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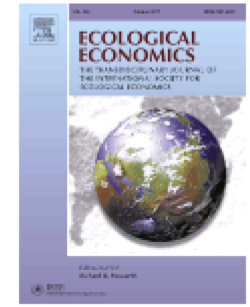

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"Is the gasoline tax regressive in the twenty-first century? Taking wealth into account"

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Public support for carbon pricing

- Carbon pricing requires sufficient public support.
- Various factors influencing climate policy support (Drews and van den Bergh [2015]):
  - Social-psychological factors and climate change perception

    Left-wing political orientation; egalitarian worldviews; environmental and self-transcendent values; climate change knowledge; risk perception; emotions like interest and hope; ….
  - Perception of climate policy and its design

    Preference of pull- over push measures; perceived policy effectiveness; policy costs; perceived policy fairness; ….
  - Contextual factors

    Social trust; norms and participation; wider economic, political and geographical aspects; effects of media events and communications; ….

Is carbon pricing regressive?

- Simple answer is “Yes”: As lower-income households spend greater shares of their income on energy, carbon pricing is regressive.
- Nuanced answer is “It depends” on:

…what is actually taxed

If carbon pricing only applies to motor fuels, its impact is typically less regressive, sometimes proportional or even progressive.

…the level of economic development

If energy consumption is in fact a luxury, as in some least developed economies, carbon pricing is progressive.

…whether general equilibrium effects are considered

Progressive sources-of-income effects (e.g., changes in wages, capital returns, welfare payments) may offset regressive uses-of-income effects (energy price increases).

…whether distributional incidence is assessed over people’s lifetime

Energy consumption patterns and income mobility over a lifetime mean carbon pricing is less regressive in the long run.

Poterba's lifetime approach

- Poterba's (1991) lifetime approach consists in measuring lifetime ability to pay with annual total expenditure as a proxy for lifetime income.

Is the Gasoline Tax Regressive? 153

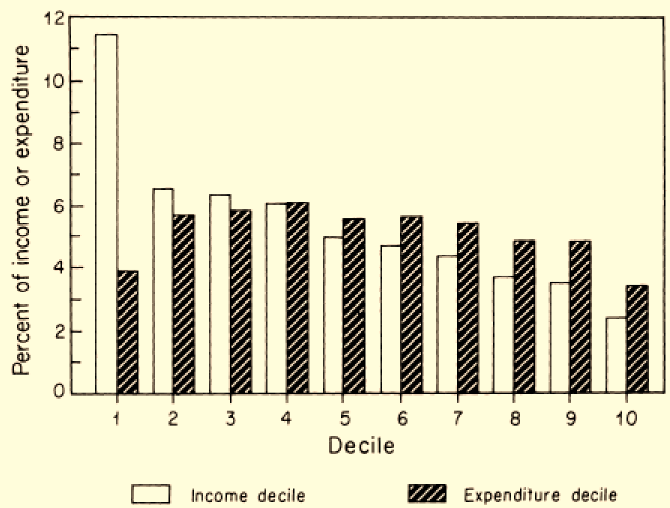


FIGURE 1. ***Gasoline share of income or expenditure.***

- As the distribution of total expenditure is structurally more uniform than that of income, carbon pricing always turns out to be less regressive.

Issues with lifetime approaches

1) Plausible?

– Poterba's approach rests on three very strong assumptions (Chernick and Reschovsky [1992], [1997], [2000]):

A. Income mobility is very high;

B. Gasoline consumption decisions are made on the basis of lifetime income;

C. Total consumption is a constant fraction of lifetime income.

2) Policy relevant?

– Equity assessments based on observed economic outcomes can inform redistributive programs. Can those based on expected outcomes?

3) Fair?

– Is it fair to compare the lifetime economic welfare of elderly people, which is largely realized (certain), with that of young people, which is largely predicted (uncertain)?

Wealth: “the elephant in the room”?

- Greater urgency – we argue – for measurement of ability to pay to be extended “in perimeter”, by considering wealth, than “in time”, as with lifetime approaches.
- Income, consumption and wealth are complementary dimensions of economic welfare (Stiglitz *et al.* [2009]).
- Wealth is highly concentrated, increasingly so (e.g., Piketty [2014]).
- Weisbrod and Hansen (1968) were the first to study the implications of considering wealth (net worth) as a store of potential consumption and, hence, of economic welfare.
- We are the first to introduce this element in the literature on distributional effects of climate policy. Implications for regressivity and intergenerational equity.

Revisiting Poterba (1991)

- We revisit Poterba's paper "Is the gasoline tax regressive?" by taking wealth into account.
- Using 2012 household-level data from the US Consumer Expenditure Survey (CE) and the Survey of Consumer Finances (SCF), we compare the distributional incidence of the federal gasoline tax (0.184 $/gallon) for different measures of ability to pay: A) Total expenditure; B) Income; C) Wealth-adjusted income.
- The CE does not contain wealth information, so this is taken from the SCF and imputed to the CE sample using statistical matching. Then, wealth-adjusted income is computed.

Wealth-adjusted income

- Wealth-adjusted income (WI) is derived using the methodology of the Levy Institute Measure of Economic Well-being (Wolff *et al.* [2005], Wolff and Zacharias [2007], [2009]):

1) $WI_h = MI_h - PI_h + WA_h + IRI_h$

- MI_h: Money income (earnings, property income, other money income)
- PI_h: Property income (interest, dividends and rents)
- WA_h: Wealth annuity
- IRI_h: Imputed rental income (≠0 only for home owners)

2) $$WA_h = \frac{\sum_{k=1}^{K=5} A_{k,h}(1+r_k)^{LifeExp_h} - \sum_{j=1}^{J=2} D_{j,h}(1+g_j)^{LifeExp_h}}{LifeExp_h}$$

$A_{k,h}$:
1) Primary residence
2) Other real estate and business
3) Liquid assets
4) Financial assets
5) Retirement assets

$D_{j,h}$:
1) Mortgage debt
2) Other debt

Composition of wealth and wealth-adjusted income

Table 1
Net worth (per adult equivalent) and its composition.

	Mean	Std. Dev.	Min	Max	Mean share of Net worth	Ownership rates[c]
Net worth	217,293	413,973	−242,446	3,446,505	100%	100%
Assets						
Asset1: Houses[a]	108,533	151,996	0	2,500,000	50%	70%
Asset2: Other real estate and business[b]	49,184	203,522	−78,000	2,894,000	23%	28%
Asset3: Liquid assets	23,510	59,821	0	815,000	11%	94%
Asset4: Financial assets	27,502	113,193	0	1,764,000	13%	33%
Asset5: Retirement assets	54,562	149,937	0	2,123,001	25%	50%
Debts						
Debt1: Mortgage debt	37,897	69,116	0	890,666	17%	44%
Debt2: Other debt	8103	19,928	0	450,000	4%	61%

[a] Houses refer to primary residences only.
[b] Other real estate consists of secondary residences, land, and rental property. Business refers to net equity in unincorporated business (both farm and non-farm).
[c] Percentage of households owning the asset.

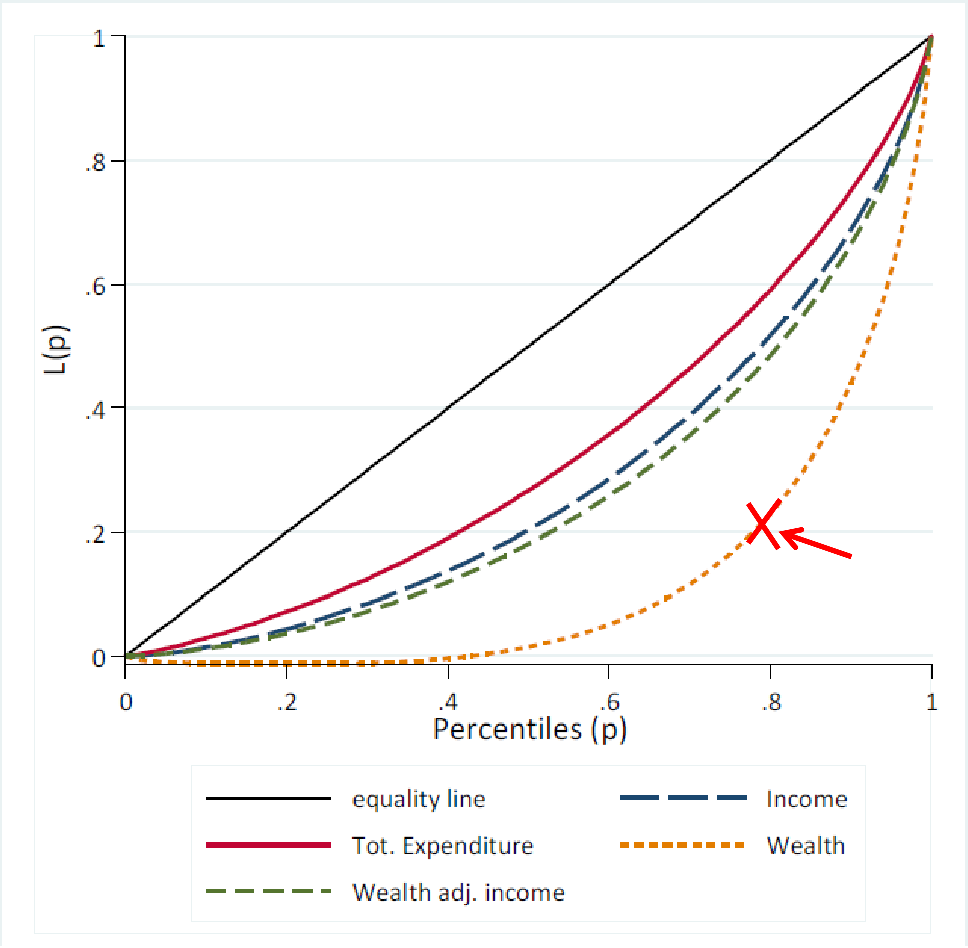
Table 2
Average composition of wealth-adjusted income (WI).

	Home owners ($N = 1553$)			Home renters ($N = 626$)		
	Mean	Std. Dev.	CV	Mean	Std. Dev.	CV
Money income (MI) of which	73.1%	21.4	0.29	94.5%	18.7	0.19
property income (PI)	(1.3%)	(8.3)	(6.13)	(1.1%)	(12.9)	(10.93)
Wealth annuity (WA)	16.1%	18.8	1.17	6.6%	14.2	2.15
Imputed rental income (IRI)	12.1%	10.5	0.87	NA	NA	NA

Fact #1: Wealth is highly concentrated

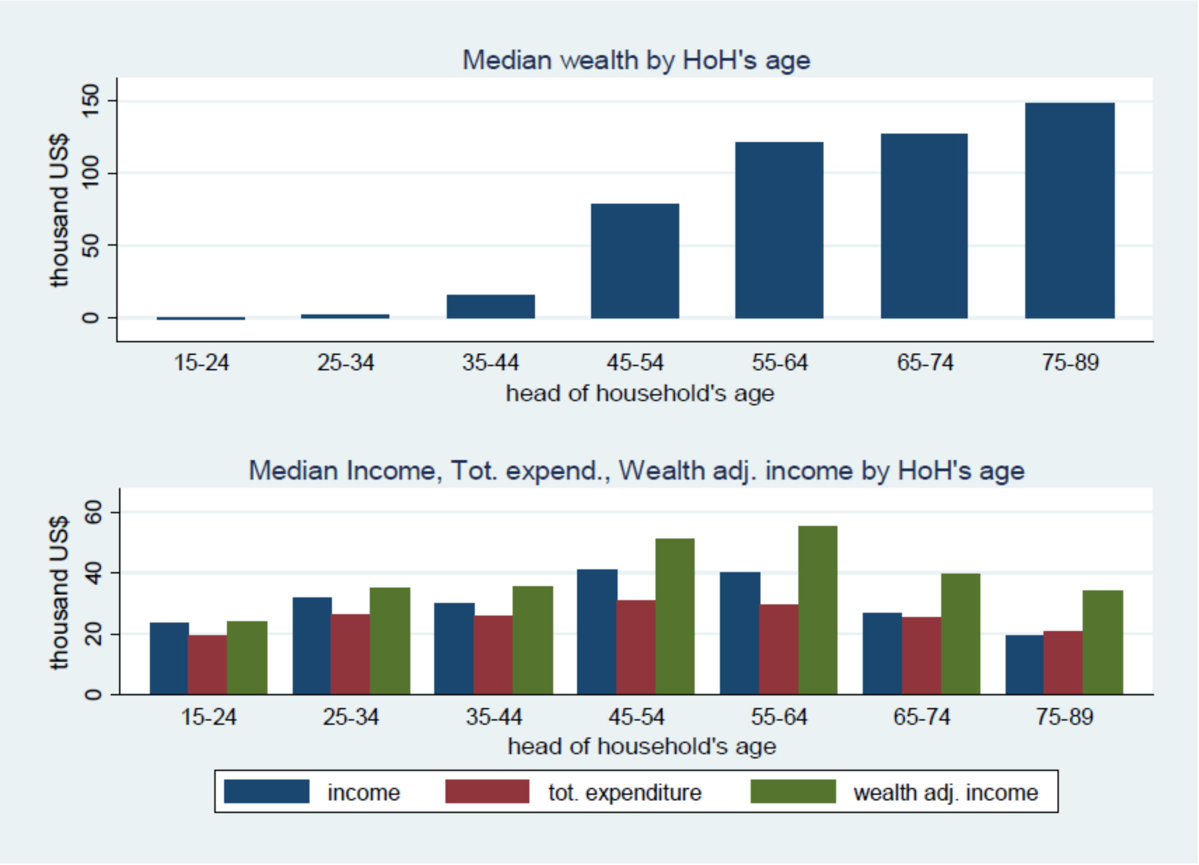
Gini coefficient	
A) Income	0.44
B) Tot. Expenditure	0.34
C) Wealth Adj. Income	0.47
D) Wealth	0.76

Lorenz concentration curves of a) Income, b) Total expenditure, c) Wealth-adjusted income, and d) Wealth.



Fact #2: Wealth accumulates with time

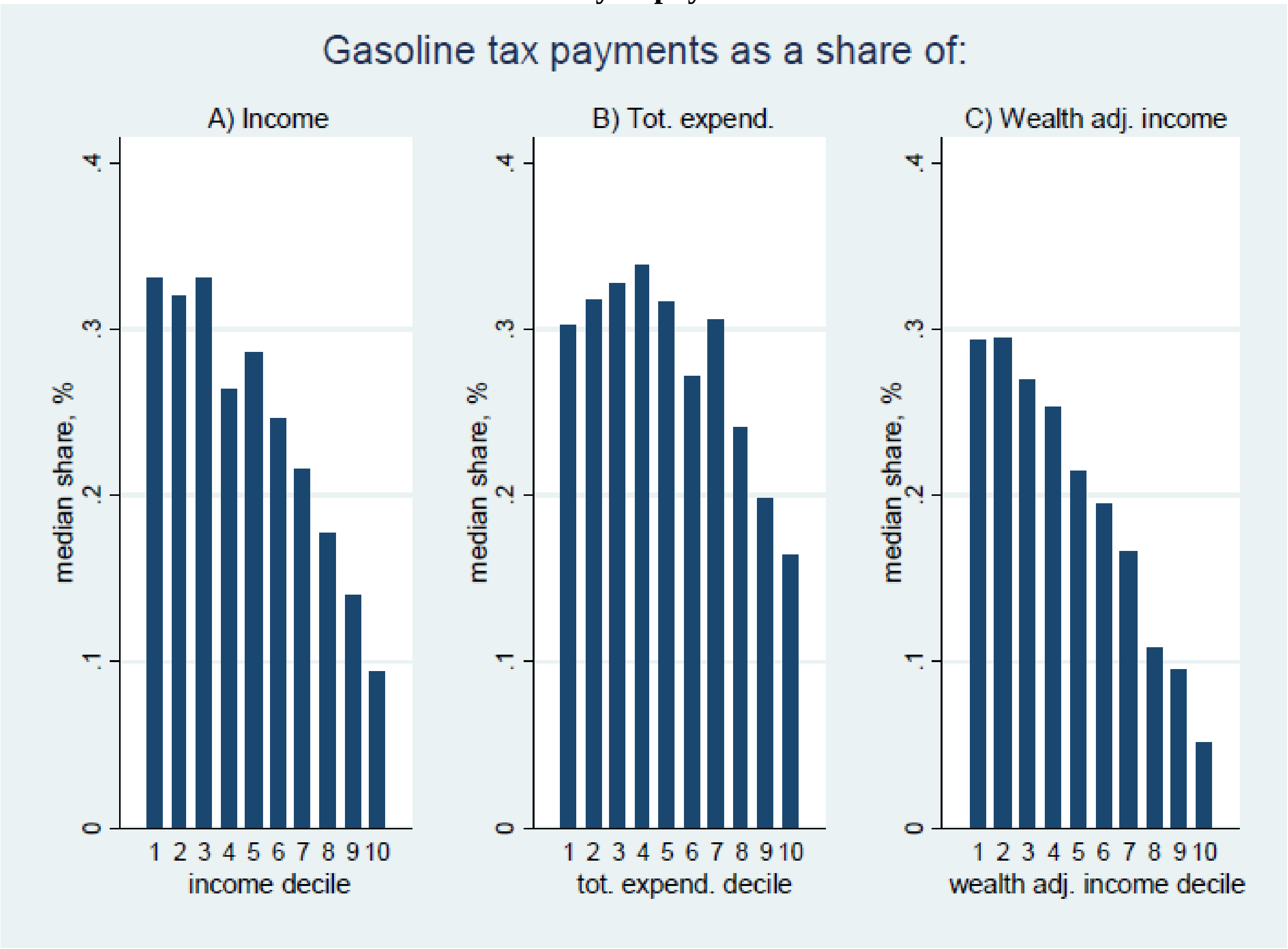
Wealth (top) and ability to pay measures (bottom) by head of household's age group.



Age group	< 25	25-34	35-44	45-54	55-64	65-74	> 74
Frequency (%)	3.5	13.0	17.2	20.7	20.0	14.4	11.3

Gasoline tax incidence (1)

Tax burdens as a share of alternative ability to pay measures.



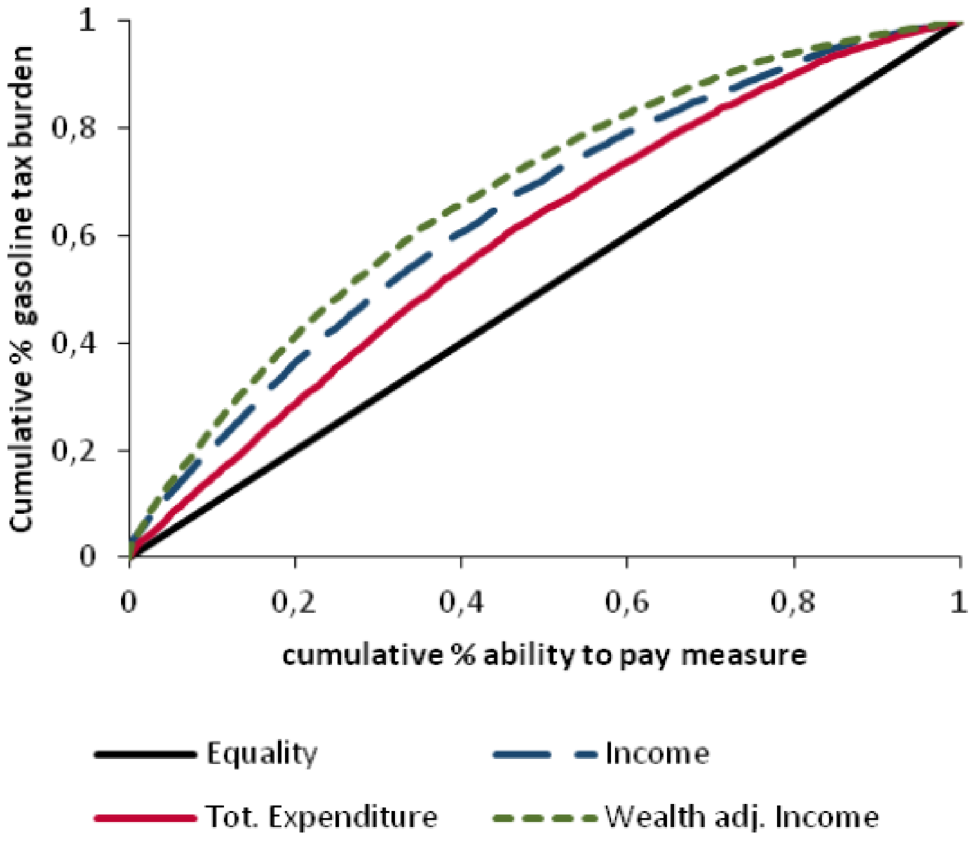
Gasoline tax incidence (2)

Suits index (S) = 1 – L/K
where L is the area under the Lorenz curve and K is the area under the 45-degree proportionality line;
$-1 \leq S \leq 1$.

Suits Index	
A) Income	-0.29
B) Tot. Expenditure	-0.15
C) Wealth Adj. Income	-0.36

↓

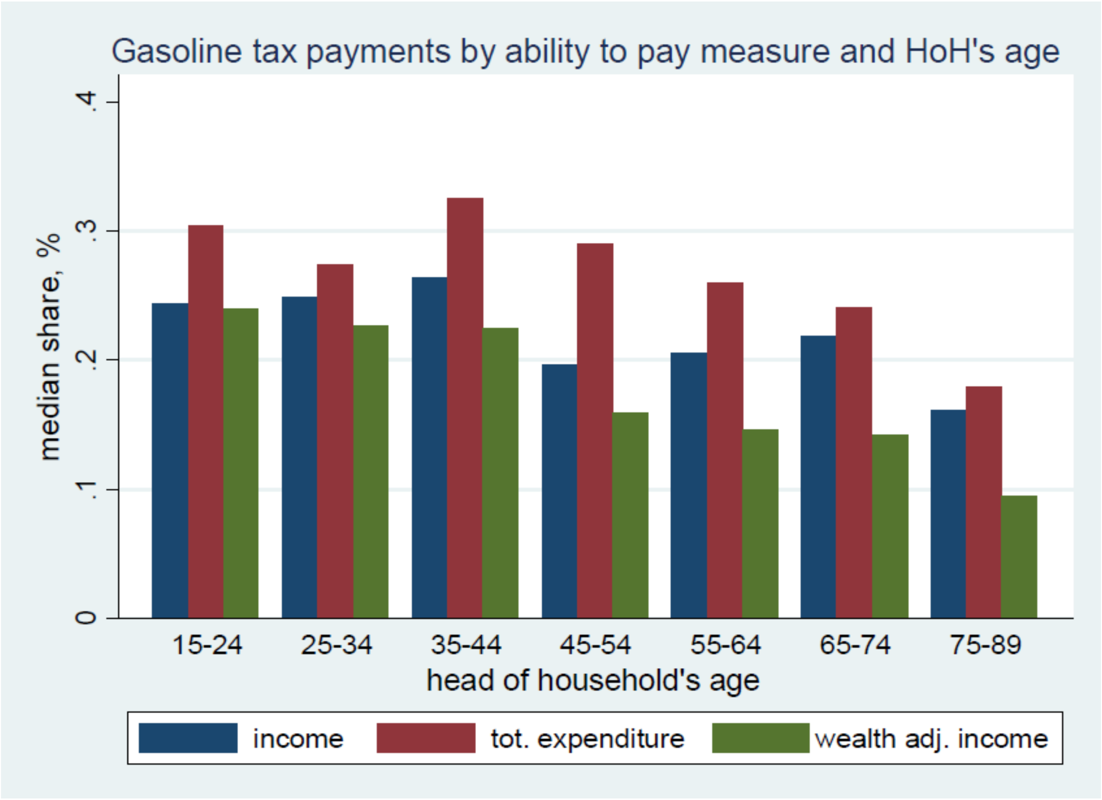
- C) VS A): 24% increase in regressivity
- C) VS B): 140% increase in regressivity



Intergenerational equity

When using wealth-adjusted income instead of income, (on average) older age groups systematically bear lower burdens than younger ones. Therefore, in relative terms, the burdens borne by older (younger) households are overestimated (underestimated) if wealth is not considered in measuring ability to pay.

Tax burdens as shares of alternative ability to pay measures, by head of household's age .



Conclusions

- The literature on the distributional incidence of carbon pricing/energy taxes ignores wealth as a component of ability to pay. We show that this omission results in underestimation of the regressivity of carbon pricing and its inequity towards younger people.
- This is particularly relevant for the case of carbon pricing, as its ultimate purpose is to preserve a stable climate, which is a public good.
- This result stems from the facts that wealth A) is highly concentrated and B) accumulates over time.
- Part of the literature draws conclusions pointing right in the opposite direction (notably, lifetime approaches).
- Greater regressivity than that emerging from the literature may help explain why so strong resistance to carbon pricing is observed.
- Appropriate redistributive measures should accompany carbon pricing for it to be fair and politically sustainable.

Statistical matching (1)

- The typical setting for statistical matching is two surveys drawn from the same population and sharing a set of common variables, **X**, but not other variables, Y (wealth) and Z (gasoline expenditure), whose relationship is of interest.
- We use Propensity Score Matching (PSM), which consists of two steps:

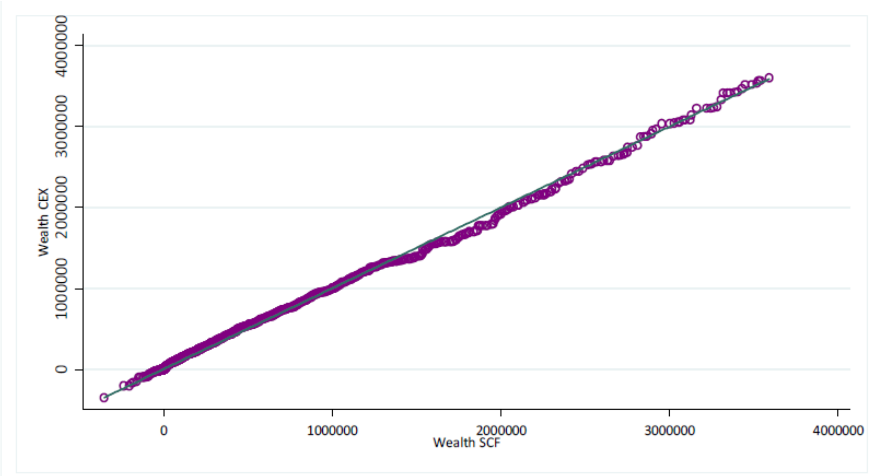
1. A logit (/probit) model is fitted to a binary variable: $D_i = 1$ if observation i belongs to the recipient dataset (the CE sample in our case); $D_i = 0$ otherwise. Selected **X*** are used as independent variables. The Propensity Score (PS) is the predicted probability of $D_i = 1$ conditional on **X***.
2. Each unit of the recipient dataset is paired to the observation in the donor dataset exhibiting the closest PS. In our application, each CE observation is matched with one SCF observation. Wealth observed on the latter is imputed to the former.

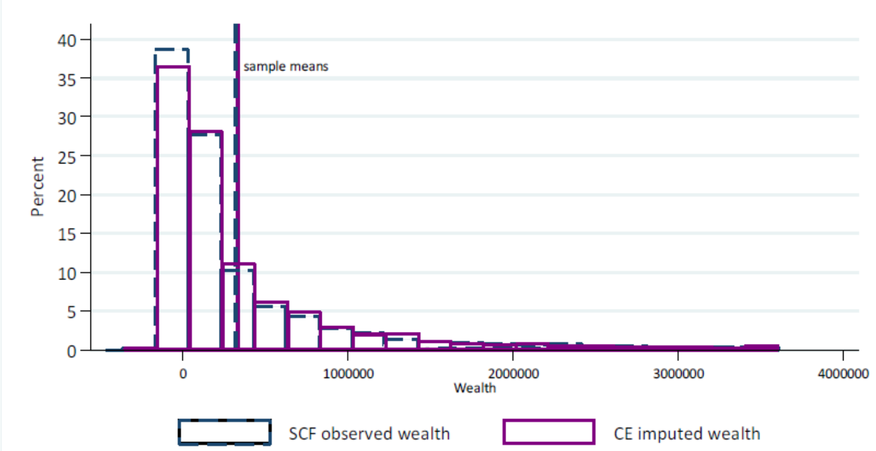
Statistical matching (2)

- The **X*** are selected based on both: A) The similarity of their distributions in the two datasets; B) The strength of their statistical association with both Y and Z.
- Our **X*** are: household income, housing tenure, age of the reference person, education level, marital status, and an indicator for self-employed.
- The size of the SCF sample (30,075 observations) is much larger than that of our CE sample (2,179): this benefits the efficiency of the matching.
- The resulting fused dataset satisfies the most stringent validity requirement of statistical matching, which is the preservation of the joint distribution of Y and **X***.

Statistical matching: validation (1)

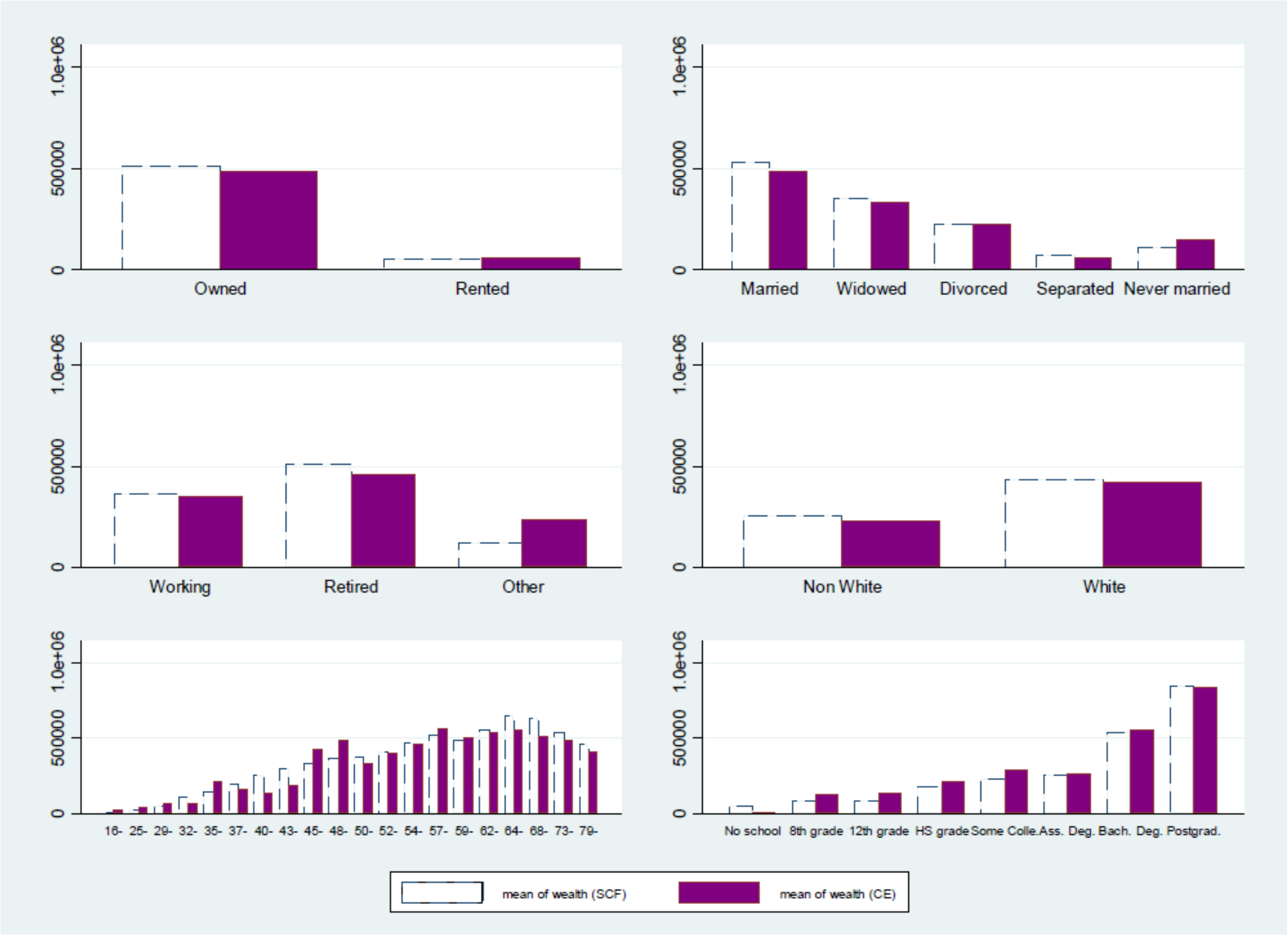
Comparing the marginal distributions of wealth in the donor dataset and imputed wealth in the recipient dataset: Q-Q plot (top) and histograms (bottom).





Statistical matching: validation (2)

Comparing conditional means of wealth in the donor dataset (white) and imputed wealth in the recipient dataset (purple).



Statistical matching: validation (3)

Testing the similarity of the joint distributions of wealth and X*, in the donor dataset, and imputed wealth and X*, in the fused dataset.

Dep. Variable: ln(Wealth)	(b) Fused (CE)	(B) Observed (SCF)	(b-B) Difference	S.E.
Family Income Before taxes	0.000022	0.000021	0.000001	0.000001
Squared Family Income Before taxes	0.000000	0.000000	0.000000	0.000000
Self employed Ref.	-0.198223	-0.162168	-0.036055	0.081554
House tenure	-1.842897	-1.721890	-0.121007	0.081784
Age Ref. Person	0.016197	0.023399	-0.007203	0.011739
Squared Age Ref. Person	0.000106	0.000054	0.000052	0.000106
No school	-1.943236	-0.259389	-1.683847	0.615699
Some College	0.436587	0.380951	0.055636	0.089805
Bach. Degree	0.744419	0.828986	-0.084567	0.089676
Postgrad.	1.010688	0.901698	0.108991	0.107256
marital st. separated	-0.755710	-0.532961	-0.222750	0.250013
chi2(8) = (b-B)'[(V_b-V_B)^(-1)](b-B)	14.390			
Prob>chi2	0.072			

Notes: Ho: difference in coefficients not systematic.