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Closing Session & Presidential Address

Maastricht 2018


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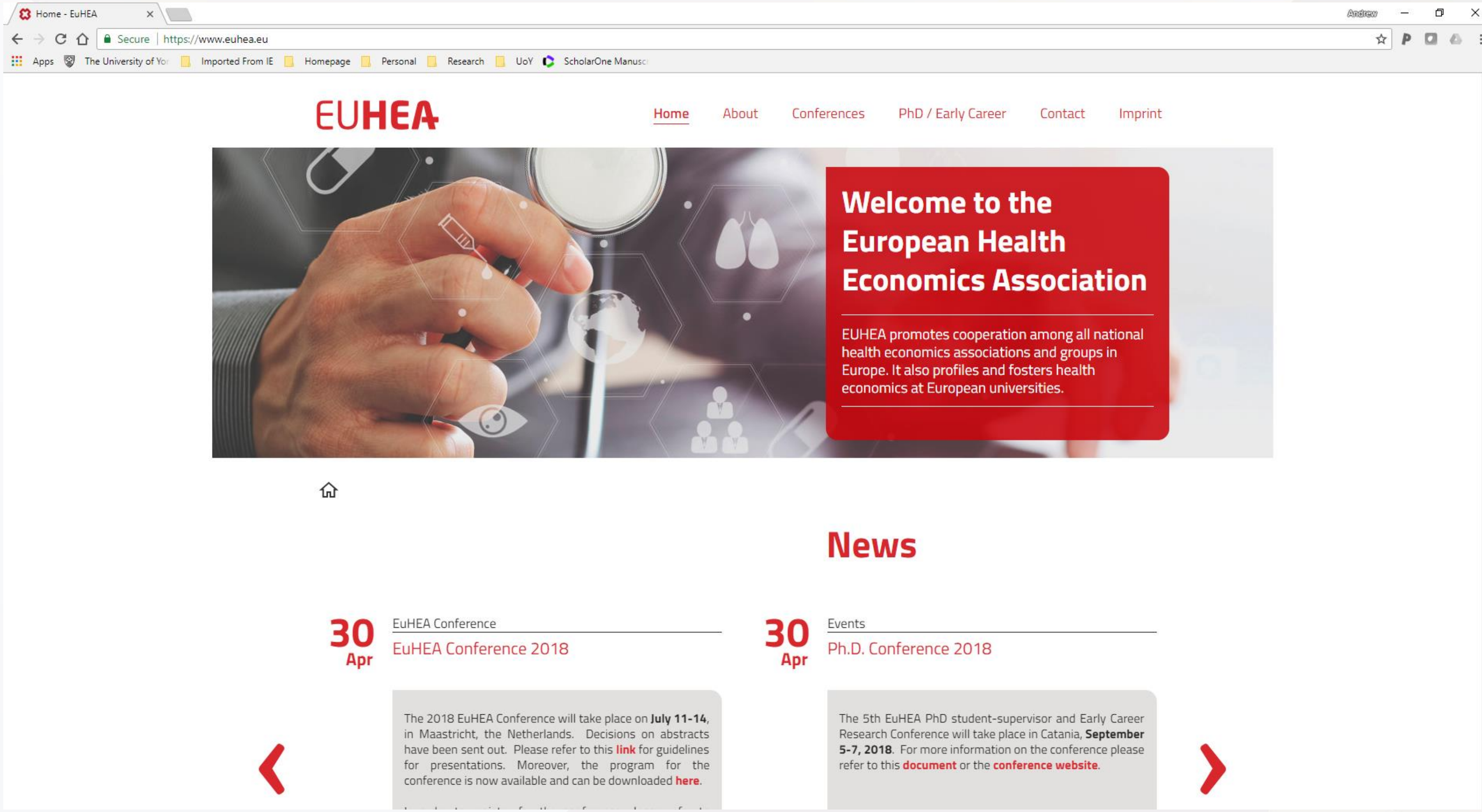

Home - EuHEA
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Home
About
Conferences
PhD / Early Career
Contact
Imprint
Welcome to the European Health Economics Association
EUHEA promotes cooperation among all national health economics associations and groups in Europe. It also profiles and fosters health economics at European universities.
News
30 Apr
EuHEA Conference
EuHEA Conference 2018
The 2018 EuHEA Conference will take place on July 11-14, in Maastricht, the Netherlands. Decisions on abstracts have been sent out. Please refer to this link for guidelines for presentations. Moreover, the program for the conference is now available and can be downloaded here.
30 Apr
Events
Ph.D. Conference 2018
The 5th EuHEA PhD student-supervisor and Early Career Research Conference will take place in Catania, September 5-7, 2018. For more information on the conference please refer to this document or the conference website.

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Financial Report – Budget 2018

Revenues	Date	EUR	Expenses	Date	EUR
Op. Bal.	01.01.	47.416,00	Bank charges		92,18
Memb.ship fees 2017*		500,00	CMS, CfP		
Memb.ship fee 2018		10.494,96	Maastricht & Catania		9.630,00
Open memb. fee		1.000,00	Reserve		4.000,00
			Exp. surplus conference		0
Total Revenues 2018		11.994,96	Total Expenses	2018	13.722,18
			Deficit	2018	-1.727,22
*due 2016			Closing balance	31.12.	45.688,78

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Early Career Committee

The Early Career Committee aims to ensure that the views of individuals at the beginning of their academic careers are reflected, and to actively engage junior members in the association and its future direction.

The EuHEA Early Career Committee consists of two representatives from each national health economics association. It is currently chaired by Rahel Meacock (UK Health Economics Study Group) and Sara Machado (Portuguese Health Economic Association).

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European Health Economics Association

Empirical health economics: fifty years in fifteen minutes

EuHEA Presidential Address
Andrew M Jones,
University of York

What would you pick if you were given 900 pages to make a selection of key articles from your own area of research?

What would you pick if you were given 900 pages to make a selection of key articles from your own area of research?

Edward Elgar Research Collection:
Empirical Health Economics

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A personal selection…

Jones, A.M., “Health econometrics”, *Handbook of Health Economics*, A.J.Culyer and J.P. Newhouse (eds.), Amsterdam: Elsevier, 265-344, 2000.

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Empirical Health Economics

PART I STRUCTURAL APPROACHES TO HEALTH AND HEALTH CARE

PART II METHODS FOR HEALTH CARE COSTS

PART III MICROECONOMETRIC METHODS APPLIED TO HEALTH

PART IV BAYESIAN APPROACHES

PART V LONGITUDINAL AND SPATIAL APPROACHES

PART VI ECONOMETRICS AND HEALTH TECHNOLOGY ASSESSMENT

PART VII FIELD EXPERIMENTS

PART VIII QUASI-EXPERIMENTS AND POLICY EVALUATION

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PART I
STRUCTURAL APPROACHES TO HEALTH AND HEALTH CARE

1. Richard Auster, Irving Leveson and Deborah Sarachek (1969), 'The Production of Health, an Exploratory Study', *Journal of Human Resources*, **4** (4), Autumn, 411–36.

2. Mark R. Rosenzweig and T. Paul Schultz (1983), 'Estimating a Household Production Function: Heterogenity, the Demand for Health Inputs, and Their Effects on Birth Weight', *Journal of Political Economy*, **91** (5), October, 723–46

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5. Marcos Vera-Hernández (2003),'Structural Estimation of a Principal Agent Model: Moral Hazard in Medical Insurance', *RAND Journal of Economics*, **34** (4), Winter, 670–93

6. Peter Arcidiacono, Holger Sieg and Frank Sloan (2007), 'Living Rationally Under the Volcano? An Empirical Analysis of Heavy Drinking and Smoking', *International Economic Review,* **48** (1), February, 37–65

PART II
METHODS FOR HEALTH CARE COSTS

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8. William G. Manning (1998),’The Logged Dependent Variable, Heteroscedasticity, and the Retransformation Problem’, *Journal of Health Economics*, **17** (3), June, 283–95

9. David K. Blough, Carolyn W. Maddena, and Mark C. Hornbrook (1999), ‘Modeling Risk Using Generalized Linear Models’*, Journal of Health Economics*, **18** (2), April, 153–71

10. Donna B. Gilleskie and Thomas A. Mroz (2004), ‘A Flexible Approach for Estimating the Effects of Covariates on Health Expenditures’*, Journal of Health Economics,* **23** (3), March, 391–418

11. Anirban Basu and Paul J. Rathouz (2005),’Estimating Marginal and Incremental Effects on Health Outcomes using Flexible Link and Variance Function Models’, *Biostatistics*, **6** (1), January, 93–109

12. Willard G. Manning, Anirban Basu and John Mullahy (2005), ’Generalized Modelling Approaches to Risk Adjustment of Skewed Outcomes Data’ *Journal of Health Economics*, **24** (3), May, 465–88

13. Andrew M. Jones, James Lomas and Nigel Rice (2015),’ Healthcare Cost Regressions: Going Beyond the Mean to Estimate the Full Distribution’, *Health Economics,* **24** (9), April, 1192–1212

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PART III
MICROECONOMETRIC METHODS APPLIED TO HEALTH

14. John Mullahy (1986),'Specification and Testing of Some Modified Count Models', *Journal of Econometrics,* **33** (3), December, 341–365

15. Bryan Dowd, Roger Felman, Steven Cassou and Michael Finch (1991), ' Health Plan Choice and the Utilization of Health Care Services', *Review of Economics and Statistics*, **73** (1), February, 85–93

16. Marcel Kerkhofs and Maarten Lindeboom (1995), 'Subjective Health Measures and State Dependent Reporting Errors', *Health Economics*, **4** (3), May/June, 221–35

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PART IV
BAYESIAN APPROACHES

20. Gary Koop, Jacek Osiewalski and Mark F.J. Steel (1997),'Bayesian Efficiency Analysis through Individual Effects: Hospital Cost Frontiers', *Journal of Econometrics*, **76** (1-2), February, 77–105

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PART V
LONGITUDINAL AND SPATIAL APPROACHES

24. José M. Labeaga (1999),'A Double-Hurdle Rational Addiction Model with Heterogeneity: Estimating the Demand for Tobacco', *Journal of Econometrics*, **93** (1), November, 49–72

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27. Francesco Moscone, Martin Knapp and Elisa Tosetti (2007),'Mental Health Expenditure in England: A Spatial Panel Approach', *Journal of Health Economics*, **26** (4), July, 842–64

PART VI
ECONOMETRICS AND HEALTH TECHNOLOGY ASSESSMENT

28. Mark McClellan, Barbara J. McNeil and Joseph P. Newhouse, (1994), ‘Does More Intensive Treatment of Acute Myocardial Infarction in the Elderly Reduce Mortality?, *Journal of the American Medical Association*, **272**, May, 859–66

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PART VII
FIELD EXPERIMENTS

31. Willard G. Manning, Joseph P. Newhouse, Naihua Duan, Emmett B. Keeler and Arleen Leibowitz (1987),'Health Insurance and the Demand for Medical Care: Evidence from a Randomized Experiment', *American Economic Review*, **77** (3), June, 251–77

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PART VIII

QUASI-EXPERIMENTS AND POLICY EVALUATION

34. David Card and Lara D. Shore-Sheppard (2004),'Using Discontinuous Eligibility Rules to Identify the Effects of the Federal Medicaid Expansions on Low-Income Children', *Review of Economics and Statistics*, **86** (3), August, 752–66

35. Arild Aakvik, James J. Heckman and Edward J. Vytlacil (2005), 'Estimating Treatment Effects for Discrete Outcomes when Responses to Treatment Vary: An Application to Norwegian Vocational Rehabilitation Programs', *Journal of Econometrics*, **125** (1–2), April, 15–51

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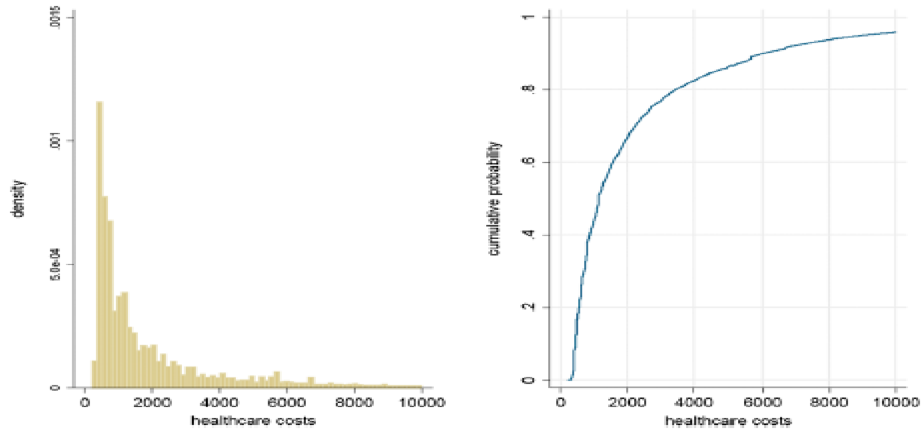

Figure 1. Empirical density and cumulative distribution of healthcare costs

Table I. Descriptive statistics for hospital costs

N	6,164,114	
Mean	£2,610	
Median	£1,126	
Standard deviation	£5,088	
Skewness	13.03	
Kurtosis	363.18	
Minimum	£217	
Maximum	£604,701	
	% Observations	% Of total costs
> £500	82.96%	97.20%
> £1,000	55.89%	89.80%
> £2,500	27.02%	72.35%
> £5,000	13.83%	54.65%
> £7,500	6.92%	38.67%
> £10,000	4.09%	29.35%

Our analysis is undertaken at the patient level and so we sum the costs in all spells for each patient to create the dependent variable, giving us 6,164,114 observations in total. The empirical density and cumulative distribution of the outcome variable can be seen in Figure 1, and descriptive statistics are found in Table I.[12]

In order to tie in with existing literature on comparisons of econometric methods for healthcare costs, we use a set of morbidity characteristics that we keep constant for each regression method. In addition, we control for age and sex using an interacted, cubic specification, which leaves us with a set of regressors similar to a simplified resource allocation formula where health expenditures are modelled as a function of need (proxied using detailed socio-demographic and morbidity information) (Dixon *et al.*, 2011). In total, we use 24 morbidity markers, adapted from the International Classification of Diseases, Tenth Revision (ICD10) chapters (WHO, 2007), which are coded as one if one or more spells occur with any diagnosis within the relevant subset of ICD10 chapters (during the financial year 2007–2008) and zero otherwise.

[12]Costs above £10,000 are excluded in these plots to make illustration clearer.

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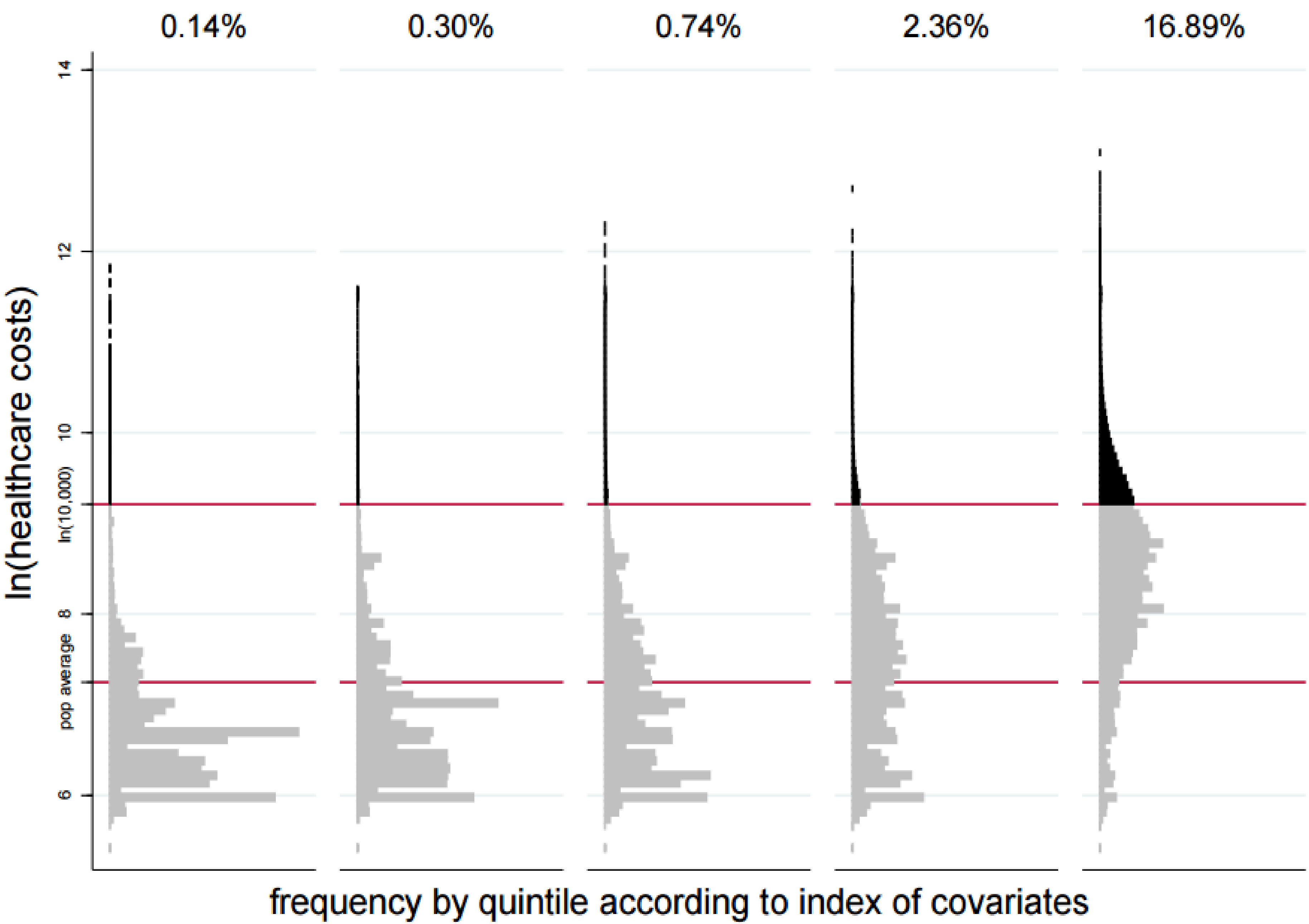
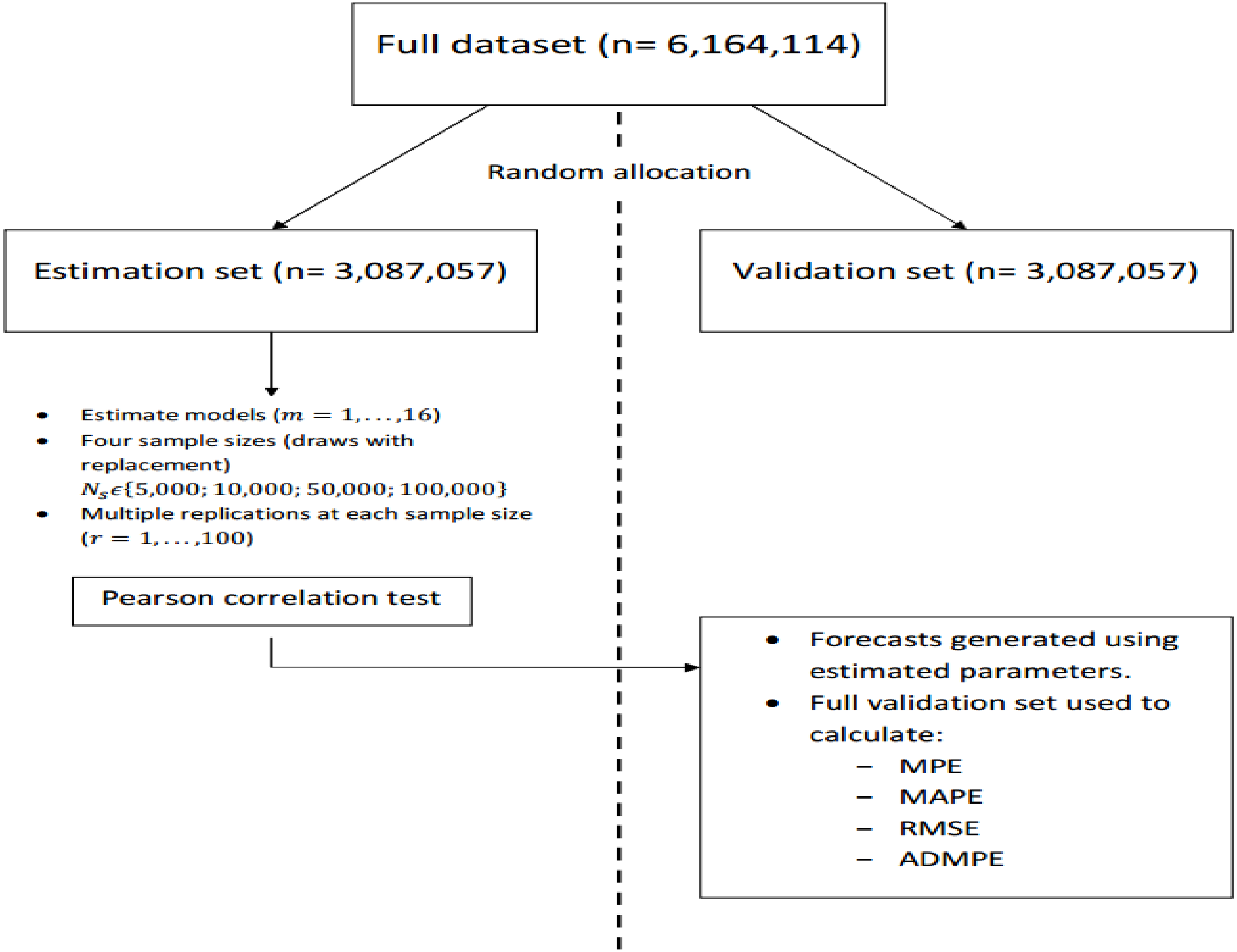


%s given above are % observations with costs > £10,000 for each quintile



Full dataset (n= 6,164,114)
Random allocation
Estimation set (n= 3,087,057)
Validation set (n= 3,087,057)
Estimate models ($m = 1,...,16$)
Four sample sizes (draws with replacement)
$N_s \epsilon \{5{,}000; 10{,}000; 50{,}000; 100{,}000\}$
Multiple replications at each sample size ($r = 1,...,100$)
Pearson correlation test
Forecasts generated using estimated parameters.
Full validation set used to calculate:
MPE
MAPE
RMSE
ADMPE

Biostatistics (2017) **18**, 4, *pp.* 682–694
doi:10.1093/biostatistics/kxx012
Advance Access publication on March 22, 2017

Computational health economics for identification of unprofitable health care enrollees

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Summary

Health insurers may attempt to design their health plans to attract profitable enrollees while deterring unprofitable ones. Such insurers would not be delivering socially efficient levels of care by providing health plans that maximize societal benefit, but rather intentionally distorting plan benefits to avoid high-cost enrollees, potentially to the detriment of health and efficiency. In this work, we focus on a specific component of health plan design at risk for health insurer distortion in the Health Insurance Marketplaces: the prescription drug formulary. We introduce an ensembled machine learning function to determine whether drug utilization variables are predictive of a new measure of enrollee unprofitability we derive, and thus vulnerable to distortions by insurers. Our implementation also contains a unique application-specific variable selection tool. This study demonstrates that super learning is effective in extracting the relevant signal for this prediction problem, and that a small number of drug variables can be used to identify unprofitable enrollees. The results are both encouraging and concerning. While risk adjustment appears to have been reasonably successful at weakening the relationship between therapeutic-class-specific drug utilization and unprofitability, some classes remain predictive of insurer losses. The vulnerable enrollees whose prescription drug regimens include drugs in these classes may need special protection from regulators in health insurance market design.

Keywords: Classification and prediction; Ensembles; Machine learning; Statistical methods in health economics; Variable selection.

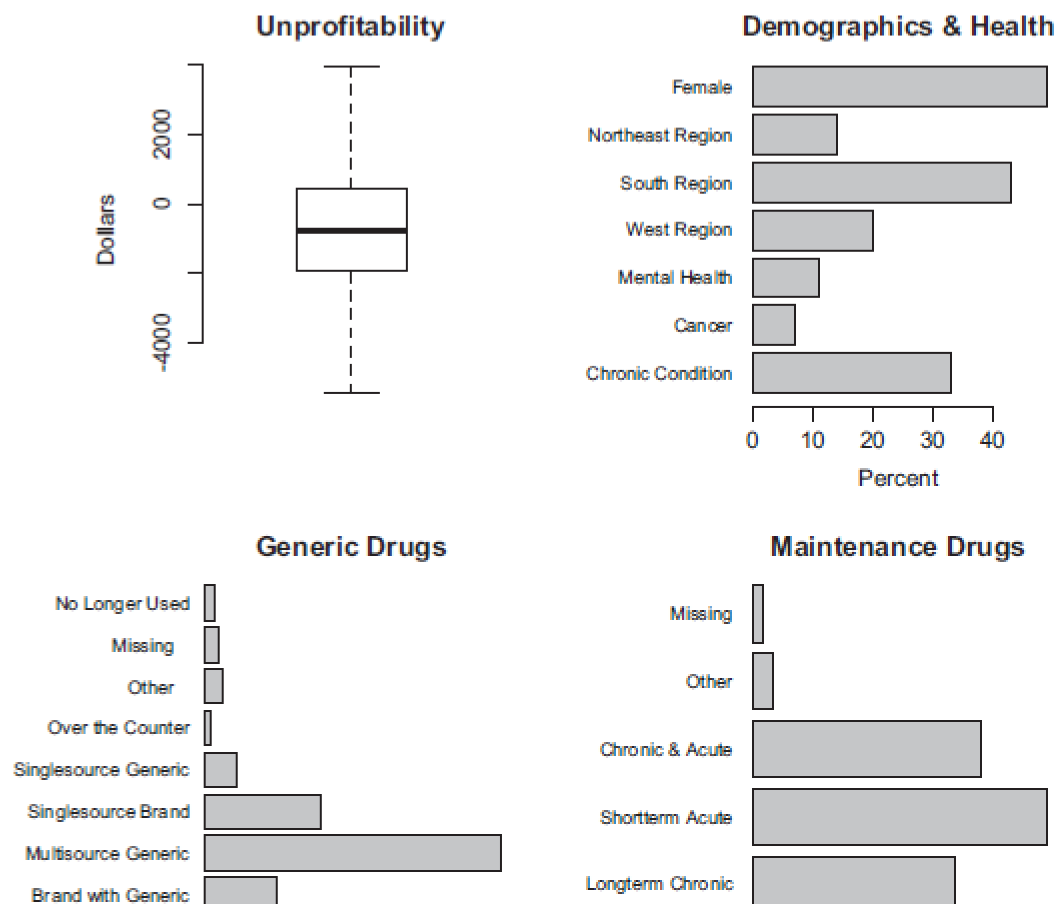
1. Introduction

It is widely recognized by economists, health care providers, and policymakers that health insurance markets suffer from *adverse selection*. Often, a particular type of adverse selection based on consumer behavior is emphasized, where the tendency of sicker consumers to enroll in more comprehensive insurance for each individual algorithm k considered, as well as the super learner. Note that in order to obtain a cross-validated mean squared error and cross-validated R^2 for the super learner, the *entire* procedure described in Section 3.1 is itself cross-validated with 10-fold cross-validation.

4. Predicting unprofitability results

Summary information for key variables in the Truven MarketScan data are described in Figure 1. The median value of unprofitability was −\$762 (indicating the median enrollee was not, in fact, unprofitable), with a mean of \$0 (standard deviation: \$15 617). Mean age was 42 years, 49% of our sample was female, and 33% of enrollees have one or more chronic conditions. The final super learner algorithm was defined by:

$$\hat{\Psi}(P)_{SL} = 0.15\hat{\Psi}(P)_{\texttt{nnet.f}} + 0.04\hat{\Psi}(P)_{\texttt{nnet.g}} + 0.69\hat{\Psi}(P)_{\texttt{glm.f}} + 0.03\hat{\Psi}(P)_{\texttt{glm.g}} + 0.09\hat{\Psi}(P)_{\texttt{glm.1}},$$



Journal of Statistical Software
August 2013, Volume 54, Issue 7. http://www.jstatsoft.org/

ebalance: A Stata Package for Entropy Balancing

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Massachusetts Institute of Technology

Yiqing Xu
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Abstract

The Stata package **ebalance** implements entropy balancing, a multivariate reweighting method described in Hainmueller (2012) that allows users to reweight a dataset such that the covariate distributions in the reweighted data satisfy a set of specified moment conditions. This can be useful to create balanced samples in observational studies with a binary treatment where the control group data can be reweighted to match the covariate moments in the treatment group. Entropy balancing can also be used to reweight a survey sample to known characteristics from a target population.

Keywords: causal inference, reweighting, matching, Stata.

1. Introduction

Methods such as nearest neighbor matching or propensity score techniques have become popular in the social sciences in recent years to preprocess data prior to the estimation of causal effects in observational studies with binary treatments under the selection on observables assumption (Ho, Imai, King, and Stuart 2007; Sekhon 2009). The goal in preprocessing is to adjust the covariate distribution of the control group data by reweighting or discarding

Beyond LATE with a Discrete Instrument

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BI Norwegian Business School

Magne Mogstad

University of Chicago, Statistics Norway, and National Bureau of Economic Research

Matthew Wiswall

Arizona State University, University of Wisconsin–Madison, and National Bureau of Economic Research

We show how a discrete instrument can be used to identify the marginal treatment effects under a functional structure that allows for treatment heterogeneity among individuals with the same observed characteristics and self-selection based on the unobserved gain from treatment. Guided by this identification result, we perform a marginal treatment effect analysis of the interaction between the quantity and quality of children. Our estimates reveal that the family size effects vary in magnitude and even sign and that families act as if they possess some knowledge of the idiosyncratic effects in the fertility decision.

$$Y = \mu + \beta D + X'\delta + \epsilon, \quad (1)$$

where Y is the dependent variable, X is a vector of covariates, D is the binary regressor of interest, and ϵ is the error term. The standard problem of selection bias (D correlated with ϵ conditional on X) is solved with a valid instrumental variable Z. Influential work by Imbens and Angrist (1994) has clarified the interpretation of IV estimates as local average treatment effects (LATE) when β is a random coefficient. With selection on the unobserved gain from treatment (β correlated with D), the LATE is informative only about the average causal effect of an instrument-induced shift in D. In general, agents induced to treatment by Z need not be the same agents induced to treatment by a given policy change, and the average β of the two groups can differ substantially. This raises concerns about the external validity and policy relevance of the LATE, unless the instrument-induced effect of treatment is the parameter of interest.

To move beyond the LATE, Heckman and Vytlacil (1999, 2005, 2007) generalize the marginal treatment effect (MTE) introduced by Björklund and Moffitt (1987). The MTE has several useful features: it plays the role of a functional that is invariant to the choice of instrument; it has an attractive economic interpretation as a willingness to pay parameter for persons at a margin of indifference between participating in an activity or not; and all conventional treatment parameters can be expressed as different weighted averages of the MTEs, such as the average treatment effect (ATE) and the average treatment effect on the treated (ATT). Using the method of local instrumental variables (LIV), the MTE can be identified and estimated under the standard IV assumptions of conditional independence and monotonicity (see Vytlacil 2002; Heckman 2010).

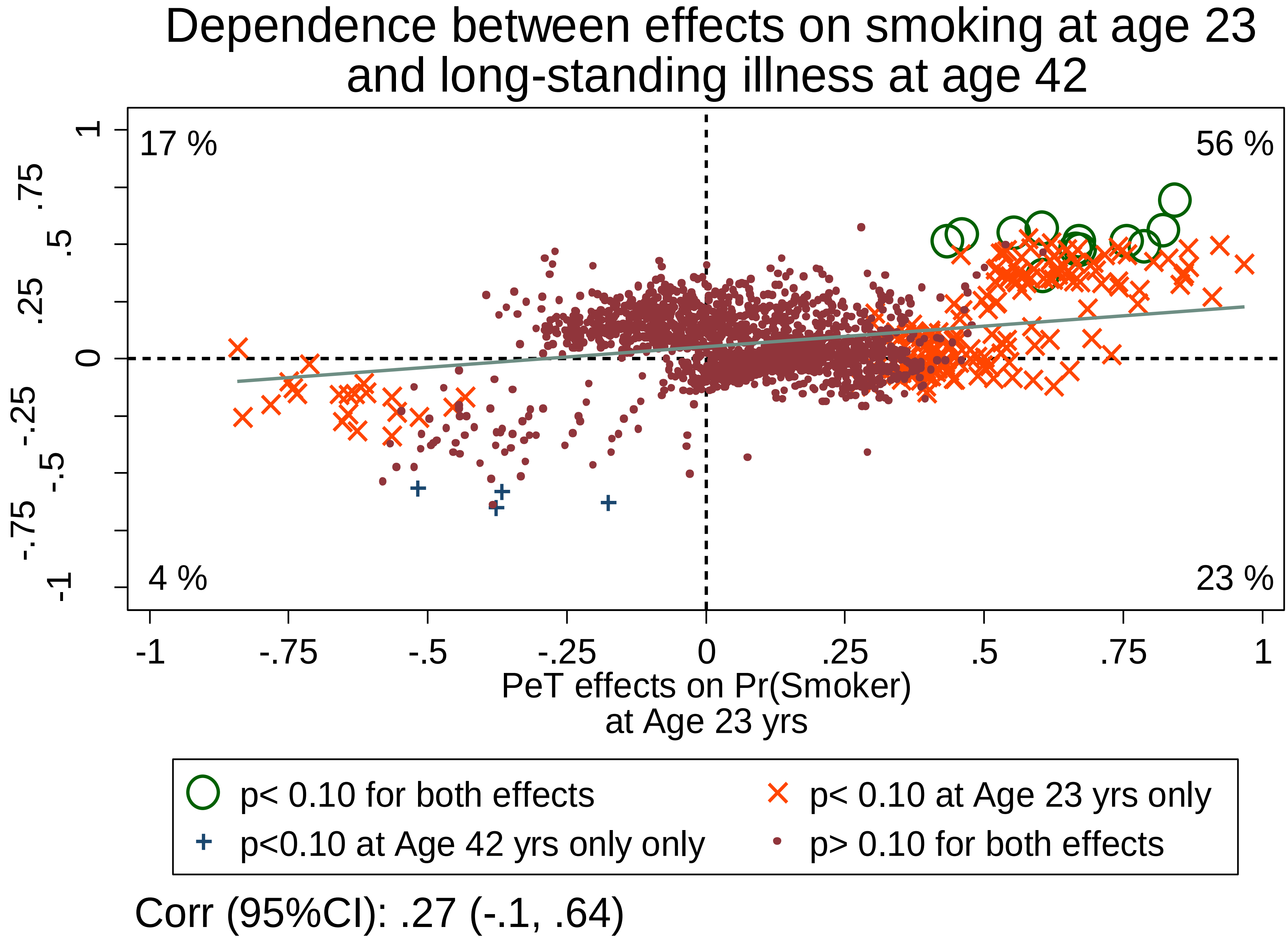
While the MTE has several useful features, full nonparametric identification is challenging because it requires instruments that generate con-

TABLE 3
OLS AND IV ESTIMATES

<table>
<tr><th></th><th>$P(Z)$ as Instrument (1)</th><th>$Z\_$ as Instrument (2)</th></tr>
<tr><td>IV:</td><td></td><td></td></tr>
<tr><td>Same-sex instrument</td><td>−.208
(.105)</td><td>.174
(.115)</td></tr>
<tr><td>Twins instrument</td><td>−.065
(.060)</td><td>.050
(.062)</td></tr>
<tr><td>Both instruments</td><td>−.015
(.053)</td><td>.076
(.055)</td></tr>
<tr><td>OLS</td><td colspan="2">−.052
(.007)</td></tr>
</table>

NOTE.—This table reports OLS and IV estimates of the effect of family size on the educational attainment of firstborn children. Column 1 reports linear IV estimates with $P(Z)$ as instrument. We construct $P(Z)$ using the parameter estimates from the logit model with average derivatives reported in table 2. Column 2 reports standard linear IV estimates with $Z\_$ as instrument. We use the same specification for the covariates as reported in table 2. The first row excludes the same sex, first and second children instrument from the second stage, the second row excludes the twins at second parity instrument from the second stage, and the third row excludes both instruments from the second stage. The OLS estimate of the second-stage specification (20) is reported in the fourth row. Standard errors in parentheses are robust to heteroskedasticity.

mates from the logit model, for which average marginal effects are reported in table 2. When excluding the same-sex instrument from the outcome equation, we estimate that being in a family with two or more siblings rather than one sibling lowers the educational attainment of firstborn children by 0.208 year. If instead we exclude the twins instrument from the outcome equation, we still find a negative point estimate but cannot reject no effect of family size at conventional significance levels. When we exclude both instruments from the outcome equation, the IV estimate is close to zero. Indeed, the LATE based on both instruments is significantly different from the LATE based on the same-sex (twins) instrument at the 5 (10) percent significance level.[15] The fact that the


Dependence between effects on smoking at age 23
and long-standing illness at age 42
17 %
56 %
4 %
23 %
1
.75
.5
.25
0
-.25
-.5
-.75
-1
-1
-.75
-.5
-.25
0
.25
.5
.75
1
PeT effects on Pr(Smoker)
at Age 23 yrs
p< 0.10 for both effects
p< 0.10 at Age 23 yrs only
p<0.10 at Age 42 yrs only only
p> 0.10 for both effects
Corr (95%CI): .27 (-.1, .64)

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