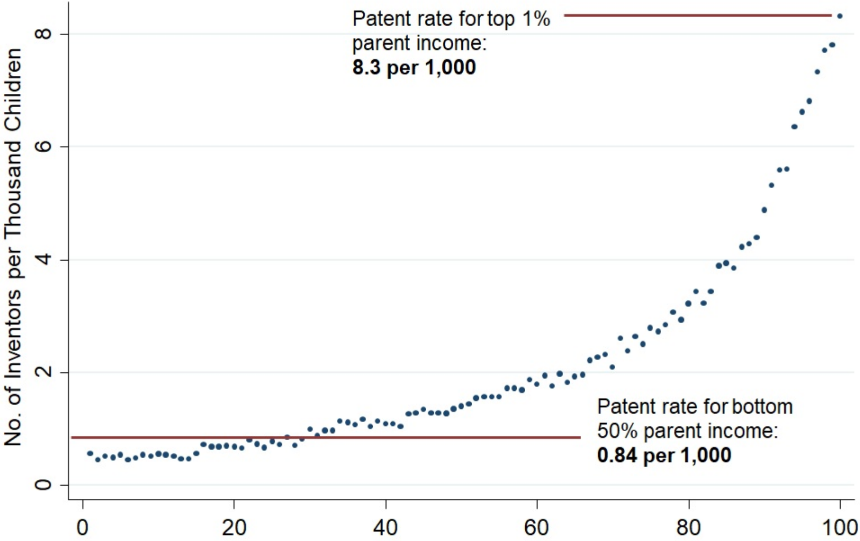
Notes: We compute the share of IMO participants getting a PhD in mathematics by the number of IMO points scored (5-year bands) and plot the resulting share against the number of points scored.

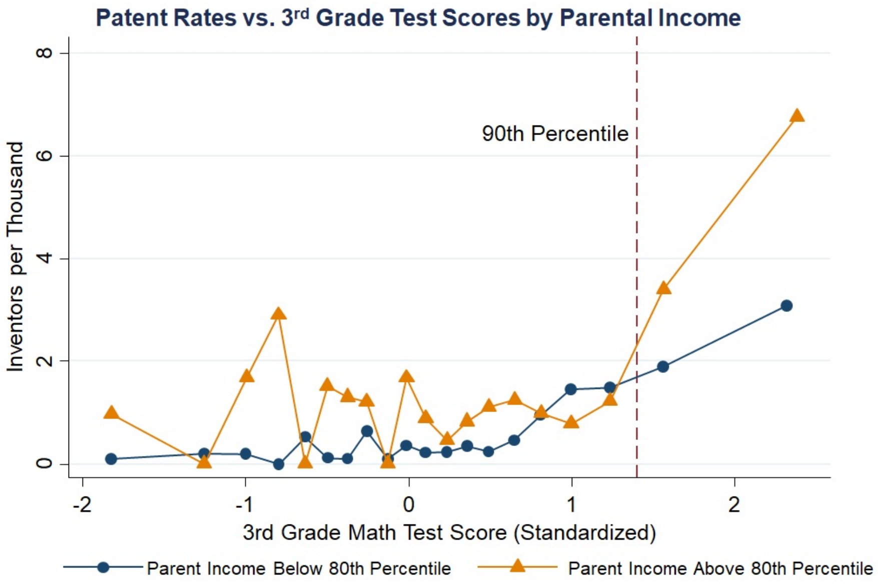
United States, 1880-1940 (Akcigit,Grigsby & Nicholas 2019)

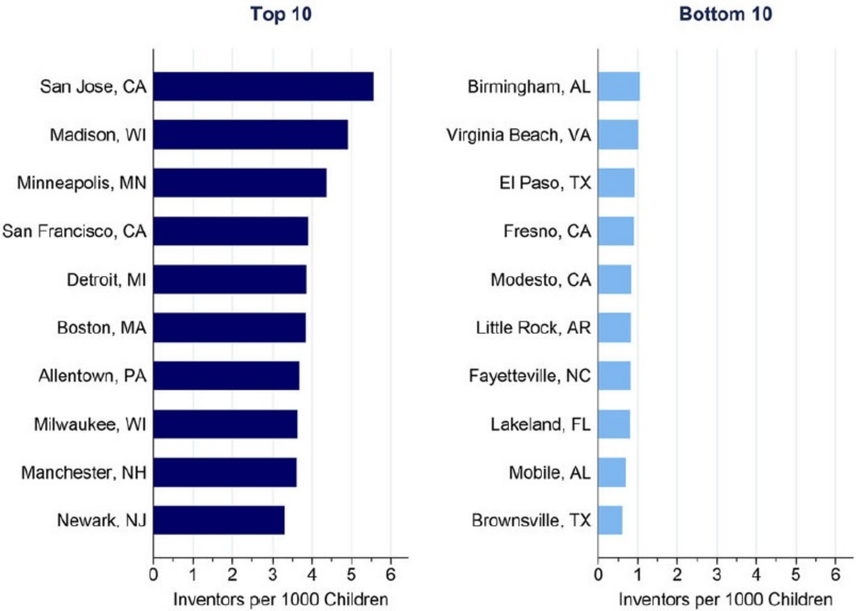


United States post 1980

(Bell, Chetty, Jaravel, Petkova and Van Reenen 2019)




Patent Rates vs. 3rd Grade Test Scores by Parental Income
Inventors per Thousand
0
2
4
6
8
90th Percentile
-2
-1
0
1
2
3rd Grade Math Test Score (Standardized)
Parent Income Below 80th Percentile
Parent Income Above 80th Percentile



Top 10
San Jose, CA
Madison, WI
Minneapolis, MN
San Francisco, CA
Detroit, MI
Boston, MA
Allentown, PA
Milwaukee, WI
Manchester, NH
Newark, NJ
0 1 2 3 4 5 6
Inventors per 1000 Children
Bottom 10
Birmingham, AL
Virginia Beach, VA
El Paso, TX
Fresno, CA
Modesto, CA
Little Rock, AR
Fayetteville, NC
Lakeland, FL
Mobile, AL
Brownsville, TX
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Inventors per 1000 Children

Unequal access to innovation and the direction of innovation

- Previous results suggest a large effect on the *rate* of innovation
- But unequal access to innovation and entrepreneurship can also have an impact on the *direction* of innovation

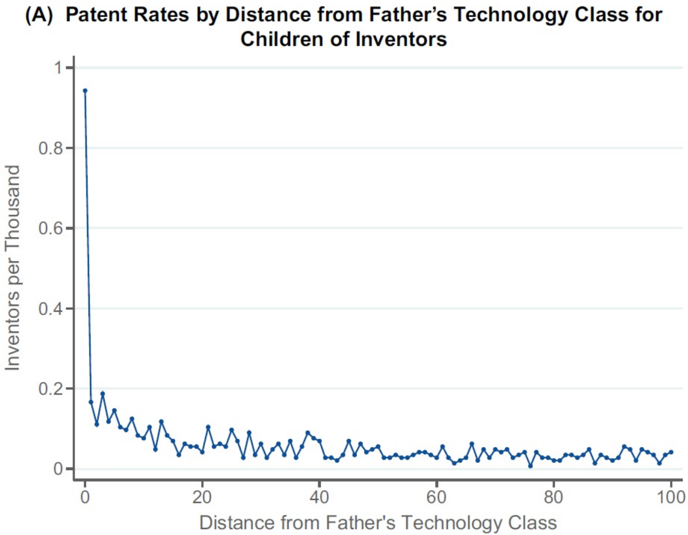
Example: Invention of Dishwasher

Josephine Cochrane *resolved to wash the fine china herself, but soon became tired of this tedious task. She was convinced there had to be a mechanical solution that would make the job easier not just for herself, but others as well.*

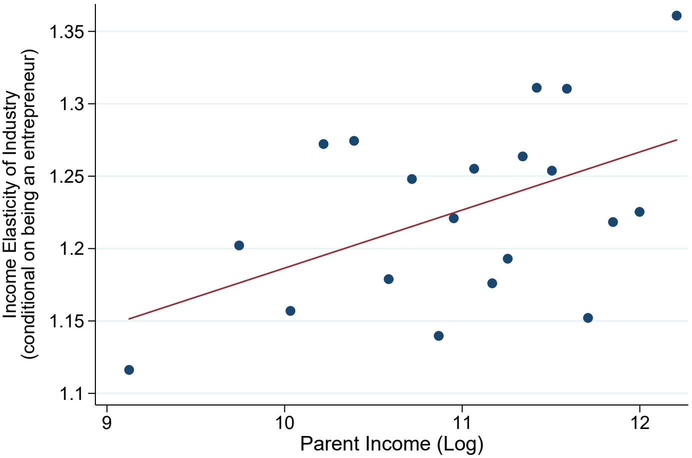
USPTO Profile on the Inventor of the Dishwasher

Children of Inventors

(Bell, Chetty, Jaravel, Petkova and Van Reenen 2019)



Entrepreneur-Consumer Homophily - Parental Income, PSID (Einio, Feng, Jaravel 2020)



Coeff. = 0.04** (s.e. 0.0175). The sample includes entrepreneurs only (N=275).
Parent income is measured as the sum of father's income and mother's income.

Clean/Green Patents (USPTO)

(Einio, Feng, Jaravel 2020)

	Clean Patent	
	(1)	(2)
Female Inventor	0.326***	
	(0.014)	
Average Inventor Age		-0.001*
		(0.0006)
Mean	0.286	0.132
N	53,984	1,243

Policy Implications

- Exposure to innovation is an important lever to increase growth
  - Mentorship, internships, etc.
  - Targeting exposure programs to women, minorities, and children from low-income families who excel in math and science at early ages
- Developing and testing methods to increase exposure to innovation among disadvantaged subgroups is a promising direction for research and policy

[3/3] Financial Incentives for Creative Destruction

- High top income inequality generates financial incentives to innovate:
  - Agents decide optimally whether to become workers or innovators, and how much effort to put into innovating (e.g., Aghion and Howitt 1992, Jones and Kim 2018)

- But high top income inequality may not be necessary to induce innovation:
  - Scientists "pay to be scientists" as they value being able to pursue a "calling" or an individual research agenda (e.g., Stern 2004)
  - Top income tax reductions may have little impact on the decisions of star inventors, who matter most for aggregate innovation (e.g., Jaimovich and Rebelo 2017; Bell, Chetty, Jaravel, Petkova and Van Reenen 2019)
  - Financial incentives may attract talent into professions with lower externalities than innovation careers (e.g. finance, as in Lockwood, Nathanson, and Weyl 2017)

Tax Evasion and Inequality: Emerging Insights from New Data

Daniel Reck, London School of Economics

27 October 2021

Motivation

How is tax evasion distributed through the income/wealth distribution?

- Important for the measurement of inequality:
  - Tax data are usually the starting point for the measurement of inequality, e.g. top 1% income shares (Piketty & Saez 2003)
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  - ▷ Piketty Saez Zucman (2018) and Auten & Splinter (2019) arrive at divergent estimates for the change in US top 1% shares of national income since the 1970s
  - ▷ A sizable portion ($\approx 1/3$) of the divergence is due to assumptions about under-reported income

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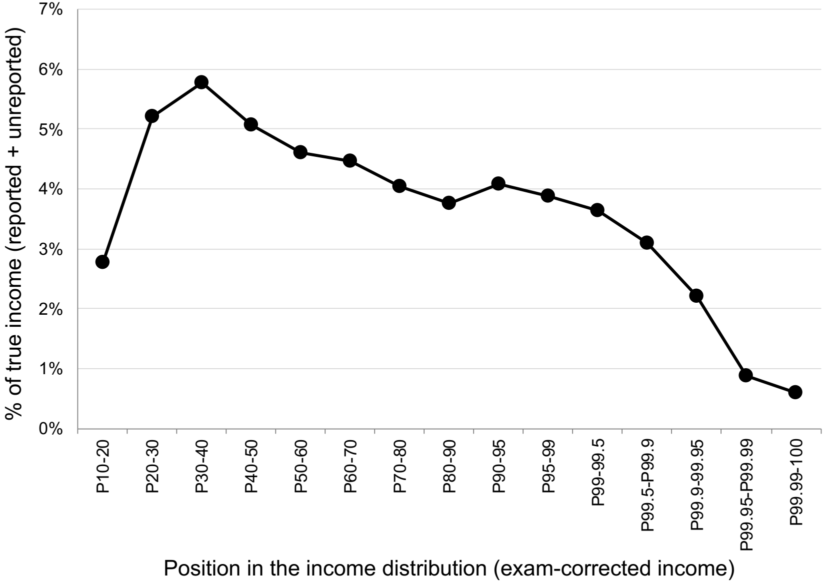
  - A sizable portion ($\approx 1/3$) of the divergence is due to assumptions about under-reported income
- Important for the study of tax policy, e.g. what should tax policy do about inequality?

How do we study tax evasion empirically?

- Main source of data: audits of a random sample of individual tax returns (e.g. IRS 2019; Kleven et al 2011)
- Important challenge: difficulty capturing top-end evasion
  - Audits do not detect all evasion
  - Likely esp. difficult at the top: complex finances and pass-through ownership structures
- Coauthors and I study this challenge in a recent working paper (Guyton, Langetieg, Reck, Risch, Zucman 2021)

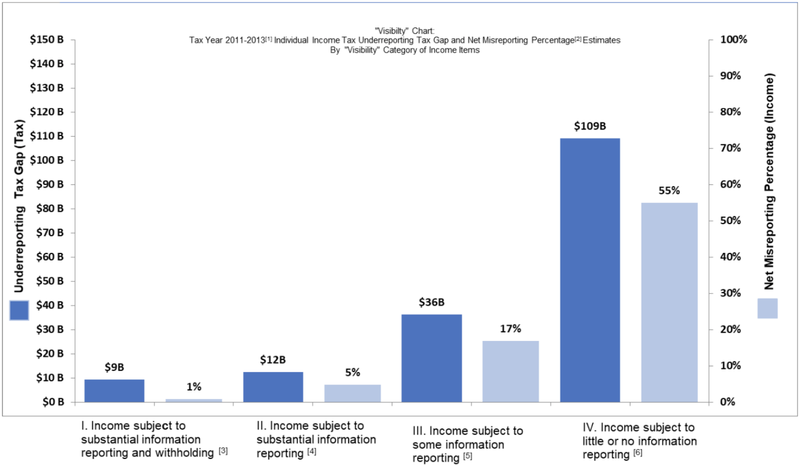
The random-audit-detected rate of evasion falls sharply at the top



Source: Guyton et al 2021

Official estimates (based on random audits): Evasion strongly related to third-party information

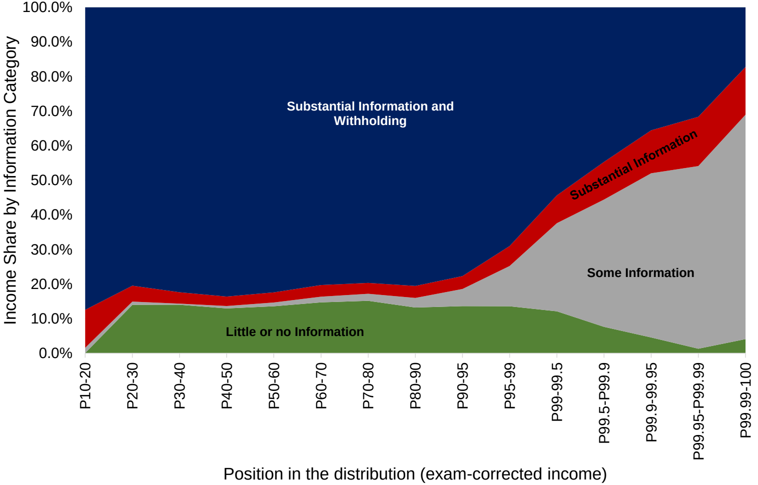
Tax Gap Estimates for Tax Years 2011–2013: Attachment 3



[1] The TY 2011--2013 estimate is the annual average for the TY 2011, 2012, and 2013 timeframe. This chart displays the tax gap attributable to the underreported income category and the rate at which that income is misreported as measured by the Net Misreporting Percentage.
[2] The Net Misreporting Percentage is the ratio of the net misreported amount to the sum of the absolute values of the amounts that should have been reported, expressed as a percentage. For categories I - IV, the net misreported amount is understatements of income less overstatements of income. On net, income is understated for these categories.
[3] Includes wages & salaries.
[4] Includes pensions & annuities, unemployment compensation, dividend income, interest income, taxable Social Security benefits.
[5] Includes partnership/S corp. income, capital gains, alimony income.
[6] Includes nonfarm proprietor income, other income, rents and royalties, farm income, Form 4797 income.

Source: IRS(2019)

The extent of third-party reporting declines with income at the very top

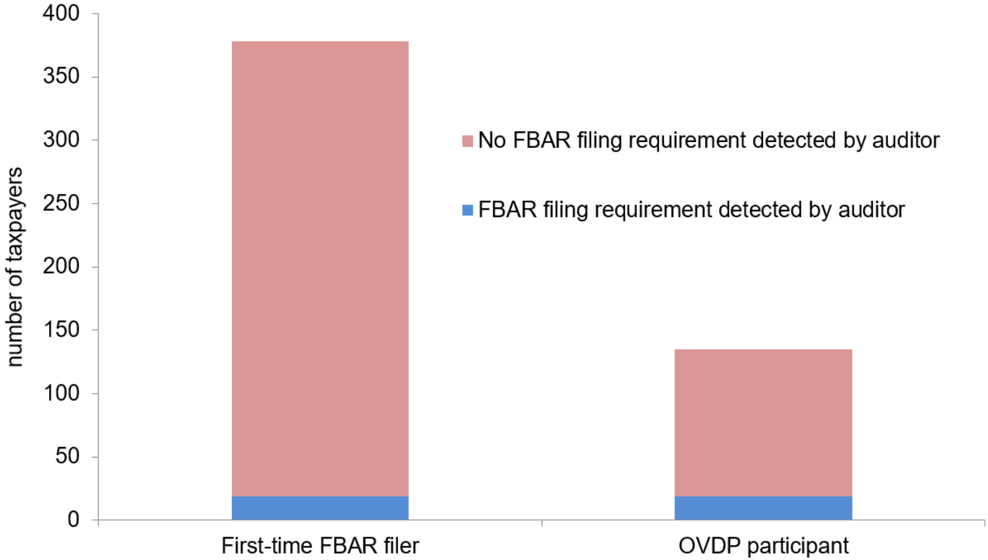


Source: Reck Risch Zucman (2021)

Enter new data

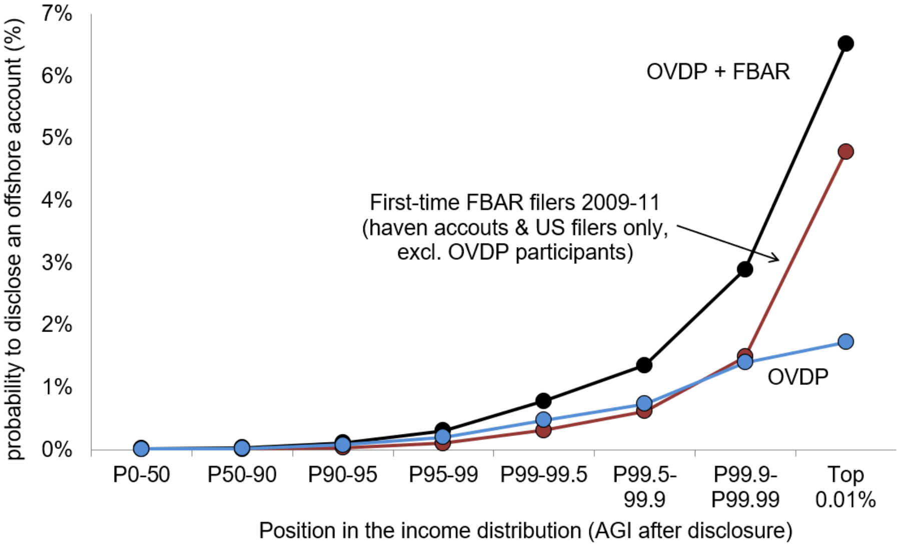
- Data used in our paper (US):
  - **Indications of prior non-compliance**: Individuals indicating prior evasion via offshore wealth, in response to a crackdown
  - **Administrative audit data**: non-random operational audits, random audits of businesses
- Similar data available in many countries:
  - Leaks & other amnesty-type programs (Alstadsaeter Johannesen Zucman 2019, Omartian 2017)
  - Information generated by legal proceedings, e.g. US "John Doe Summonses"
  - Data on **beneficial owners** of assets from recent reforms (FATCA & CRS for offshore financial assets, beneficial ownership registers)
- Challenge: these types of data can be selected or limited in scope $\Longrightarrow$ uncertainty about the total extent of evasion

Random audits do not detect offshore evasion that we know was happening



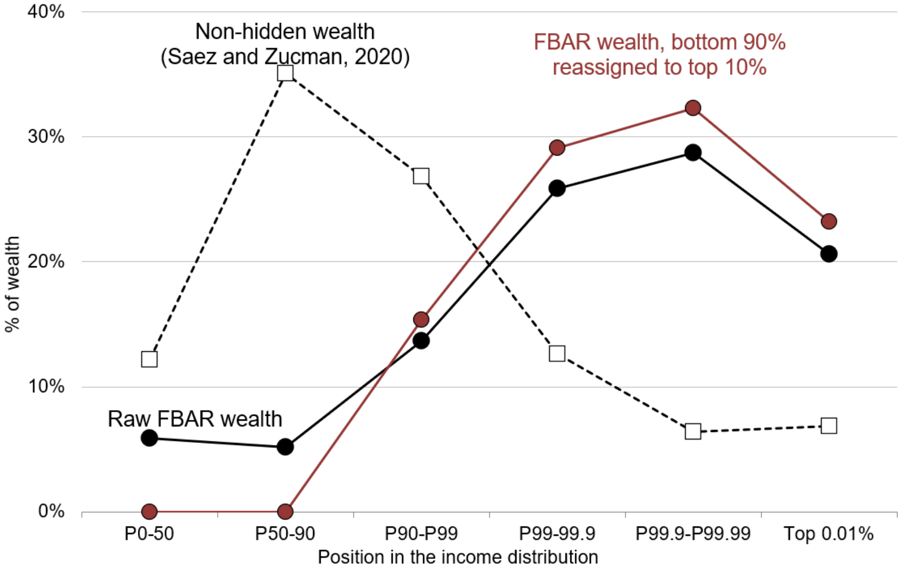
Source: Guyton et al 2021, using data from Johannesen Langetieg Reck Risch Slemrod 2020

About 7% of top earners disclosed an offshore account in our data



Source: Guyton et al 2021, using data from Johannesen et al 2020

Estimated distribution of hidden and non-hidden wealth



Source: Guyton et al 2021, using data from Johannesen et al 2020

Evasion in private businesses creates additional measurement challenges

- ▷ Many US businesses, esp closely held, are "pass-through" entities whose income is distributed and taxed to their owners.
- ▷ Importance of pass-through income at the top of the income distribution is high and growing (Smith et al 2019)

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- Auditing tiered ownership structures is especially resource-intensive.

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- Auditing tiered ownership structures is especially resource-intensive.
- *Business-level* pass-through compliance is rarely examined in NRP audits, but when it is, auditors find signifiant non-compliance.
  - Audits detect *entity-level* under-reporting for 3.8% of individuals with S-corp or Partnership income
  - These 3.8% comprise $\approx$ 58% of all detected pass-through under-reporting

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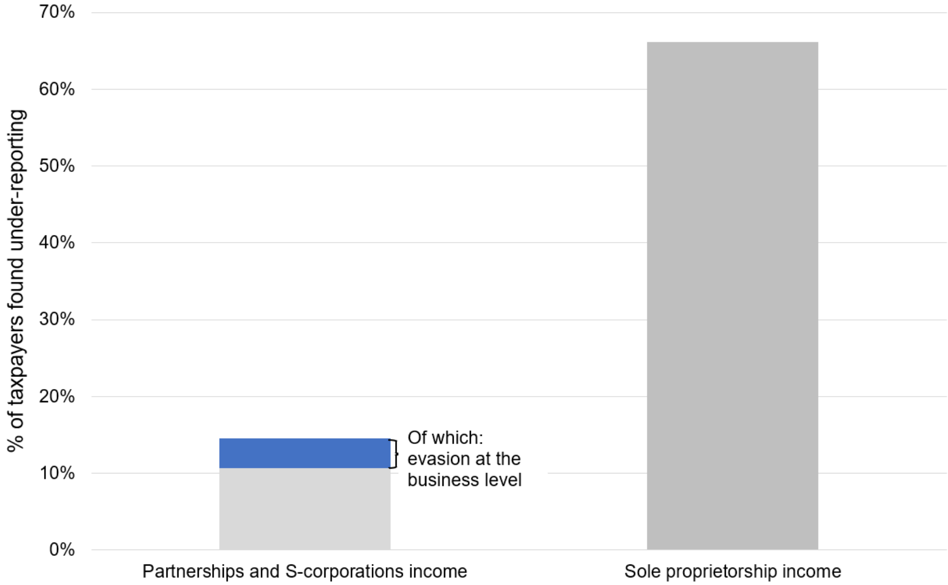
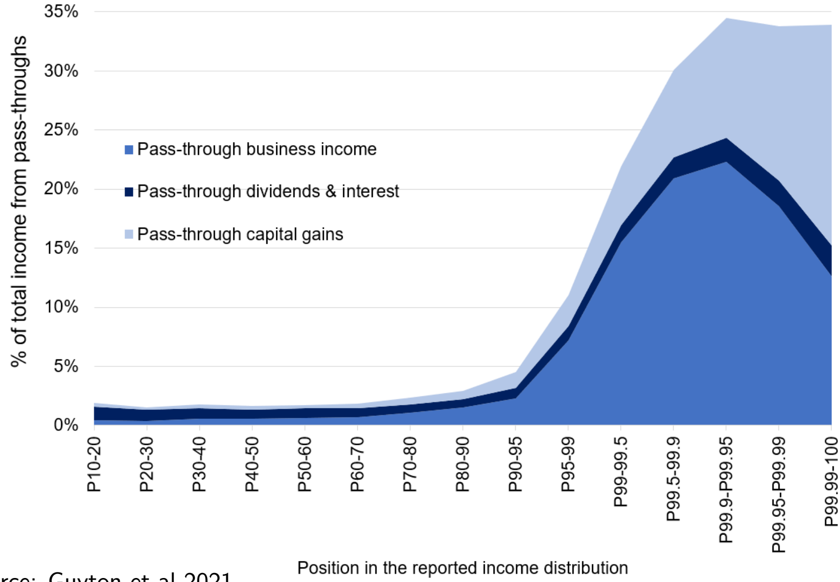
$\Longrightarrow$ *Estimates based on individual random audits likely do not detect all evasion via pass-through business entities*

Rarity of business-level audits $\Longrightarrow$ Rarity of detected under-reporting for S corps and partnerships



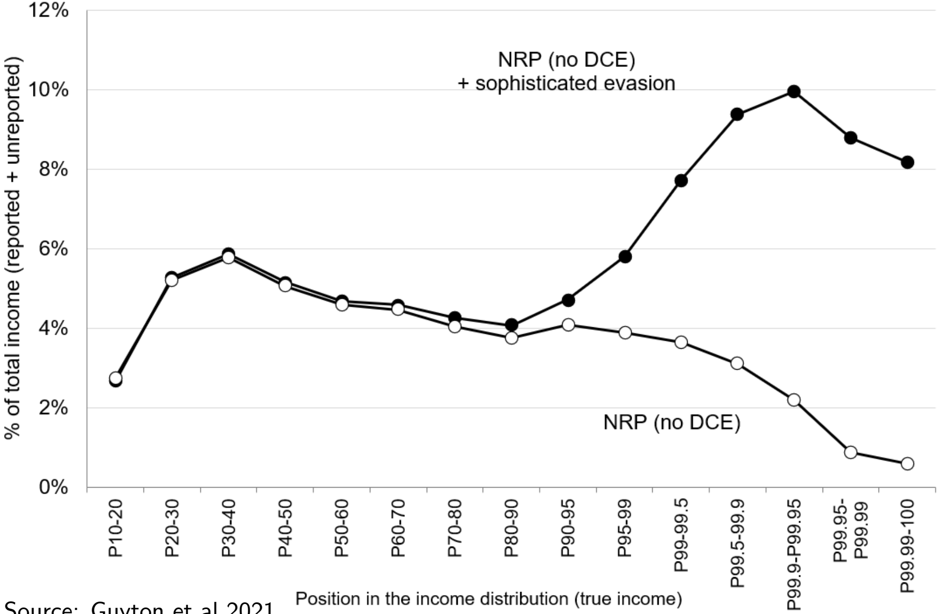
Source: Guyton et al 2021

Pass-through Income is Highly Concentrated



Source: Guyton et al 2021

Adding Pass-Through *and* Offshore Evasion To Random Audit Estimates



Source: Guyton et al 2021

Implications for inequality

- From detected evasion in random audit data alone:
  - Accounting for under-reported income would decrease US top 1% income share by 0.5 pp, c.f. $\approx$ 20% in the period we study
  - High-income individuals rarely evade $\implies$ little fiscal return to cracking down on top end evasion
- After accounting for undetected offshore and pass-through evasion:
  - Accounting for under-reported income would *increase* top 1% income share by 0.7-1.5 pp
  - High-income individuals evade as much or more than others $\implies$ sizable potential return to cracking down
  - Which policies could meaningfully reduce evasion by these individuals? More research is needed!

Health Inequalities

Johannes Spinnewijn (LSE)

October 2021

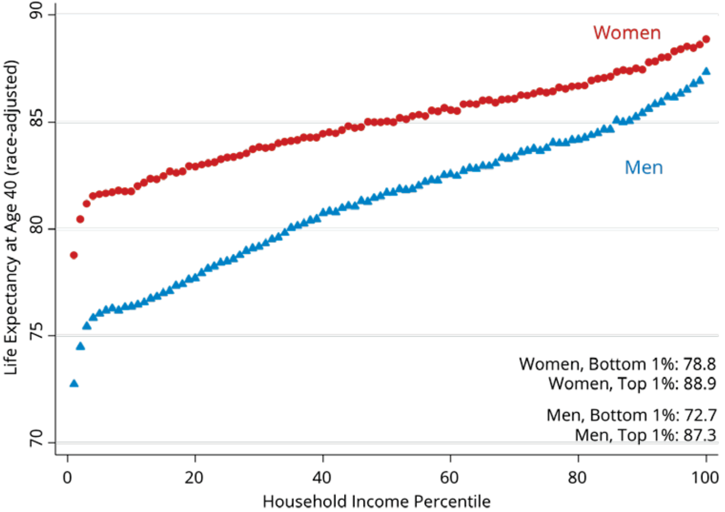
Introduction

- **Motivation:** Important and persistent inequalities in health outcomes
- **Policy:** Repeated policy intentions to close the gap.
  - E.g., WHO ['85,'08], UK ['98], Netherlands ['01], Sweden ['17], Belgium ['20], ...
- **Research:** Lots of research, but still limited understanding of its determinants. Deaton ['02]:

  "there is no general agreement about [its] causes . . . [and] what apparent agreement there is is sometimes better supported by repeated assertion than by solid evidence."

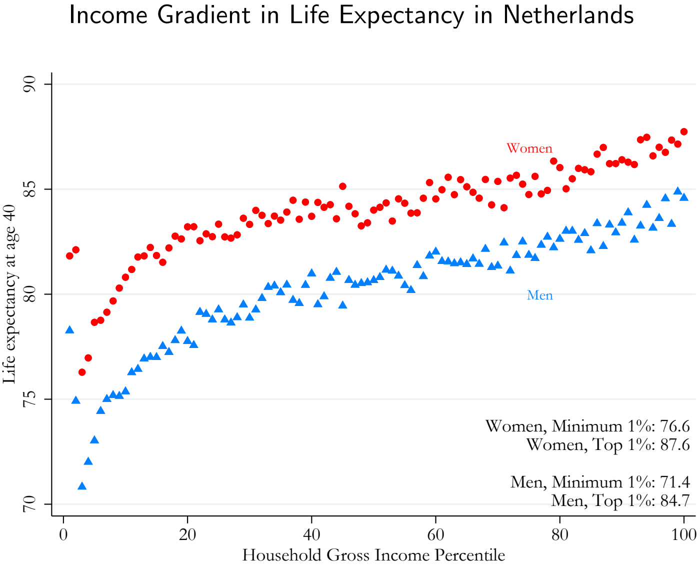
Stylized Fact: Health Gap is Large

Income Gradient in Life Expectancy in US



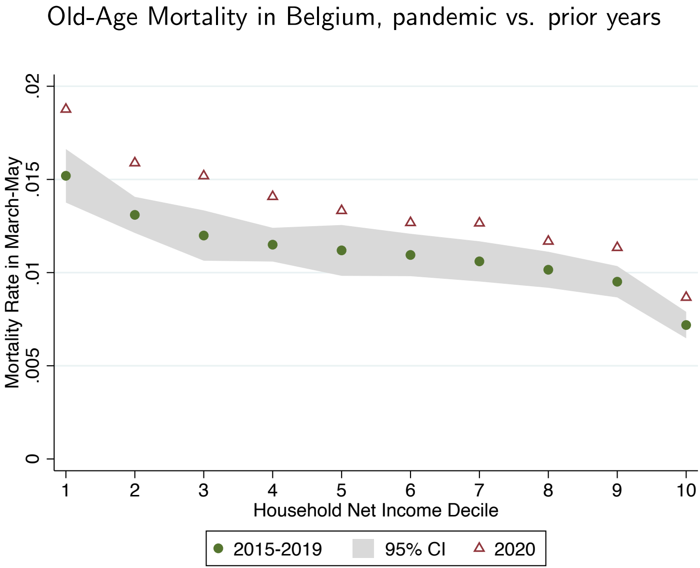
Source: Chetty et al, JAMA 2016

Stylized Fact: ... also in Europe



Source: Own estimates

Stylized Fact: ... also during the Pandemic



Source: Decoster, Minten, Spinnewijn ['21]

Prior Work vs. New Data Opportunities

- **Prior work:** general patterns vs. specific conditions
- **New data:** granular and comprehensive; individually-linked and population-wide
- **New opportunities:** mechanisms and magnitudes

Prior Work vs. New Data Opportunities

- **Prior work:** general patterns vs. specific conditions
  - socio-economic gradients in health outcomes and behavior, using health surveys and mortality registers
  - differences in incidence/treatment/survival for specific health conditions, using cohort studies and health records
  - impact of specific health and economic shocks, using administrative registers and quasi-experiments
- **New data:** granular and comprehensive; individually-linked and population-wide
- **New opportunities:** mechanisms and magnitudes

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Prior Work vs. New Data Opportunities

- **Prior work:** general patterns vs. specific conditions
- **New data:** granular and comprehensive; individually-linked and population-wide
  - rich health data: patient records, hospital diagnoses, healthcare exps, health insurance, ...
  - rich socio-economic data: income, wealth, employment, education, networks (neighborhood, firm, family),...
- **New opportunities:** mechanisms and magnitudes

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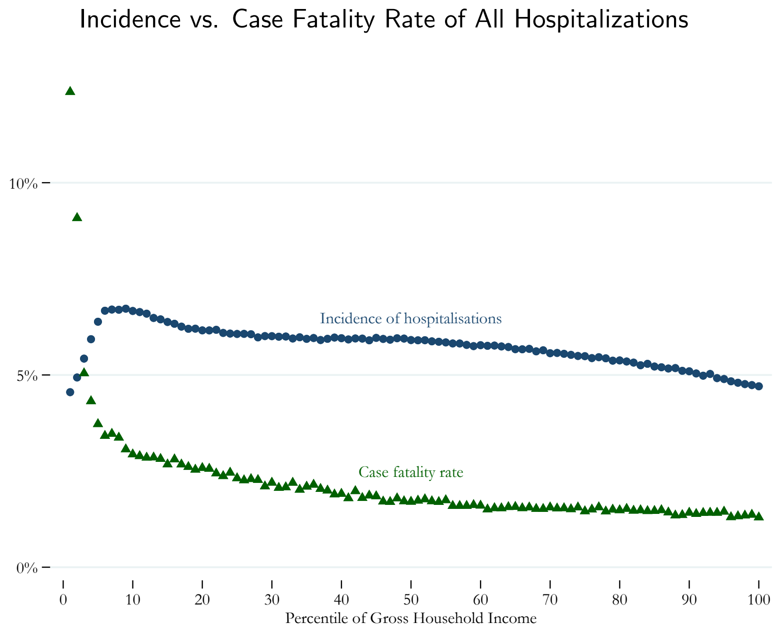
  - Illustration 1: Role of healthcare access and take-up
  - Illustration 2: Role of behavior and 'behavioral biases'

Illustration 1: Access to Healthcare



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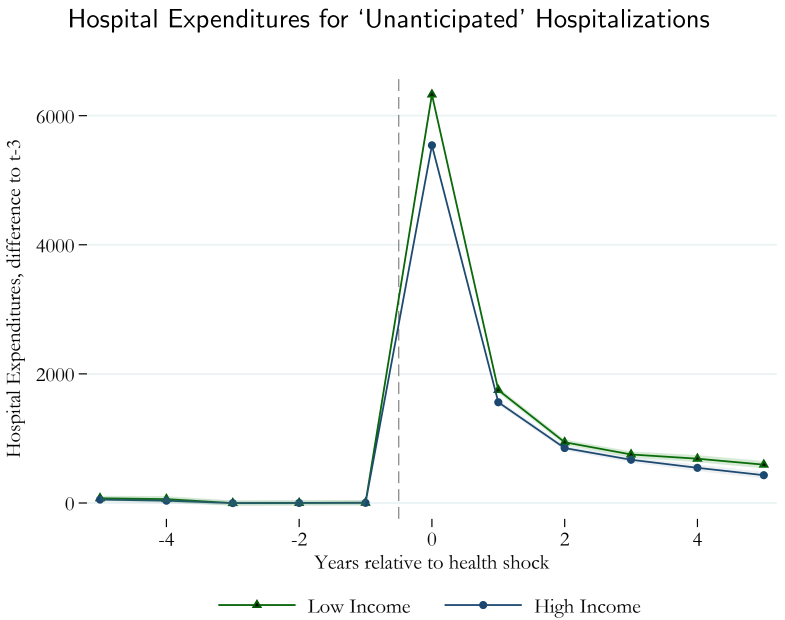

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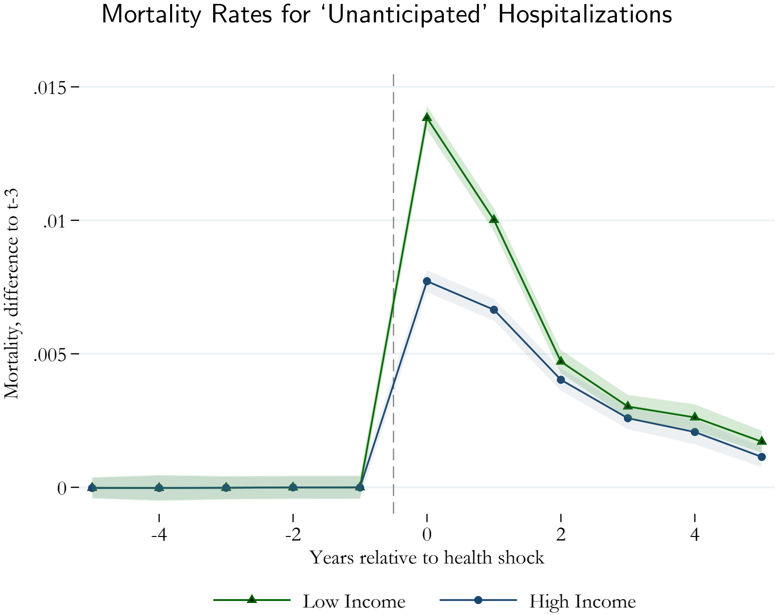
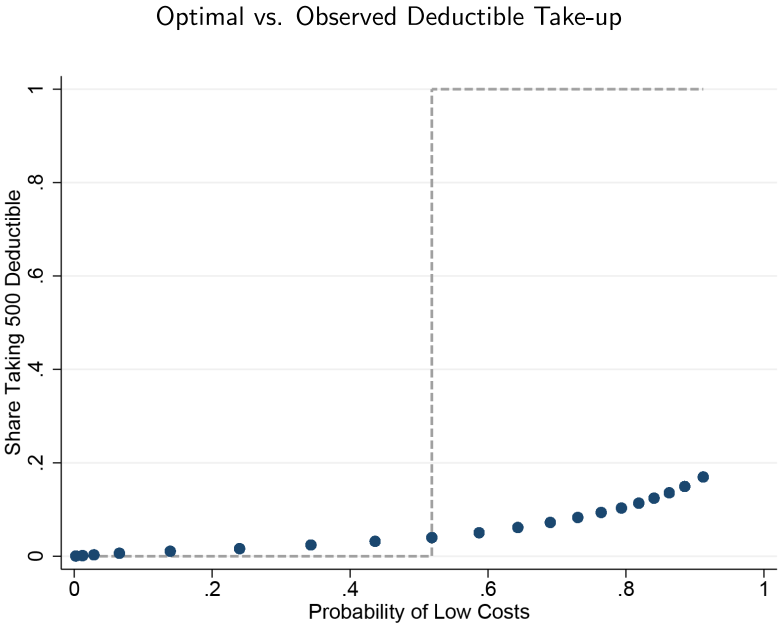


Illustration 2: Behavioral Frictions



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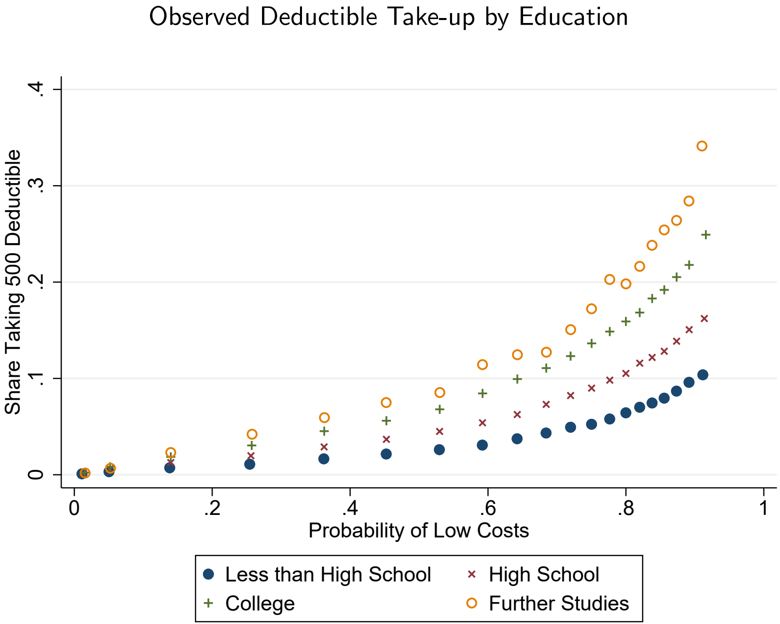

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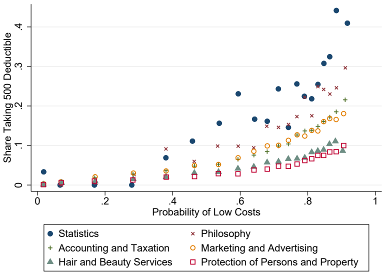
Observed Deductible Take-up

A. By Education Field



B. By Professional Sector

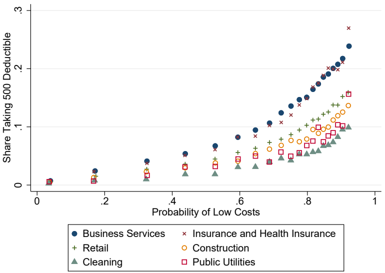


Illustration 2: Behavioral Frictions (ALT)