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Abstract

This study evaluates unfair inequality, namely inequality of opportunity (IOp), in access to medical care among the elderly population. I compare the magnitude of IOp across 14 European countries using data from the Survey of Health, Aging and Retirement in Europe (SHARE) collected in 2013. Self-reported unmet medical need caused by cost-related reasons is used as a measure of medical access. Separate models are introduced to accommodate two competing philosophical views (e.g. control and preference approaches) that result in a different definition of the scope of individual responsibility. A joint estimation strategy is applied to take unobserved heterogeneity into account. We find the highest IOp to exist in medical access in EE and IT, and the lowest in AT, CH, SI, NL, SE and DK. However, some results are sensitive to normative assumptions. For instance, EE, IT and DE show greater IOp when it is assumed that individuals are responsible for their decisions made on the basis of genuine preference rather than control. Additional results from a policy simulation suggest that IOp could have been significantly reduced due to educational promotion in many countries, with the exception of EE, NL, SI, SE and DK.

JEL classification: D63, I14, I18

Keyword: inequality of opportunity, unmet medical need, medical access

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1 Introduction

This paper investigates unfair disparity in access to health care services in Europe. Particularly, it focuses on financial accessibility, which is measured by self-reported unmet medical need caused by cost-related reasons. Considering the fact that most European societies guarantee universal health coverage, such a perceived financial barrier prior to the utilization of services should be trivial. However, as Allin, Grignon, and Le Grand (2010) point out, such a barrier is unavoidable to a limited extent due to the scarcity of resource; hence what is more important is whether its prevalence is equitable.

The stance taken by this study regarding equality of opportunity is that the access should be equalized if the barrier is associated with the factors which are not governed by individual responsibility. For instance, if an individual deliberately chooses or prefers luxurious alternatives instead of standard medical treatment, her/his resulted forgone care may not be considered as inequitable. One of the advantages of this approach is that it explicitly shows the magnitude of unfairness that should be eradicated by government intervention. Nonetheless, the definition of what individuals should be held responsible for will ultimately depend on our normative positions. In this paper, I attempt to quantify varying degrees of unfairness by incorporating different viewpoints.

So far few empirical analyses have been conducted regarding unequal or unfair distribution of medical access in Europe. On the other hand, there have been rigorous discussions about inequality in the actual use of medical services, which is particularly related to socioeconomic status (SES). Numerous studies have revealed the pro-rich inequality in specialist (SP) contacts in most countries. The income-related difference is more pronounced in Portugal, Finland, Ireland, Italy, and Denmark (van Doorslaer et al., 2000; 2004) as well as Greece and Austria (Bago d'Uva and Jones, 2009). In terms of contacts with a general practitioner (GP), the literature reports mixed results. While the pro-poor inequality is found from Ireland, Spain, and Belgium, (van Doorslaer and Koolman, 2004), an opposite result is obtained from Portugal, Sweden, Austria and Greece (Doorslaer, Wagstaff, et al., 2000; Bago d'Uva and Jones, 2009). Sweden also shows relatively high inequality in terms of the number of doctor visits for both GP and SP services (van Doorslaer et al., 2000). In general, existing studies suggest that the universal coverage is weakly associated with equality of medical use.

However, by focusing on gaps in actual utilization, policy implications may actually be limited since lower use can be driven by various reasons such as difficult physical access, excessive cost, inflexible time arrangement, a long waiting list, limited information, and so on. In other words, results based on service use do not directly inform us as to which type of barriers should be eliminated to equalize service utilization across people with different SES. Another concern is unobserved quality of services. The pro-poor inequality in GP contacts can be caused by ineffective service provision for the low income group, which worsens their health condition and thus further increases their medical need. The quality of services, even from the same doctor, may vary due to the fact that medical diagnosis is often related to communication with patients. Research documents that a patient's disadvantageous background can be associated with her/his limited health literacy (Verlinde et al., 2012), a doctor's prejudice (Balsa and McGuire, 2003) or discriminatory behavior (Waitzkin, 1985) which all prohibit effective communication. Furthermore, if the amount of forgone care is not negligible, the magnitude of inequality might be biased. Therefore, it may improve the understanding of prior findings and provide additional insights for policy guidance if disparity is analyzed in terms of barriers to medical access pertaining to each policy-relevant reason. Due to a lack of data, however, this paper discusses barriers from a financial aspect only.

Using an aggregated measure of unmet medical need caused by multiple reasons, two prior studies demonstrate a systematic association between low income and a higher prevalence of unmet medical need in most European countries. Relatively higher income-related inequality is reported in Italy, Estonia and Belgium among 11 countries in the Survey of Health, Aging and Retirement in Europe (SHARE) from 2004 (Koolman, 2007) and in Greece and Germany among 14 countries in EU-SILC data from 2004 (Mielck et al., 2009). I analyze a more recent sample of older adults over the age of 50 using SHARE from 2013. I focus on this subgroup population due to the fact that they are in greater medical need than their younger counterparts, and that equitable medical access is critical for aging in a healthy way.

As mentioned above, an important distinction from earlier investigations is that I evaluate the inequality of opportunity (IOp) for access, rather than inequality related to SES which is measured by income or education. To do so, in addition to SES, I consider more detailed individual characteristics such as parental background and personal taste in a model, and disentangle illegitimate components from all explanatory factors. Moreover, I compute counter-factual IOp using a plausible scenario of government intervention in education. The results are compared across 14 countries: Austria (AT), Germany (DE), Sweden (SE), Netherlands (NL), Spain (ES), Italy (IT), France (FR), Denmark (DK), Switzerland (CH), Belgium (BE), Czech Republic (CZ), Luxembourg (LU), Slovenia (SI), and Estonia (EE).

I find excessive IOp in medical access in EE and IT. On the other hand, stably low inequity is observed in AT, CH, SI, NL, SE and DK. Other countries such as DE, FR, LU, BE, ES and CZ are ranked in between these groups. Varying pictures based on different normative assumptions demonstrate that careful consideration is needed when choosing a technical tool and value judgment to be used in evaluation. The policy simulation suggests that educational promotion may have a visible impact on equalizing opportunities for enjoying affordable services in many countries except for EE, NL, SI, SE and DK.

2 Overview of health care financing system

In this section, a brief overview is provided regarding institutional characteristics that might be related to financial accessibility to health care services. Table 1 summarizes the population coverage of statutory and voluntary health insurance (VHI), as well as the relative contributions of various financing sources. Countries are listed according to the prevalence of unmet medical need.

In most countries, universal health insurance is available except for EE and DE. They show relatively higher unmet medical need. In these countries, private insurance substitutes the statutory one by covering those who are neither eligible nor obliged to join the statutory scheme. Such cases are those who are of working age but economically inactive in EE (Lai et al., 2013), as well as high income earners, the self-employed or civil servants in DE (Busse and Blümel, 2014).

We do not observe any particularity of the Italian system, which potentially explains its excessive cost-related barrier. Both in IT and in Nordic states where forgone care is almost absent, health care expenditures are mostly financed by taxation. Moreover, although CH shows substantial dependence on out of pocket expenditure (OOP) compared to other countries, it shows one of the lowest prevalence of unmet need. These facts demonstrate that generous public financing may not be sufficient to ensure easier access.

Table 1: Financing health care expenditures by country

	Unmet need in SHARE (%)	Pop. with statutory insurance (%)	Elderly pop. with VHI in SHARE (%)	Financing of health expenditure (%)			
				Gov't	Social Security	OOP	VHI
EE	15.078	93.3	1.9	10.5	69.1	18.4	0.3
IT	10.922	100	5.4	77.0	0.3	18.8	1.0
DE	4.397	88.9	26.9	6.8	70.4	12.2	9.6
FR	4.229	99.9	95.5	3.9	73.8	7.8	13.8
CZ	3.330	100	4.1	4.5	79.2	15.3	0.2
BE	3.274	99	82.2	10.9	64.3	20.4	4.2
ES	3.114	99	10	67.0	4.7	22.1	5.8
LU	3.051	97	73.9	8.6	74.0	11.6	4.6
AT	1.511	99.9	23.0	32.6	44.6	16.7	4.8
SI	1.190	100	79.6	3.2	68.6	12.5	14.6
NL	1.168	99.8	83.0	7.5	78.3	6.0	5.5
CH	1.166	100	75.4	20.3	45.5	26.0	7.2
SE	0.818	100	17.6	81.2	0.0	17.4	0.3
DK	0.485	100	47.1	85.2	0.0	12.9	1.8

Source: OECD health statistics (2014)

In Table 1, we also observe varying degrees of popularity and financial contribution of VHI. Overall, VHI is only limitedly used in EE and IT where the cost-related barrier is most pronounced.

As mentioned above, VHI is mainly used for substitutive purpose by those excluded from the statutory system in EE. On the other hand, in IT, people can join VHI either collectively through private insurance funds (organized by specific employers, professional groups or mutual aid societies) or individually through private insurance companies (Ferré et al., 2014).

Among all countries, VHI is most widely used in FR, which has been stimulated by government intervention (Chevreul et al., 2010)[1]. In BE, it is provided by both the sickness funds and private profit-making insurance companies (Gerkens and Merku, 2010). In SE, VHI is usually offered by employers.

The role of VHI also differs in each country. We do not find a clear relationship between the role of VHI and financial constraints using this aggregated data. In LU, NL, FR, BE, and IT, VHI offers a complementary coverage of extra reimbursement or extra services. On the other hand, in ES and SE, it provides supplementary coverage for services that are already covered by statutory insurance. People with VHI in ES enjoy various benefits-in-kind such as quicker access, wider choice and better amenities (García-Armesto et al., 2010). Similarly, VHI is mainly used to obtain shorter waiting times for ambulatory or elective care in SE (Anders, Anna, and Sherry, 2012).

In addition, mixed coverage also exists. In AT[2], it is primarily purchased for greater comfort (e.g. better accommodation and shorter waiting times) and free choice in physicians in hospitals. However, it also provides extra reimbursement for hospital cost (Hofmarcher and Quentin, 2013). In CH and DK, its role is supplementary for hospital services[3] but complementary for other services (e.g. adult dental services, drugs, glasses and physiotherapy) (Minder, Schoenholzer, and Amiet, 2000; Olejaz et al., 2012). In SI, both benefits are available, but complementary coverage for co-payment is more common (Albreht et al., 2009). In CZ, VHI is used in a limited way for various purposes such as traveling abroad, extra reimbursement, substitutive coverage for foreigners, and complementary coverage for cosmetic surgery and dental care (Jan et al., 2015).

3 Data

I use data from the fifth wave of SHARE which is collected in 2013. It contains detailed information on the population over the age of 50 such as their household characteristics, SES, childhood back-

[1]The subscription rate increased from 50% in the 1970s to 90% in the 2000s. The French government offers fiscal incentives to both employers and employees under the group contract for VHI. The government also provides public complementary insurance or vouchers for those who cannot afford privately arranged VHI.

[2]The Austrian SHI covers 99.9% of the population, including dependents of the insured, the self-employed, free-lancers, apprentices, recipients of unemployment benefits or childcare allowance. The rest of the population with permanent residency can also enter the statutory scheme through a voluntary self-insurance. Health insurance funds are decentralized by region and occupational groups. In principle, free choice in insurance fund is not permitted, but there is no strict regulation in practice. As a result, some professional groups (e.g.physicians, pharmacists, lawyers, architects, public accountants, veterinarians and notaries) have exited the statutory scheme, comprising 5% of the privately insured.

[3]In DK, although some VHI also covers expenses incurred from examination or treatment at private hospitals, its main aim is to provide greater choice and comfort. Acute care is not covered.

grounds, health condition, medical services utilization, lifestyle, etc. Samples from 14 countries are included in a pooled analysis: Austria (AT), Germany (DE), Sweden (SE), Netherlands (NL), Spain (ES), Italy (IT), France (FR), Denmark (DK), Switzerland (CH), Belgium (BE), Czech republic (CZ), Luxembourg (LU), Slovenia (SI), and Estonia (EE).

3.1 Medical access vs. use

Among various indicators of health care utilization that are available in SHARE data, I use self-reported unmet medical need due to costs as a measure of medical access. This binary indicator is mirrored so that 1 refers to having barrier-free access and 0 to having forgone services due to financial constraints at least once in 12 months[4]. SHARE data also provides objective information about individual use of medical services such as frequency and expenditure regarding doctor consultation, dental care, hospitalization, and nursing home/home care services for the 12 months before the survey. As mentioned above, literature has paid relatively more attention to the issue of inequality/inequity in the use of medical services, although access is also a policy relevant question.

A difference between the two types of outcome, medical care access and use, is not only limited to a conceptual distinction. The lack of use of medical services, which is demonstrated in lower consumption conditional on medical need, may not always coincide with a lack of access, depicted by forgone care. For example, even if individuals i and j, with the same health problem, spent equal amounts of medical services at some point, i could have been forced to postpone this due to financial constraints in the first place. Such a cost-related barrier can only be captured by self-reported forgone care. Furthermore, if delayed treatment worsens i's illness, it is also possible that she/he ends up spending more than j in the end.

To better understand the discrepancy between two measures, I compare the average amount of medical expenditure[5] between people with and without unmet medical need (Table 2). To control medical need, only those who report fair or poor health are selected. Overall, I observe higher expenditure among people with unmet need, which is consistent with Allin and Masseria (2009)'s findings from a pooled sample of SHARE 2004. The gap is statistically significant in many cases, which is particularly prevalent in terms of doctor visits and medication.

[4] Any type of doctor, qualified nurse, emergency room, outpatient clinic, and visits are considered.

[5] Zero expenditure is also considered, which means full reimbursement. Non-spending is coded as missing.

Table 2: Average out-of-pocket expenditure among people in fair/poor health (€)

	Doctor visit		Dental care		Hospitalization		Medication		Total	
	Met	Unmet	Met	Unmet	Met	Unmet	Met	Unmet	Met	Unmet
EE	13	18	172	194	32	23	**216**	**244**	**241**	**276**
IT	224	257	957	1,011	169	18	**274**	**542**	664	918
DE	**79**	**205**	222	279	112	150	165	229	**394**	**622**
FR	46	90	288	199	41	23	110	130	222	246
BE	172	179	227	229	**230**	**486**	**356**	**516**	**494**	**740**
LU	**159**	**468**	332	379	223	102	305	351	507	718
ES	25	36	721	377	45	0	144	171	253	235
CZ	**14**	**31**	44	81	**68**	**118**	**115**	**163**	**147**	**234**
AT	119	154	**347**	**1,102**	146	350	**292**	**444**	**473**	**1,161**
CH	344	335	739	801	458	138	319	240	961	947
SI	21	5	205	189	12	0	99	77	136	119
NL	**18**	**79**	119	142	19	75	122	135	141	244
SE	88	86	**337**	**1,127**	100	98	166	169	**488**	**802**
DK	21	22	396	849	36	0	339	310	584	634
N	39,523	2,274	22,196	952	7,940	491	28,226	2,036	45,411	2,627

Note: Numbers are highlighted in bold if a difference is significantly different from zero($p < 0.05$).

3.2 Validation

Reporting heterogeneity is one of the challenges of using self-reported unmet need as an outcome. People might have different expectations concerning affordable service. Therefore, self-reported unmet need may reflect not only barriers to access but also personal preferences (Allin and Masseria, 2009). For this reason, I attempt to validate my subjective measure by comparing with other data.

In Table 3, we observe that less than 5% of elderly Europeans experienced unmet need due to cost except for EE and IT in SHARE of 2013[6]. I compare this measure with similar information surveyed in the first wave of SHARE from 2004[7]. Between 2004 and 2013, cost-related barriers in health care service have intensified in IT, DE, BE, ES, AT and NL to varying degrees. Among these countries, IT shows the most visible increase (7.4% points)[8]. In other countries, the magnitude of the increase is about 1% point or less. On the contrary, the situation has been slightly improved

[6]All numbers are based on the raw data before cleaning. More than 80% of respondents had seen a doctor in the preceding 12 months before the survey of 2013. The lowest rate is 82% in Sweden and the highest is 95% in Luxembourg.

[7]The questions on forgone care are missing in other waves.

[8]The rise is pronounced in the Southern and insular regions (Appendix A). The Eurozone crisis can be one explanation for this upward shift as it has hit these regions more severely compared to northern areas. In addition, sampling bias can be another underlying factor. Between Waves 1 and 5, a fraction of samples collected in the north slightly decreases while samples from the central and southern areas increase. Therefore, further research is needed to identify whether a sharp increase in forgone health care in IT is an emerging social phenomenon or a resulting artifact from a sampling procedure.

in FR, CH, SE, and DK. From the subsample that appears in both Wave 1 and 5, we observe a persistent level of unmet need in all countries.

Table 3: Unmet need due to cost in SHARE and EU-SILC (%)

	SHARE (2013)	SHARE (2004)	Balanced sample (2004 & 2013)	EU-SILC (2013, over age 45)
EE	15.078	.	.	1.8
IT	10.922	3.496	4.012	14.0
DE	4.397	3.681	4.038	1.5
FR	4.229	4.756	5.434	3.6
CZ	3.330	.	.	0.9
BE	3.274	2.063	1.981	3.4
ES	3.114	2.244	1.832	1.0
LU	3.051	.	.	1.9
AT	1.511	1.115	1.563	0.5
SI	1.190	.	.	0.1 (in 2012)
NL	1.168	0.576	0.479	0.2
CH	1.166	2.546	2.347	1.4
SE	0.818	2.523	2.222	0.9
DK	0.485	0.706	0.674	0.5
	62,676	25,336	10,998	

- Note: Figures in EU-SILC are retrieved from Eurostat.

EU-Statistics on Income and Living Conditions (EU-SILC) from 2013 provides a similar measure. Nonetheless, it is important to note that there is a dependency in terms of framing questions among datasets (See Appendix B for detailed questions). While SHARE surveys unmet need by separating reasons, EU-SILC combines them into a multiple choice question. Because a simultaneous choice is not allowed in EU-SILC, the measure from SHARE tends to be higher except for IT. The biggest discrepancy is found in EE. However, both datasets consistently suggest that the cost-related barrier is relatively high in IT, FR, and BE. In case of EE, only 1.8% of people choose financial constraints as a major reason for unmet need, which deviates substantially from what is reported in SHARE (2013).

SHARE data also contains unmet medical need due to waiting time which is another crucial policy concern. In Appendices C-D, I conduct a similar exercise regarding this variable. In a nutshell, we observe even larger discrepancy between SHARE and external data with respect to service availability. Furthermore, a non-ignorable gap between our subjective measure and objective records on actual waiting time suggests potential reporting bias. To avoid misleading interpretation, I discard the issue of waiting time and focus only on unmet need due to cost in the analysis. I hope the issue of waiting time can be investigated by future researchers, when better measures are provided. Appendix E presents summary statistics of all covariates incorporated in the models, which are illustrated in Section 5.

4 Socioeconomic inequality in medical access vs. use

We cannot measure disparity in health care in a comparable way by simply switching from one measure to another. I demonstrate this point empirically by comparing income-related inequality of both outcomes. I use a concentration index (CI) defined in eq. (1) to measure inequality in medical expenditures. All individuals i are ranked by her/his income from 1 for the highest to n for the lowest position, which is denoted as κ. CI indicates whether an outcome, y, is concentrated among the richer or the poorer groups, which is denoted by a positive and a negative sign respectively. The closer to 1 in an absolute value, the greater the inequality. CI reaches 1, namely the maximal inequality, in a situation where the richest individual monopolizes all available medical services.

$$CI = \frac{2}{n^2\bar{y}}\sum_{i=1}^{n} w_i y_i, \quad where \quad \bar{y} = \frac{1}{n}\sum_{i=1}^{n} y \quad and \quad w_i = \frac{n+1}{2} - \kappa_i \tag{1}$$

Nevertheless, when an outcome always lies within a certain range, the standard CI is an inappropriate measure of inequality. CI is variant on the mean. For a bounded outcome, this feature is problematic because it produces inconsistent pictures once the outcome is mirrored. For instance, Clarke et al. (2002) demonstrate how different conclusions may be reached if CI is measured in terms of morbidity instead of health. To tackle this drawback, Wagstaff (2005) and Erreygers (2009a) modify CIs into W and E specified in (2)-(3). They incorporate the upper (U_y) and lower (L_y) limits in the normalization of a weighted sum of y. Both indices are applicable to self-reported unmet medical need which is a binary outcome bounded by 0 and 1. These indices display an equal magnitude of inequality in an opposite sign, if inequality is measured in terms of the presence of a cost-related barrier instead of the absence of it.

$$W = \frac{2(U_y - L_y)}{n^2(U_y - \bar{y})(\bar{y} - L_i)}\sum_{i=1}^{n} w_i y_i, \quad where \quad 0 \leq L_y \leq y_i \leq U_y \leq +\infty \tag{2}$$

$$E = \frac{8}{n^2(U_y - L_y)}\sum_{i=1}^{n} w_i y_i, \quad where \quad 0 \leq L_y \leq y_i \leq U_y \leq +\infty \tag{3}$$

As Erreygers and Van Ourti (2011) as well as Kjellsson and Gerdtham (2013) highlight, there are several distinctions between W and E. From a normative perspective, W shares a somewhat similar view on maximal inequality with CI. It defines the extreme inequality as a situation where only the richest individuals enjoy available barrier-free access to medical services for a given average level of medical access. To elaborate further, W becomes 1 if an easy access is guaranteed only to richest $\bar{y}$% of the population. On the other hand, E reaches 1 when the access is given to the richest

50% of the population regardless of $\bar{y}$. Two indices converge to each other as $\bar{y}$ moves towards a midpoint of U_y or L_y, and they diverge from each other as $\bar{y}$ moves towards either limit.

From a technical point of view, the most obvious difference is the level independence which is satisfied only by E. That is, E is invariant to equal amounts of increase in y_i of all i since it quantifies the absolute inequality. On the other hand, W changes ambiguously by decreasing as long as $\bar{y} < 0.5$ but increasing once $\bar{y} > 0.5$. This is a consequence of synthesizing relative inequalities into one as well as its mirrored outcomes at the same time. Another important distinction is the convergence property. Only E satisfies this property by moving towards 0 when y_i of all i is equiproportionality reduced by r, where $0 \leq r < 1$.

$$lim_{r \to 0} I(ry_i) = 0 \tag{4}$$

Considering the normative similarity, CI of medical use is only compared to W of medical access. An additional comparison is made between W and E of access.

SHARE data provides two variables of household income. One aggregates various income-related components (*thinc*) and another is derived from a one-shot question on total household income (*thinc*2). Because there is no scientific ground for preferring one to another (Malter and Börsch-Supan, 2015), I take an average of two measures[9] and divide it by the size of the household. Due to a large number of missing cases, I also use an average of imputed values[10]. Instead of total income-related inequality, I compute Wagstaff and Doorslaer (2000)'s horizontal inequity, HI_{WV}, which indicates need-adjusted inequality attributed to income. Using indirect standardization, HI_{WV} is computed by subtracting income-related inequality in needed use/access, C_N, from that in actual use/access, C_M. Medical need is measured by self-reported health status (excellent, very good, good, fair or poor)[11].

$$HI_{WV} = C_M - C_N \tag{5}$$

The results are presented in Figure 1(a)-(c). We find pro-rich HI in medical use in most countries. Better medical access is concentrated among the rich in half of the countries, which is represented by positive W or E values for 'fully met need' as well as negative W or E values for 'unmet need'. Regardless of indices, the magnitude of HI is not statistically different from zero in

[9] *thinc* can be preferred in terms of accuracy, but it has more missing data compared to *thinc2*.

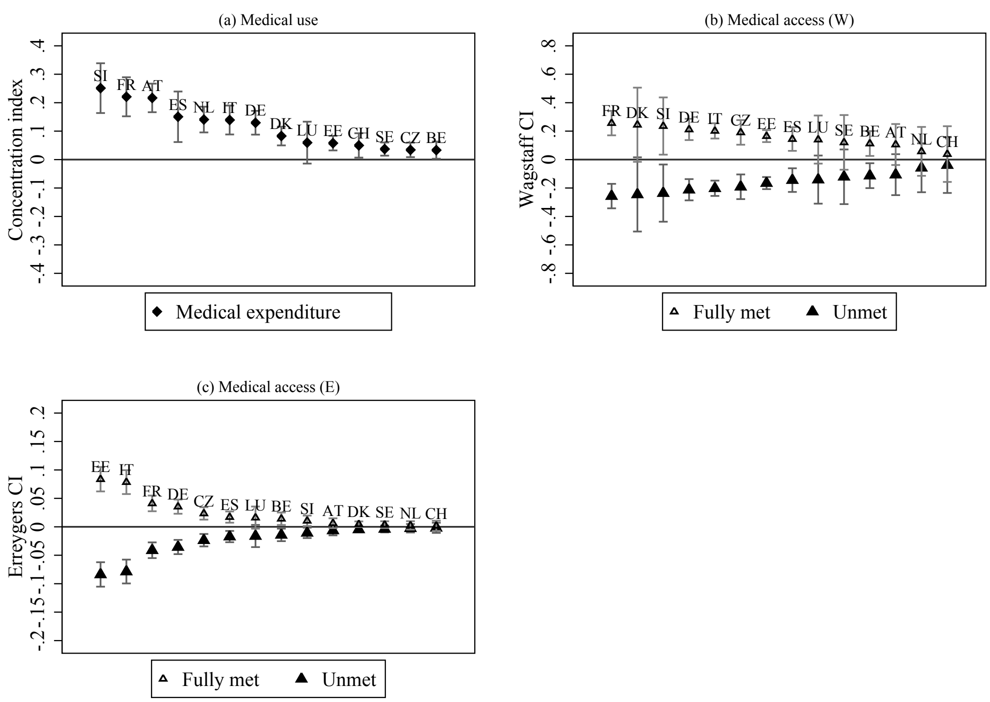
[10] The data distributor provides five imputed datasets to enhance availability of variables with missing data.

[11] Other variables (e.g. demographic background) are intentionally ignored. Adding more factors raises the question of what an (in)equitable inequality is, which I will answer though an analysis based on a framework of equal opportunity. Some researchers implicitly assume that unequal utilization of health care services related to individual characteristics other than medical need is unjustifiable (e.g. Koolman, 2007; Doorslaer and Koolman, 2004). Others deem that all other factors but socioeconomic status (SES) are justifiable (e.g. Allin, Grignon, and Le Grand, 2010). Instead of arbitrary classification, this preliminary analysis is kept simple by taking only SES and medical need into account. A user-written STATA command, *conindex* (O'Donnell et al., 2016) is used for computation, which applies the convenient covariance approach.

DK, LU, SE, BE, AT, NL and CH. Dissimilar results from medical use and access imply that policy importance differs greatly across countries. For instance, HI in use requires more attention in AT, DK and NL yet that in access does in CZ. Inequality in both use and access should be a concern in FR, SI, ES, IT, DE and EE.

Different rankings of W across countries across countries in Figure 1(b) and E in Figure 1(c) advocates the importance of the choice in index. Due to the convergence property (eq. 13), DK and SI are ranked low in E, but not in W. In both indices, inequality is relatively high in FR, DE and IT.

Figure 1: Need adjusted income-related inequality in medical use vs. access



Note: 95% confidence intervals are displayed.

Although a definition of the maximum inequality of E is debatable, I deem that E allows for a more natural interpretation compared to W, in the context of measuring disparity in access to medical service. I consider the fact that the issue of inequality would require less attention if almost everyone enjoys barrier-free access (e.g. DK). On the other hand, it becomes a policy concern if the population being deprived easy access is rather noticeable (e.g. EE and IT). Ideally, a government would aim at lowering the barrier further as well as equalizing the disparity of it at the same time.

E, an index of absolute inequality, incorporates both aspects thanks to its convergence property. Based on this position, in Section 7.2, IOp is also measured in an absolute term.

5 Model

5.1 Baseline model

I directly apply Fleurbaey and Schokkaert (2009)'s stylized model of medical consumption in my baseline model of medical access. Their model assumes that individuals maximize their utility, U, which is a function of health status, h, as well as their choice over medical and general consumption (m and c respectively) and, finally, job characteristics, o. Under budget constraints, the sum of consumption (pc) and out-of-pocket medical expenses (OOP), which is determined by m and insurance status, pi, should not exceed labor income, y , after payment/transfer of tax, T, and insurance premium, ρ. ρ differs by pi and initial health, e, across individuals (eq. 7). Furthermore, y is an outcome of c, o, and h, as well as innate productivity, a, and social background, s.

$$U(h, m, c, o) \tag{6}$$

$$pc + OOP(m, pi) \leq y - T(y, c) - \rho(pi, e), \quad where\ y = Y(c, o, h, a, s) \tag{7}$$

Considering exogenous factors only, in a reduced form, m can be expressed as a function of e, s, a, stochastic health shock, ε, available information, I, time/risk preference, r, environmental factors, z, and other heterogeneity, U. ε and I have an influence through h, which shapes individuals' own perception of h, while r does through their decisions on pi. Moreover, z concerns supply-side constraints that influence service providers' heterogeneous responses to each patient.

$$m = f(e, s, a, \varepsilon, I, r, z, U) \tag{8}$$

Using SHARE data, I attempt to identify e with age, gender (fe) and childhood health status (ch). ch is proxied by a decile of current height by gender and birth cohorts within a country (1-10). s and a are depicted with mother ($medu$) and father's education ($fedu$), and a respondent's own educational attainment (edu). Parental education is measured according to ISCED (International Standard Classification of Education) of 1997. The seven categories in the original variable are combined into three, representing none, primary, and (post) secondary degrees. On the other hand, SHARE provides two measures of edu, educational qualification and years of schooling. The latter is chosen to minimize the number of missing cases[12]. In spite of the fact that personal input plays a role in educational attainment, edu is assumed to be exogenous. In addition, country dummies

[12]Similar to household income, I use mean years of schooling across five imputed datasets. If a variable is categorical, such a simple approach might be problematic. The same exercise is applied to height.

(*con*) are included in a pooled analysis to capture an environmental factor, z.

Having no direct measures for ε, I, r, or U, I incorporate related endogenous variables such as y, h, and pi in a baseline model. I measure y by adjusting household income per capita with purchasing power parity of 2013 for cross-country comparability (*inc*). As a measure of h, five categories of self-assessed health (*health*) are simplified into two, such as 0 (fair/poor) and 1 (excellent/very good/good) to lower country-specific reporting heterogeneity. The remaining unobserved individual characteristics are considered as an error term, ϵ. pi is a binary indicator of having supplementary insurance. Finally, the baseline model is expressed as follows. *access* is a binary indicator of not having unmet medical need due to costs.

$$\begin{aligned} access_i &= \alpha + \beta age_i + \gamma fe_i + \delta ch_i + \zeta medu_i + \eta fedu_i + \theta edu_i + \\ &\quad \lambda inc_i + \nu health_i + \tau pi_i + \rho con_i + \epsilon_i \end{aligned} \tag{9}$$

5.2 Model specification and normative positions

Inequality of opportunity (IOP) distinguishes illegitimate inequality from the overall disparity. Therefore, all explanatory variables should be classified either into circumstance (C) or effort (E) depending on the legitimacy of their influence on the outcome. In many empirical studies, C is often identified by childhood background (i.e. parental SES) or innate characteristics (i.e. race). In my model, I consider that e, s, a and z lead to illegitimate inequality in access to health care services. On the other hand, I deem that the influence of preference-related components such as ε, r , I and U are at least partially legitimate.

In this position, however, I encounter a challenge with classifying endogenous intermediate outcomes such as *inc*, *health*, and *pi*, as they are a mixture of circumstances (C) and effort (E). Hereafter, these mixed factors are denoted M. A distinction between the two depends on a researcher's normative judgment on the scope of personal responsibility. I modify the baseline model to portray individual responsibility, explicitly following two contrasting approaches which are initiated by philosophers and revisited by economists for empirical applications.

On one hand, the control view (Arneson, 1989; Cohen, 1989; Roemer, 1998) defines individual responsibility to the extent of what falls under the individual's genuine control. Based on this view, many researchers follow Roemer (1998)'s approach which purges E of any relationship with C. That is, they interpret any correlation between C and E as C. A simple way of realizing this view in a model is to use a reduced form specification which only contains C. E is captured by the residuals which are orthogonal to C. This approach is especially useful when E is not observed, which is often the case. However, we should also bear in mind that data only allows us a partial glance at C. To deal with an omitted variable issue, Rosa Dias (2010) introduces a joint estimation strategy that enables the identification of common unobserved factors across interrelated outcomes. In his investigation on equality of opportunity for health, he simultaneously estimates reduced-form models of several health indicators and related behaviors. By letting error terms be freely correlated with each other, he captures common unobserved heterogeneity across equations.

Following his method, I express medical access and endogenous intermediate outcomes, M, as functions of observed C and unobserved factors, μ.

$$\begin{aligned} access &= g_a(C, \mu_a) \\ M &= g_m(C, \mu_m), \quad M = (inc, health, pi) \end{aligned} \tag{10}$$

Using the variables introduced above, a full model is specified as eq. (11). The unobserved factor, μ, falls under the error terms, ϵ, which are assumed to follow a multivariate normal distribution. By estimating a recursive system of equations simultaneously, we can identify the contribution of C to each of the outcomes through corresponding parameters, as well as the presence of common unobserved factors, μ through correlation coefficients among ϵ. I apply probit estimation for three binary outcomes (e.g. *access*, *health* and *pi*), and OLS regression for the logarithm of income per capita[13]. A user-written Stata command, *cmp* (Roodman, 2011), is used for a joint estimation of four mixed processes, which applies full-information maximum likelihood (FIML) .

$$\begin{cases} access_i = \alpha + \beta age_i + \gamma fe_i + \delta ch_i + \zeta medu_i + \eta fedu_i + \theta edu_i + \rho con_i + \epsilon_i \\ inc_i = \alpha^{'} + \beta^{'} age_i + \gamma^{'} fe_i + \delta^{'} ch_i + \zeta^{'} medu_i + \eta^{'} fedu_i + \theta^{'} edu_i + \rho^{'} con_i + \epsilon_i^{'} \\ health_i = \alpha^{''} + \beta^{''} age_i + \gamma^{''} fe_i + \delta^{''} ch_i + \zeta^{''} medu_i + \eta^{''} fedu_i + \theta^{''} edu_i + \rho^{''} con_i + \epsilon_i^{''} \\ pi_i = \alpha^{'''} + \beta^{'''} age_i + \gamma^{'''} fe_i + \delta^{'''} ch_i + \zeta^{'''} medu_i + \eta^{'''} fedu_i + \theta^{'''} edu_i + \rho^{'''} con_i + \epsilon_i^{'''} \end{cases} \tag{11}$$

On the other hand, the preference view (Rawls, 1971; Dworkin, 1981) asserts that individuals are responsible for their choices made based on preference or taste. To apply this view, I adapt García-Gómez et al. (2015)'s strategy which incorporates instrumental variables of individual preference. In their study of IOp in mortality and morbidity, they introduce region, urbanization and religion as preference shifters, π. They assume that π affects death and health only through lifestyle (e.g. smoking, exercising and obesity), by shaping preference. In a nutshell, this strategy allows the identification of a preference-driven component, E, in endogenous lifestyle as well as the consistent estimation of their parameters in a main model.

Even if π captures exogenous variations of lifestyles successfully, it is nonetheless still questionable as to whether its influence on a health outcome by governing preference is truly legitimate. For instance, geographic differences in prevalence of obesity can also be attributed to institutional or market constraints (e.g. available sports facilities, etc.). For this concern, I impose an additional

[13]Considering zero income cases, one is added before a log transformation.

criterion for π such that it at least partially reflects individual-specific authentic preference itself. Potential π is searched among a set of variables that describe usual activities during the year such as playing games, reading newspapers, attending training courses, joining sport clubs, and so on. It is assumed that these behaviors portray what kind of life an individual pursues.

Having no related literature, π is selected based on its observed relationship with M and $access$. That is, I choose variables that are significantly correlated with any of M but not with $access$ conditional on C and other M. Finally, binary indicators of participating in volunteer (vol) and political (pol) activities, as well as regular consumption of vegetable/egg ($vege$, meaning 1 for at least twice a week and 0 for less.) are chosen.

As shown in eq. (12), I recover endogenous variables, M, in a main equation and include π in three auxiliary ones pertaining to M.

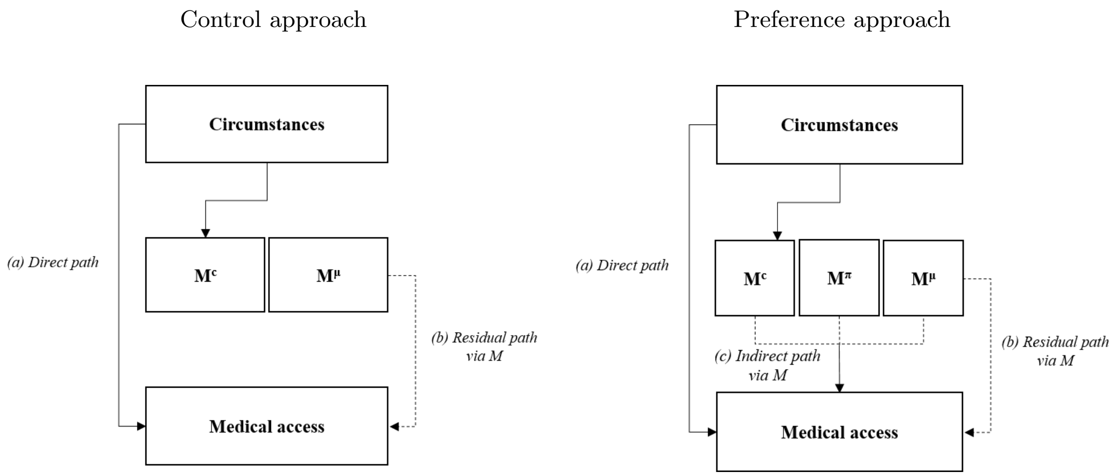
$$\begin{aligned} access &= g_a(C, M(C, \pi, \mu_m), \mu_a) \\ M &= g_m(C, \pi, \mu_m), \qquad\qquad M = (inc, health, pi) \end{aligned} \tag{12}$$

A full model is specified as eq. (11). Multivariate normality is assumed with respect to a distribution of ϵ. *cmp* (Roodman, 2011) is applied for a joint estimation, which applies the limited-information likelihood method (LIML) when only the final stage equation is structural.

$$\begin{cases} access_i = \alpha + \beta age_i + \gamma fe_i + \delta ch_i + \zeta medu_i + \eta fedu_i + \theta edu_i + \rho con_i + \\ \qquad\qquad \lambda inc_i + \nu ill_i + \tau pi + \epsilon_i \\ inc_i = \alpha^{'} + \beta^{'} age_i + \gamma^{'} fe_i + \delta^{'} ch_i + \zeta^{'} medu_i + \eta^{'} fedu_i + \theta^{'} edu_i + \rho^{'} con_i + \\ \qquad\quad \sigma^{'} vol_i + \phi pol_i + \varphi^{'} vege_i + \epsilon_i^{'} \\ health_i = \alpha^{''} + \beta^{''} age_i + \gamma^{''} fe_i + \delta^{''} ch_i + \zeta^{''} medu_i + \eta^{''} fedu_i + \theta^{''} edu_i + \rho^{''} con_i + \\ \qquad\quad \sigma^{'''} vol_i + \phi^{''} pol_i + \varphi^{''} vege_i + \epsilon_i^{''} \\ pi_i = \alpha^{'''} + \beta^{'''} age_i + \gamma^{'''} fe_i + \delta^{'''} ch_i + \zeta^{'''} medu_i + \eta^{'''} fedu_i + \theta^{'''} edu_i + \rho^{'''} con_i + \\ \qquad\quad \sigma^{'''} vol_i + \phi^{'''} pol_i + \varphi^{'''} vege_i + \epsilon_i^{'''} \end{cases} \tag{13}$$

To aid in comprehension, two models based on different normative positions are conceptualized as Figure 2. The channels (a) and (c) are parametrized in the models. In addition to these observed paths, there is an unobserved path (b) which involves the residuals of mediating factors, M.

Figure 2: Model conceptualization



6 Quantifying IOp

6.1 Standardization

After estimating the parameters specified in the models above, we need to disentangle legitimate and illegitimate inequality. We interpret the latter as inequality of opportunity. In the control approach, its computation is relatively simple because the model (eq. 11) considers only illegitimate determinants, C. Therefore, IOp is equivalent to the disparity of an outcome which is explained by all covariates. That is, IOp can be measured as a dispersion of a predicted probability of having full access conditional on the actual value of C, as shown in eq. (14). The choice of index, I, is discussed in Section 6.2.

$$IOp = I\left[Pr(access = 1 \mid C)\right] \tag{14}$$

On the other hand, in the model of preference approach (eq. 13), both legitimate and illegitimate factors are included. Two theoretical principles provide guidance on how to abstract the unethical component only. First, "reward (or responsibility) principle" states that unequal outcomes among individuals with the same circumstances but different efforts are equitable. In other words, to identify illegitimate inequality, we should eliminate within-circumstance variation in outcome and measure between-circumstance variation only. Fleurbaey and Schokkaert (2009) propose "direct standardization", equivalently "conditional equality", as a solution. It substitutes individual efforts with reference values, E^*, assuming an artificial situation where everyone exerts the same effort. Consequently, the remaining inequality is exclusively driven by C, which is called "direct unfairness

(DU)".

I compute DU as expressed in eq. (15). I replace the original variables of *inc*, *health*, and *pi* with their predicted values, which are computed via three auxiliary models after setting authentic tastes, π, using reference values. I choose a combination of efforts which is presumed to be the most desirable. I use a linear prediction of income after running OLS regression, and predicted probability of being healthy and that of having supplementary insurance after probit estimation. After plugging them into the model, IOp is quantified by a disparity of a predicted probability of having barrier-free access.

$$IOp_{DU} = I\left[Pr(access = 1 \mid C, \hat{inc}, \hat{health}, \hat{pi})\right] \tag{15}$$
$$\begin{cases} \hat{inc} = C\psi^{'} + \pi^{*}\omega^{'} + \varepsilon^{'} \\ \hat{health} = Pr(health = 1|C, \pi^{*}) = \Phi(C\psi^{''} + \pi^{*}\omega^{''} + \epsilon^{''}) \\ \hat{pi} = Pr(pi = 1|C, \pi^{*}) = \Phi(C\psi^{'''} + \pi^{*}\omega^{'''} + \epsilon^{'''}) \end{cases}$$

Second, "compensation principle" asserts that individuals exerting the same efforts should enjoy the same outcomes regardless of their circumstances. A fair society enables this situation by compensating disadvantageous backgrounds. Accordingly, to measure IOp under this condition, we should eliminate between-effort variation that is legitimate.

Fleurbaey and Schokkaert (2009) introduce "indirect standardization" for this purpose. It compares predicted outcomes for the same individual, using current status and a counter-factual situation that her/his circumstances are compensated. A virtual compensation occurs in the data by substituting C with its reference value, C^{*}, which is expressed in eq. (16). I suppose that all individuals are placed in the best circumstances. A difference between two predictions is called "fairness gap (FG)". It demonstrates how far a society is from a fair situation.

$$IOp_{FG} = I\left(Pr(access = 1 \mid C, inc, health, pi) - Pr(access = 1 \mid C^{*}, \hat{inc}, \hat{health}, \hat{pi})\right) \tag{16}$$
$$\begin{cases} \hat{inc} = C^{*}\psi^{'} + \pi\omega^{'} + \varepsilon^{'} \\ \hat{health} = Pr(ill = 1|C^{*}, \pi) = \Phi(C^{*}\psi^{''} + \pi\omega^{''} + \epsilon^{''}) \\ \hat{pi} = Pr(pi = 1|C^{*}, \pi) = \Phi(C^{*}\psi^{'''} + \pi\omega^{'''} + \epsilon^{'''}) \end{cases}$$

Two principles complement each other, yet a tension exists between them as well. It is often the case that neither DU nor FG satisfies both principles at the same time. They only satisfy both principles if the outcome function is additively separable in C and E (Fleurbaey et al., 2009; 2011). Both measures of IOp are presented in Section 7.

6.2 Index of inequality of opportunity

As an index of IOp, I use a modified coefficient of variation, CV, specified in (17), which is characterized by Erreygers (2009b). It rests on the same value judgment as E explained in Section 4. That is, it quantifies an absolute disparity. CV measures dispersion of attainment (A) and shortfall (S) of an outcome equivalently (i.e. it satisfies a mirror property). Unlike E in Section 4, which is a rank-dependent index ranging from -1 to 1, CV is bounded between 0 and 1. It reaches 1, the maximal inequality, when half the population has perfect access to medical services while the rest half has none.

$$\begin{aligned} CV &= \frac{2}{U_A - L_A}\sqrt{\frac{\sum_{i=1}^{n}(A_i - \overline{A})^2}{n}} \qquad where \qquad \overline{A} = \frac{\sum_{i=1}^{n} A_i}{n}, \\ &= \frac{2}{U_S - L_S}\sqrt{\frac{\sum_{i=1}^{n}(S_i - \overline{S})^2}{n}} \qquad where \qquad \overline{S} = \frac{\sum_{i=1}^{n} S_i}{n}. \end{aligned} \tag{17}$$

In case of a directly standardized probability, the upper (U) and lower (L) limits are 1 and 0 respectively. Therefore, CV of the direct unfairness is simply twice the standard deviation. In case of an indirectly standardized probability, I consider a difference between two probabilities predicted by original and best circumstance, which let its upper (U) and lower (L) limits be 0 and -1. Consequently, CV of the fairness gap is also quantified as twice the standard deviation.

7 Results

When the frequency of (non)occurrence of the event is too low, it is known that a conventional statistical method (e.g. logistic regression) leads to biased estimation (King and Zeng, 2001). As shown in Table 4, several countries in our data are under potential threat of such bias (e.g. LU, AT, NL, CH, SI, SE and DK). Although some advanced methods have been developed to solve this issue (i.e. penalized likelihood, exact logistic regression, etc.), they are limited to univariate models. For this reason, I present the results obtained from a pooled sample of fourteen countries (N=57,140). In the case of countries that are unlikely to suffer the rare event bias, additional results obtained from an individual analysis are discussed in Section 8.

This section is divided into two parts. Subsection 7.1 identifies which subgroups of the elderly population are deprived of the opportunity to enjoy barrier-free access to medical services. Subsection 7.2 illustrates how far each country is from providing these groups with an equitable access.

Table 4: Number of observations with unmet medical need by country

	EE	IT	DE	FR	BE	CZ	ES	LU	AT	CH	NL	SI	SE	DK
Unmet (%)	14.604	10.97	4.223	4.127	3.169	3.138	3.086	2.881	1.564	1.14	1.117	1.049	0.769	0.466
Unmet (N)	707	491	215	169	159	162	186	42	61	32	41	27	32	18
N	4,841	4,476	5,091	4,095	5,018	5,162	6,028	1,458	3,901	2,807	3,670	2,573	4,161	3,859

Note: Statistics are slightly different from that in Section 2 observed before data cleaning.

7.1 Marginal effect

The estimation result is presented in terms of the marginal effect at means with respect to three models of medical access, health, and insurance status, which are binary. In addition, coefficients obtained from a linear regression are presented regarding income. Marginal effect or correlation coefficients of country dummies and constant terms are omitted in all tables.

According to the control approach (Table 5), we find that males and older cohorts tend to enjoy better access to medical service. This positive role of age is surprising because the demand for services increases with aging. A demographic disparity in medical access is plotted over all age groups in Appendix F. We find that the age and male premiums in terms of enjoying better access gradually shrink with age.

The results suggest that higher paternal education is correlated with easier access to medical services. For instance, if a father attained at least a secondary level of education, the probability of his descendants to have (financial) barrier-free access increases by 0.010 percentage points. Better initial health represented by a height decile within cohort and gender is significantly correlated with better accessibility. In addition, with one additional year of schooling, the same probability rises by 0.002.

The results from three auxiliary models show strong correlations between each intermediate outcome and circumstance-related variables. As expected, in general, the higher parental education is correlated with their descendants' higher income, better health and more active use of supplementary insurance. In addition, we find that a respondent's own height and years of schooling are also positively correlated with income, health and insurance status. Lastly, Table 6 shows that error terms in auxiliary models are positively correlated with that of the main equation, which demonstrates an indirect positive link between M and medical access through unobserved factors.

Table 5: Estimation results based on control approach

	Access		*Log income*		*Health*		*Insurance*	
	Margin	SE	Coefficient	SE	Margin	SE	Margin	SE
Age	0.001**	(0.000)	0.000	(0.000)	-0.008**	(0.000)	-0.002**	(0.000)
Female	-0.015**	(0.002)	-0.003	(0.005)	-0.020**	(0.004)	0.001	(0.003)
Mother's edu= Primary	0.012**	(0.003)	0.053**	(0.010)	0.025**	(0.007)	0.053**	(0.005)
= Secondary	0.006	(0.004)	0.119**	(0.012)	0.043**	(0.008)	0.061**	(0.006)
Father's edu= Primary	0.008+	(0.003)	0.086**	(0.010)	0.028**	(0.007)	0.011+	(0.006)
= Secondary	0.010*	(0.004)	0.154**	(0.011)	0.067**	(0.008)	0.038**	(0.006)
Height decile	0.001**	(0.000)	0.012**	(0.001)	0.006**	(0.001)	0.004**	(0.001)
Years of schooling	0.002**	(0.000)	0.027**	(0.001)	0.013**	(0.001)	0.006**	(0.000)

Note: A reference category of parental education is "less than primary education".
$+p < 0.05$ $*p < 0.01$ $**p < 0.001$

Table 6: Correlation coefficients of pairs of error terms based on control approach

	Coefficient	SE
Access—Income	0.139**	(0.010)
Access—Health	0.270**	(0.014)
Access—Insurance	0.122**	(0.018)
Income—Health	0.113**	(0.006)
Income—Insurance	0.124**	(0.007)
Health—Insurance	0.088**	(0.009)

$+p < 0.05$ $*p < 0.01$ $**p < 0.001$

Parallel results from the model based on the preference approach are presented in Table 7. In this model, intermediate outcomes are also included in the main equation. The marginal effect of explanatory variables in the second column depicts their direct contribution to medical access, while pairwise correlations between error terms of the equations in Table 8 indicate indirect relevance. Compared to the results from the control approach, we observe that the statistical significance of marginal effect of most circumstance-related variables largely diminishes. It implies that intermediate outcomes substantially mediate a direct link between C and medical access.

Table 7: Estimation results based on preference approach

	Access		*Log income*		*Health*		*Insurance*	
Dependent variable:	Margin	SE	Coefficient	SE	Margin	SE	Margin	SE
Age	0.002**	(0.000)	0.000	(0.000)	-0.008**	(0.000)	-0.002**	(0.000)
Female	-0.014**	(0.002)	-0.001	(0.005)	-0.019**	(0.004)	0.002	(0.003)
Mother's edu= Primary	0.011+	(0.004)	0.051**	(0.010)	0.022*	(0.007)	0.052**	(0.005)
= Secondary	0.004	(0.007)	0.115**	(0.012)	0.038**	(0.008)	0.059**	(0.006)
Father's edu= Primary	0.006	(0.005)	0.086**	(0.010)	0.026**	(0.007)	0.010	(0.006)
= Secondary	0.008	(0.008)	0.152**	(0.011)	0.064**	(0.008)	0.036**	(0.006)
Height decile	0.001	(0.001)	0.012**	(0.001)	0.005**	(0.001)	0.003**	(0.001)
Years of schooling	0.002	(0.001)	0.026**	(0.001)	0.012**	(0.001)	0.006**	(0.000)
Log income	-0.000	(0.043)						
Health	0.031*	(0.010)						
Insurance	0.005	(0.008)						
Volunteer activity			0.036**	(0.007)	0.083**	(0.005)	0.034**	(0.004)
Political activity			0.059**	(0.011)	0.029**	(0.008)	0.023**	(0.006)
Vegetable intake			-0.004	(0.006)	0.026**	(0.004)	-0.006	(0.003)

Note: A reference category of parental education is "less than primary education".
$+p < 0.05$ $*p < 0.01$ $**p < 0.001$

Among intermediate outcomes, income and insurance statuses are neither directly nor indirectly correlated with medical access. Only health is significantly and directly correlated, with a 0.031 higher probability of having full access. The results from auxiliary models imply that individual authentic taste is not ignorable in the formation of M. For instance, people who participate in volunteer and political activities tend to be wealthy and healthy. They are also more likely to hold supplementary insurance. Vegetable consumption is significantly correlated with better health status only. To emphasize, these factors are assumed to affect medical access only through intermediate outcomes, which embodies individual responsibility.

Table 8: Correlation coefficients of pairs of error terms based on preference approach

	Coefficient	SE
Access—Income	0.127	(0.369)
Access—Health	0.037	(0.068)
Access—Insurance	0.082	(0.064)
Income—Health	0.111**	(0.006)
Income—Insurance	0.123**	(0.007)
Health—Insurance	0.082**	(0.009)

$+p < 0.05$ $*p < 0.01$ $**p < 0.001$

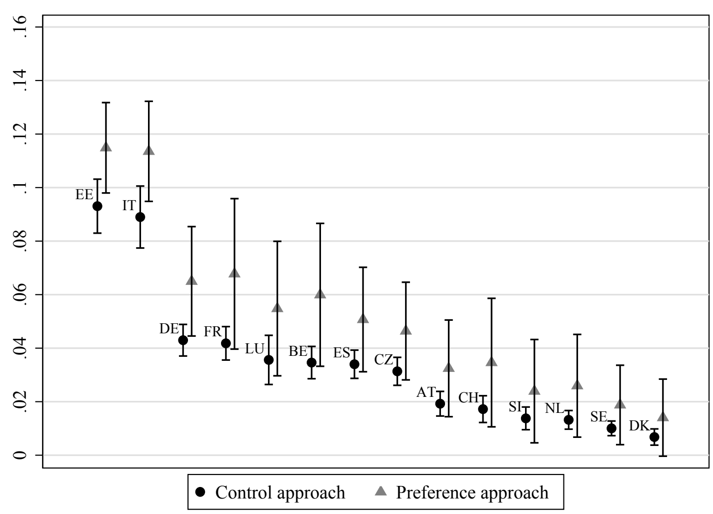
7.2 Inequality of opportunity

Based on estimated results, the magnitude of inequity in medical access is quantified using CV. For easier comparison, all results are graphically presented in this section. 95% confidence intervals are computed based on bootstrapped standard errors with 100 replications. The computed IOps can be found in Appendix G.

First of all, in Figure 3, results from the control and preference models (in terms of the direct unfairness) are presented simultaneously. Under the control approach, EE and IT are outliers showing the highest level of inequity, which is close to 0.1. IOps in other countries are lower than 0.05. Other countries where forgone care is rare show a minimal level of IOp, which is lowest in DK. Additionally, a one-sided test is conducted to check if IOp of one country is significantly higher than that of another (See Appendix H). To summarize, 14 countries are ranked as follow according to their magnitude of IOp, where > means that IOp is significantly higher in countries that are positioned on the left-hand side.

$$EE, IT > DE, FR, LU, BE, ES, CZ > AT, CH, SI, NL, SE > DK$$

Figure 3: IOp in medical access based on various normative positions (direct unfairness)



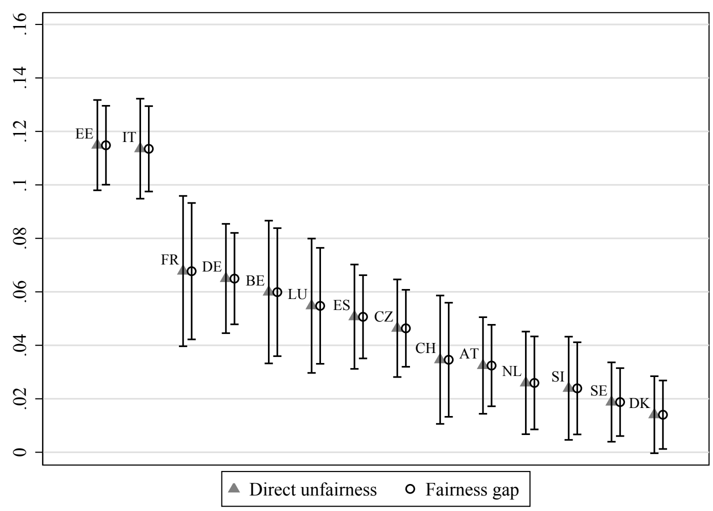
Note: 95% confidence intervals are displayed.

Once authentic preference is introduced as individual responsibility, the magnitude of IOp is higher in most countries. At 5% significance level, the difference is significantly different from zero in EE, IT and DE (Appendix G). Wider confidence intervals imply that greater uncertainty is generated while taking predicted values of intermediate outcomes into account. In the preference model, relative ranks also shift between certain countries (See Appendix I). For instance, higher IOp in DE (or FR) in comparison to BE is no longer significant, whilst that in CH is so with respect to SI. In addition, we do not have enough evidence to distinguish DK as a more equitable country than SE.

$$EE, IT > FR, DE, BE, LU, ES, CZ > CH, AT, NL, SI, SE, DK$$

Figure 4 visualizes the degree of IOp under the preference view in terms of the direct unfairness (DU) and the fairness gap (FG). As the results from the previous subsection suggest, π^* is set to participating in volunteer and political activities, and consuming vegetables regularly. Likewise, C^* is set to being oldest, male, most highly educated, and having parents with secondary education and best initial health. A distance between DU and FG implies interaction between C and E. For instance, higher FG indicates positive interaction between the two. In many countries, both measures closely coincide with each other. This means that a theoretical tension between reward and compensation principles is not a critical issue in this empirical assessment.

Figure 4: IOp under the preference view measured through various standardizations



Note: 95% confidence intervals are displayed.

How do we interpret a difference in IOp between two countries j and k in Figure 3-4? By applying Oaxaca-type decomposition (Contreras et al., 2012; Juárez and Soloaga, 2014), the gap in I can be decomposed into two parts, namely 'composition (or endowment)' and 'association (or price)' effects as follows.

$$I_j - I_k = I(X_j^{'}\beta_j) - I(X_k^{'}\beta_k) = \underbrace{I(X_j^{'}\beta_j) - I(X_j^{'}\beta_k)}_{association} + \underbrace{I(X_j^{'}\beta_k) - I(X_k^{'}\beta_k)}_{composition} = \Delta_\beta + \Delta_X \quad (18)$$

When a pooled sample is used on each control and preference model, βs are identical for all countries. Therefore, the gap is primarily attributed to the composition effect. For instance, we can interpret the largest gap in IOp between EE and DK to be due to a more disperse distribution of (standardized) endowments in EE.

8 Discussion

8.1 Country specific model

Additional analysis is conducted by using separate samples of seven countries (EE, IT, DE, FR, BE, CZ, and ES) to take into account country-specific heterogeneous relationships between C and medical access. Marginal effects of all predictors in the main equation are reported in Appendices J-K. Although the overall direction of marginal effect is mostly consistent with what is found from a pooled sample, there are some cross-country variations. First, regarding demographic factors, there is no significant age premium in ES and BE when the preference approach is applied. A gender gap is statistically insignificant in EE regardless of normative judgment. Second, initial health status proxied by relative height is significantly correlated with medical access only in EE under the control approach. Third, the role of childhood SES is obscure in general, yet higher education of the mother is still correlated with better accessibility in IT and ES. A joint significance test suggests that medical access is not independent of paternal SES in DE ($p = 0.010$), ES ($p = 0.026$), CZ ($p = 0.001$) or BE ($p = 0.023$) under the control approach. Nevertheless, the significance fades away under the preference approach, implying that paternal education is mediated by intermediate outcomes, M. The same interpretation is applicable to a respondent's own educational attainment. Lastly, we observe a strong positive correlation between supplementary insurance and medical access via unobserved factors only in DE, FR and BE under the control approach. This finding is plausible considering eligibility (i.e. high income earners in DE) and major benefits (i.e. extra reimbursement in FR and BE) with regard to VHI in these countries, which is explained in Section 2.

Some findings substantially deviate from the previous ones. Under the control view, for example, father's secondary education is correlated with a 0.023 lower probability of having barrier-free access in BE. However, its statistical significance is weakened once the mediating factors, M, are introduced into the preference model. In addition, it is shown that a 10% increase in per capita income is correlated with a 0.0368 lower accessibility to medical services in CZ under the preference view. Nonetheless, income is still positively correlated with medical access through a common unobserved factor in CZ.

Table 9 compares Is computed from combined and separate samples with respect to seven countries. For each country, switching from pooled to individual estimation does not affect the distribution of explanatory factors but alters βs. Therefore, following Oaxaca-style decomposition (eq.18), the gap in IOp between two estimations, $\Delta\ (b) - (a)$, can be interpreted as the association effect.

Under the control approach, we observe that IOps in IT and BE significantly increase when country-specific heterogeneous effects are accounted. Likewise, IOp in IT and CZ under the preference approach also increases when samples are separated by each country, which is even statistically significant in terms of FG. This means that the association between (standardized) C and medical access is stronger in these countries than the average of fourteen European countries.

Table 9: IOp from pooled and country-specific samples

		EE	IT	DE	FR	BE	ES	CZ
Control approach	(a) Pool	0.093**	0.089**	0.043**	0.042**	0.035**	0.034**	0.031**
		(0.005)	(0.006)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
	(b) Individual	0.097**	0.140**	0.044**	0.047**	0.046**	0.029**	0.041**
		(0.009)	(0.009)	(0.006)	(0.008)	(0.007)	(0.005)	(0.007)
	$\Delta\ (b) - (a)$	0.004	0.051**	0.001	0.005	0.012+	-0.005	0.009
		(0.008)	(0.008)	(0.006)	(0.007)	(0.006)	(0.005)	(0.006)
Preference approach (DU)	(a) Pool	0.115**	0.114**	0.065**	0.068**	0.060**	0.051**	0.046**
		(0.009)	(0.010)	(0.010)	(0.014)	(0.014)	(0.010)	(0.009)
	(b) Individual	0.113**	0.191**	0.050+	0.049	0.111+	0.074+	0.089**
		(0.025)	(0.043)	(0.020)	(0.035)	(0.051)	(0.030)	(0.023)
	$\Delta\ (b) - (a)$	-0.002	0.078	-0.015	-0.018	0.051	0.023	0.043
		(0.024)	(0.042)	(0.022)	(0.035)	(0.050)	(0.029)	(0.022)
Preference approach (FG)	(a) Pool	0.115**	0.113**	0.065**	0.068**	0.060**	0.051**	0.046**
		(0.008)	(0.008)	(0.009)	(0.013)	(0.012)	(0.008)	(0.007)
	(b) Individual	0.122**	0.194**	0.049*	0.056	0.110+	0.065*	0.079**
		(0.020)	(0.040)	(0.018)	(0.034)	(0.050)	(0.021)	(0.017)
	$\Delta\ (b) - (a)$	0.007	0.080+	-0.016	-0.012	0.05	0.015	0.033+
		(0.020)	(0.039)	(0.019)	(0.034)	(0.049)	(0.021)	(0.017)

Note: Bootstrapped standard errors are in parentheses. $+p < 0.05$ $*p < 0.01$ $**p < 0.001$

8.2 Policy simulation

Counter-factual IOps are computed by manipulating the distribution of educational attainment. Literature has addressed the important role of education in mitigating inequality/inequity in health and health care (i.e. Jones et al., 2014). The gap between the baseline and counter-factual IOps explains to what extent inequity could have been reduced if people had attained education differently.

It is important to note that this exercise does not reveal any causal effect. However, it is still useful to explore a possible distributional effect of education. I consider a scenario where everyone has received at least the country-specific average years of schooling. It is a somewhat plausible situation that could have been reached by an earlier introduction of compulsory education. García-Gómez et al. (2015) also consider a similar scenario to simulate IOp in mortality.

The link between education and medical access is complex. By adapting Jones et al. (2014)'s strategy, separate simulations are conducted with respect to each channel. First, under the control approach, a counter-factual IOp, I^C, is computed with respect to an observed channel, (a) in Figure 2, after compensating those who complete less schooling than the national average, $\bar{edu}$, with additional education. All estimated parameters are kept constant. In this exercise, the gap between I^B and I^C specified in eq. (19) reveals an (unconditional) distributional effect of education. C^{edu} refers to all factors in C except for edu.

$$\Delta IOp = I^B \left[Pr(access = 1|C)\right] - I^C \left[Pr(access = 1|C^{edu}, \bar{edu} \leq edu)\right] \tag{19}$$

Next, to take into account an unobserved path, (b) in Figure 2, $I^B$and I^C are computed in terms of conditional probabilities with respect to each of the factors in M or m_j ($j = inc, health, pi$). I^B is computed while assuming m_j to be ranged between the minimum, $\hat{a}_j$, and maximum values, $\hat{b}_j$, as predicted in the auxiliary equations in (11). Its I^C is computed with updated minimum, $\tilde{a}_j$, and maximum values, $\tilde{b}_j$, after holding $\bar{edu} \leq edu$. The difference between I^B and I^C is specified in eq. (20). It indicates a conditional distributional effect of education with respect to m_j. If correlations between residuals of $access$ and m_j are almost absent, meaning that two corresponding events are independent of each other, conditional $I^B$and I^C will coincide with unconditional ones. Note that residuals are composed of unobserved C as well as (unobserved) E. The latter exercise therefore necessitates a strong assumption that any differences in medical access due to unobserved factors are illegitimate.

$$\begin{aligned} \Delta IOp \quad &= \quad I^B \left[Pr(access = 1|C, \hat{a}_j \leq \hat{m_j} \leq \hat{b}_j)\right] - \\ &\quad\quad I^C \left[Pr(access = 1|C^{edu}, \bar{edu} \leq edu, \tilde{a}_j \leq \tilde{m_j} \leq \tilde{b}_j)\right] \end{aligned} \tag{20}$$

Likewise, under the preference approach, the simulation regarding the two observed paths, (a) and (c) in Figure 2, is considered first[14]. The unconditional distributional effect of education is quantified as eq. (21).

[14] π^*refers to reference authentic tastes which are used in direct standardization ($vol = 1$, $pol = 1$, and $vege = 1$)

$$
\begin{aligned}
\Delta IOp &= I^B\left[Pr(access = 1|C, \hat{M}(C, \pi^*))\right] - \\
&\quad I^C\left[Pr(access = 1|C^{edu}, e\bar{d}u \leq edu, \pi^*, \tilde{M}(C^{edu}, e\bar{d}u \leq edu, \pi^*))\right]
\end{aligned} \tag{21}
$$

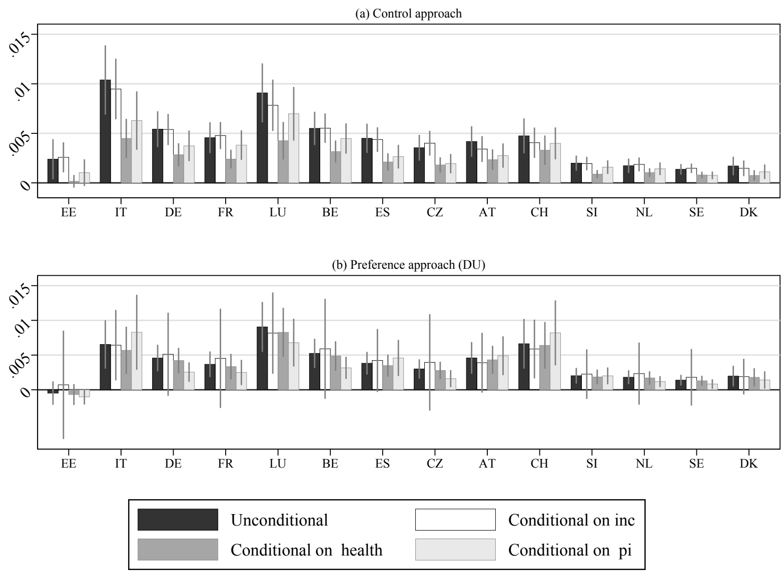
In addition, a simulation conditioning on each m_j involved in an unobserved path, (b) in Figure 2, is conducted as follows.

$$
\begin{aligned}
\Delta IOp &= I^B\left[Pr(access = 1|C, \hat{M}(C, \pi^*), \hat{a}_j \leq \hat{m_j} \leq \hat{b}_j)\right] - \\
&\quad I^C\left[Pr(access = 1|C^{edu}, e\bar{d}u \leq edu, \tilde{M}(C^{edu}, e\bar{d}u \leq edu, \pi^*), \tilde{a}_j \leq \tilde{m_j} \leq \tilde{b}_j)\right]
\end{aligned} \tag{22}
$$

For interpretation, results are presented in terms of ΔIOp in Figure 5. In all cases, I^Cs are smaller than I^Bs as expected, which suggests that educational promotion may help reduce inequity in most countries. The magnitude of each I^B and I^C is presented in Appendices L-M. Under the control approach, the largest change is found in IT and LU. On the other hand, SI, NL, SE and DK, the most equitable countries, are modestly affected. When a residual path is also considered, the largest drop is found with respect to income, while the smallest decrease is observed when direct and health-related residual paths are considered simultaneously.

Compared to the control approach, ΔIOp is smaller under the preference approach when just observed paths are considered in eight countries (EE, IT, DE, FR, LU, BE, ES and CZ) which show a visible magnitude of IOp in Section 7. This can be due to the fact that direct contribution of education to medical access is already mediated by preference variables. A cumulative change through a residual path related to health is higher in all countries except for EE. In EE, none of ΔIOp values are significantly different from zero, which suggests that education plays different roles in the two least equitable countries, EE and IT.

Figure 5: Drop in IOp under the simulated educational policy



Note: 95% Confidence intervals are presented at the top of each bar.

9 Conclusion

I investigate inequality of opportunity for having barrier-freer access to medical services among the European elderly population. Medical access is measured by self-reported unmet (or fully met) medical need due to cost, which is surveyed in SHARE in 2013. In contrast to earlier studies that mostly focus on socioeconomic inequality in the utilization of medical services, this study attempts to explicitly show ethically unjustifiable disparities in medical access, which calls for government intervention. Moreover, it delves into the issue of inequity in terms of financial constraints that exist prior to the attempt to access to medical services, which has a direct policy relevance but has been less rigorously investigated.

In addition to socioeconomic status and medical need, I incorporate more detailed individual characteristics (e.g. parental backgrounds) into the model. Since measuring IOp or inequity involves ethical considerations regarding unfairness, all covariates are disentangled into either illegitimate (circumstance) or legitimate (effort) factors. The distinction between these two may vary based on individual normative positions of researchers. I consider two competing philosophical views on the scope of individual responsibility, namely control and preference approaches. The former defines responsibility as what falls under individual control. The latter supposes that individuals are responsible for their choices according to their authentic preference. Separate models are applied with respect to each of the viewpoints.

In the model based on the control view, it is shown that males, older cohorts and descendants of high educated parents tend to enjoy better access to medical services. Better initial health and more educational attainment are also positively correlated with medical access. However, in the model based on the preference view, we find that a direct contribution of such factors to access is largely mediated by current income, health and insurance status. In both approaches, the highest inequity is found in EE and IT, and only minimal inequity is found in DK, SE, SI, NL and CH. In terms of bilateral comparison of IOp, different results are obtained depending on normative assumption. For instance, DE and FR show higher IOps relative to BE under the control approach only, whilst CH does so compared to SI under the preference approach. Moreover, shifting from the control to the preference approach, EE, IT and DE show greater inequity.

In addition, counter-factual IOps are computed by assuming a hypothetical situation which could have been achieved through an earlier introduction of compulsory education. That is, those who have attained lower education than the national average are compensated with additional schooling. Our simulation exercise suggests that the partial equalization of educational attainment may help reduce inequity in most countries. Overall, changes in IOp are somehow smaller under the preference approach. The improvement of equity is most pronounced in ES as well as IT. On the other hand, almost no change is found in EE, the least equitable country.

There are a few limitations to this study. Due to the unavailability of data, first of all, it only deals with financial constraints to medical access, although there are other important policy concerns such as the issues of waiting time and physical accessibility. With more reliable data, future researchers can extend this analysis to those topics to obtain more comprehensive policy recommendations. More critically, this study is limited in having to take detailed country-specific institutional settings into account, while trying to grasp an overall picture of the situation of 14 countries at once. Therefore, further investigation is needed to compare the situation of different periods or regions within each country, which would enable the evaluation of specific policy or program.

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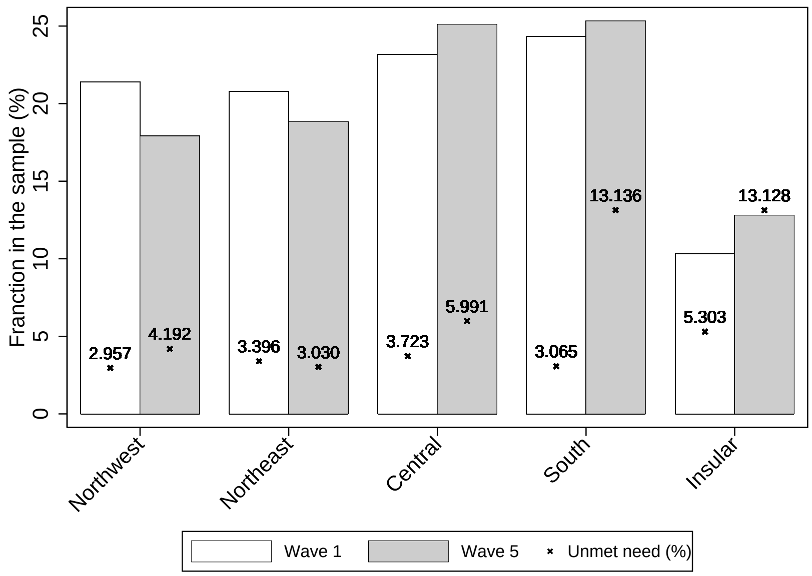
Appendix

A Regional disparity in unmet medical need due to cost in Italy



Note: NUTS 1 (Nomenclature of Territorial Units for Statistics) is used for regional classification. It is asked only once during the first survey that respondents joined.

B Questions on unmet medical need in SHARE and EU-SILC

Survey	Item	Questions
SHARE (2014)	Unmet need due to service affordability	During the last twelve months, did you forgo any types of care because of the costs you would have to pay?
	Unmet need due to service availability	During the last twelve months, did you forgo any types of care because they were not available or not easily accessible?
SHARE (2004)	Unmet need due to service affordability	During the last twelve months, did you forgo any types of care because of the costs you would have to pay?
	Unmet need due to service availability & accessibility	During the last twelve months, did you forgo any types of care because they were not available or not easily accessible?
	Type of service that did not meet need†	• Surgery* • Care from a general practitioner* • Care from a specialist physician • Drugs* • Dental care • Hospital (inpatient) rehabilitation* • Ambulatory (outpatient) rehabilitation* • Aids and appliances • Care in a nursing home* • Home care • Paid home help • Any other care not mentioned on this list
EU-SILC (2013)	Overall unmet need	Was there any time during the last twelve months when, in your opinion, you personally needed a medical examination or treatment for a health problem but you did not receive it?
	Reason for unmet need‡	• Could not afford to (too expensive) • Waiting list • Could not take time because of work, care for children or for others • Too far to travel/no means of transportation • Fear of doctor/hospitals/examination/ treatment • Wanted to wait and see if problem got better on its own • Didn't know any good doctor or specialist • Other reasons

Note: † Multiple choice is allowed. Services marked with * are relevant for comparison.
‡ Multiple choice is not allowed.

C Unmet medical need due to waiting time

	Unmet need (%)		Self-reported waiting time (SHARE, 2004)			
	SHARE (2013)	SILC (2013, over age 45)	Emergency consultation (day)	Non-emer. consult. (week)	Inpatient surgery (month)	Outpatient surgery (month)
EE	19.194	17.1	.	.	.	.
IT	17.204	2.9	6.406	2.794	2.650	3.088
FR	6.355	0.8	10.833	3.224	2.257	1.338
DE	4.697	1.6	0.895	1.826	1.529	0.625
CZ	4.599	0.6	.	.	.	.
BE	4.507	0.1	5.079	1.742	1.271	0.718
SE	4.380	2.0	8.829	9.081	6.851	4.291
LU	4.234	0.3	.	.	.	.
SI	3.842	0.0	.	.	.	.
ES	3.690	0.3	9.714	5.386	5.841	3.576
AT	2.974	0.1	4.109	1.846	1.969	0.554
DK	2.960	1.8	11.958	5.802	2.227	2.636
NL	0.803	0.5	7.516	3.621	2.673	1.773
CH	0.800	0.1	1.714	1.357	1.444	0.773
N	62,676		1,060	2,239	1,214	1,389

- Note: Figures in EU-SILC are retrieved from Eurostat.

Our measure shows that waiting time causes substantial unmet need among the elderly in EE (19%) and IT (17%). Less than 10% of the elderly are constrained by waiting time in most countries. EE or IT are also highly ranked according to EU-SILC from 2013. I drop a similar variable contained in SHARE 2004, because it measures forgone care due to unavailability in the context of excessive waiting time as well as difficult physical access. Instead, I consider self-reported waiting time for various medical services surveyed in SHARE 2004 (Column 4-6). Waiting time is reported by a small fraction of the total sample (N=31,008) who received emergency consultation (N=1,325), non-emergency consultation (N= 2,911), inpatient surgery (N=1,392) and outpatient surgery (N=1,587). This information is missing in other waves. We see that the average duration of waiting time in ES and SE is similar or longer than that for IT or FR. This suggests that the situation of ES and SE might be underestimated by our indicators, if having maintained status-quo since 2004.

D Objective data on actual waiting time

	Patients who waited longer than 3 months(%) after being accessed			after being listed		
	Cataract	Hip	Knee	Cataract	Hip	Knee
EE	52.7	52.7	74.9	90.4	90.4	91.7
SE	n.a	n.a	n.a	9.5	8.6	9
ES	56.1	69.1	77.4	34.8	50.6	53.9
DK	31.7	14.3	16.2	n.a	n.a	n.a

Source: OECD (2014)

The administrative records on waiting time for elective surgeries is available in a few countries where waiting time is a public agenda that is monitored by the government. Each country calculates waiting time based on different starting points. This limited comparison consistently suggests that our data may misrepresent the situation in ES. After initial assessment, the majority of patients wait longer than 3 months both in EE and ES. Nevertheless, we should note that objective statistics cover only those who underwent an elective surgery for all ages, while our data includes both healthy and unhealthy people over the age of 50.

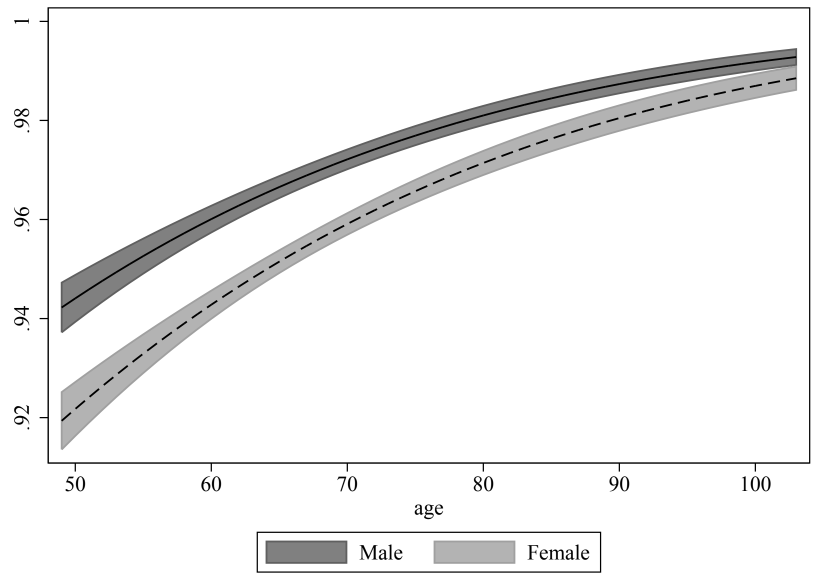
E Summary statistics by country

	AT		DE		SE		NL		ES		IT		FR	
	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
Age	66.710	9.527	64.313	9.936	68.024	9.178	65.478	9.413	67.646	10.712	66.566	9.746	67.033	10.241
Female	0.572	0.495	0.521	0.500	0.533	0.499	0.546	0.498	0.535	0.499	0.542	0.498	0.568	0.495
Mother's edu=None	0.034	0.180	0.029	0.169	0.302	0.459	0.087	0.282	0.775	0.418	0.389	0.488	0.317	0.465
=Primary	0.678	0.467	0.554	0.497	0.578	0.494	0.814	0.389	0.199	0.400	0.565	0.496	0.548	0.498
=Secondary	0.288	0.453	0.417	0.493	0.120	0.325	0.099	0.299	0.026	0.159	0.046	0.210	0.135	0.342
Father's edu=None	0.019	0.136	0.017	0.131	0.304	0.460	0.075	0.263	0.721	0.448	0.352	0.478	0.298	0.457
=Primary	0.382	0.486	0.197	0.398	0.490	0.500	0.719	0.450	0.229	0.420	0.592	0.492	0.502	0.500
=Secondary	0.599	0.490	0.786	0.411	0.206	0.405	0.207	0.405	0.050	0.218	0.057	0.231	0.200	0.400
Height decile	5.211	2.876	5.265	2.927	5.276	2.876	5.307	2.869	5.199	2.898	5.124	2.888	5.258	2.879
Years of schooling	9.273	4.411	12.714	3.600	11.643	3.856	11.860	3.639	9.416	4.627	8.845	4.438	11.592	3.565
Log income	9.934	0.708	10.001	0.698	10.072	0.467	10.019	0.546	9.465	0.705	9.491	0.798	9.916	0.729
Health	0.682	0.466	0.603	0.489	0.763	0.425	0.726	0.446	0.585	0.493	0.573	0.495	0.640	0.480
Supplementary insurance	0.230	0.421	0.269	0.444	0.176	0.381	0.830	0.376	0.104	0.305	0.054	0.226	0.955	0.208
Volunteer	0.195	0.396	0.231	0.421	0.142	0.349	0.402	0.490	0.051	0.220	0.130	0.336	0.253	0.435
Political activity	0.074	0.262	0.056	0.230	0.115	0.319	0.090	0.286	0.021	0.142	0.033	0.179	0.087	0.281
Vegetable intake	0.605	0.489	0.628	0.483	0.752	0.432	0.821	0.384	0.871	0.335	0.618	0.486	0.690	0.463
N	3,900		5,088		4,160		3,669		6,027		4,476		4,095	

Summary statistics are continued here.

	DK		CH		BE		CZ		LU		SI		EE	
	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
Age	64.689	9.858	65.979	9.490	65.267	10.299	66.330	8.949	63.995	9.427	66.323	9.999	67.904	9.736
Female	0.535	0.499	0.540	0.498	0.543	0.498	0.582	0.493	0.525	0.500	0.569	0.495	0.607	0.488
Mother's edu=None	0.017	0.129	0.276	0.447	0.210	0.408	0.039	0.193	0.167	0.373	0.372	0.483	0.066	0.248
=Primary	0.721	0.449	0.420	0.494	0.595	0.491	0.563	0.496	0.689	0.463	0.473	0.499	0.675	0.468
=Secondary	0.262	0.440	0.303	0.460	0.194	0.396	0.398	0.490	0.144	0.351	0.155	0.362	0.259	0.438
Father's edu=None	0.009	0.093	0.167	0.373	0.188	0.391	0.041	0.198	0.156	0.363	0.295	0.456	0.049	0.215
=Primary	0.431	0.495	0.247	0.431	0.534	0.499	0.298	0.457	0.524	0.500	0.337	0.473	0.652	0.477
=Secondary	0.560	0.496	0.586	0.493	0.278	0.448	0.661	0.473	0.320	0.466	0.368	0.482	0.300	0.458
Height decile	5.282	2.877	5.255	2.868	5.260	2.857	5.236	2.860	5.272	2.817	5.195	2.881	5.266	2.857
Years of schooling	11.662	4.735	8.758	5.214	12.488	3.717	12.171	3.067	11.706	4.280	10.600	3.341	11.704	3.515
Log income	10.032	0.496	10.506	0.704	10.061	0.697	9.215	0.561	10.799	0.794	9.343	0.688	9.088	0.632
Health	0.788	0.409	0.839	0.367	0.735	0.441	0.556	0.497	0.676	0.468	0.622	0.485	0.290	0.454
Supplementary insurance	0.471	0.499	0.753	0.431	0.822	0.383	0.041	0.198	0.739	0.439	0.796	0.403	0.019	0.138
Volunteer	0.293	0.455	0.295	0.456	0.253	0.435	0.076	0.265	0.239	0.426	0.136	0.343	0.064	0.245
Political activity	0.091	0.287	0.090	0.286	0.102	0.303	0.045	0.207	0.093	0.290	0.031	0.174	0.033	0.178
Vegetable intake	0.776	0.417	0.598	0.490	0.571	0.495	0.397	0.489	0.617	0.486	0.600	0.490	0.696	0.460
N	3,854		2,804		5,013		5,162		1,456		2,570		4,841	

F Predicted probability of having barrier-free access to medical services by age and gender



Note: The shaded area represents 95% confidence interval.

G Magnitude of inequity in medical access

	EE	IT	DE	FR	LU	BE	ES	CZ	AT	CH	SI	NL	SE	DK
(a) Control approach	0.093**	0.089**	0.043**	0.042**	0.036**	0.035**	0.034**	0.031**	0.019**	0.017**	0.014**	0.013**	0.010**	0.007**
	(0.005)	(0.006)	(0.003)	(0.003)	(0.005)	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)	(0.002)	(0.002)	(0.001)	(0.002)
(b) Preference approach (DU)	0.115**	0.114**	0.065**	0.068**	0.055**	0.060**	0.051**	0.046**	0.032**	0.035*	0.024+	0.026*	0.019+	0.014
	(0.009)	(0.010)	(0.010)	(0.014)	(0.013)	(0.014)	(0.010)	(0.009)	(0.009)	(0.012)	(0.010)	(0.010)	(0.008)	(0.007)
(c) Preference approach (FG)	0.115**	0.113**	0.065**	0.068**	0.055**	0.060**	0.051**	0.046**	0.032**	0.035*	0.024*	0.026*	0.019*	0.014+
	(0.008)	(0.008)	(0.009)	(0.013)	(0.011)	(0.012)	(0.008)	(0.007)	(0.008)	(0.011)	(0.009)	(0.009)	(0.006)	(0.007)
P-values from Wald test														
$H_0: (a) = (b)$	**0.001**	**0.001**	**0.023**	0.051	0.071	0.072	0.091	0.044	0.121	0.126	0.169	0.264	0.219	0.290
$H_0: (b) = (c)$	0.992	0.992	0.993	0.993	0.993	0.993	0.993	0.993	0.994	0.994	0.994	0.994	0.994	0.995

Note: Bootstrapped standard errors are in parentheses. $+p < 0.05$ * $p < 0.01$ ** $p < 0.001$

H P-value from one-sided test ($H_0 : IOP_j \geqq IOP_k$) : control

	EE	IT	DE	FR	LU	BE	ES	CZ	AT	CH	SI	NL	SE	DK	j
EE	.	0.808	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	
IT	0.192	.	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	
DE	**0.000**	**0.000**	.	0.642	0.918	0.992	0.998	1.000	1.000	1.000	1.000	1.000	1.000	1.000	
FR	**0.000**	**0.000**	0.358	.	0.866	0.986	0.984	0.998	1.000	1.000	1.000	1.000	1.000	1.000	
LU	**0.000**	**0.000**	0.082	0.134	.	0.569	0.616	0.780	0.999	1.000	1.000	1.000	1.000	1.000	
BE	**0.000**	**0.000**	**0.008**	**0.014**	0.431	.	0.579	0.834	1.000	1.000	1.000	1.000	1.000	1.000	
ES	**0.000**	**0.000**	**0.002**	**0.016**	0.384	0.421	.	0.791	1.000	1.000	1.000	1.000	1.000	1.000	
CZ	**0.000**	**0.000**	**0.000**	**0.002**	0.220	0.166	0.209	.	1.000	1.000	1.000	1.000	1.000	1.000	
AT	**0.000**	**0.000**	**0.000**	**0.000**	**0.001**	**0.000**	**0.000**	**0.000**	.	0.711	0.970	0.988	0.999	1.000	
CH	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	0.289	.	0.849	0.918	0.993	1.000	
SI	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.030**	0.151	.	0.583	0.922	0.997	
NL	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.012**	0.082	0.417	.	0.931	0.998	
SE	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.001**	**0.007**	0.078	0.069	.	0.952	
DK	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.003**	**0.002**	**0.048**	.	
k															

Note: Countries in columns are ordered by the magnitude of IOp in Figure 3.

I P-value from one-sided test ($H_0 : IOP_j \geqq IOP_k$) : preference (DU)

	EE	IT	FR	DE	BE	LU	ES	CZ	CH	AT	NL	SI	SE	DK	j
EE	.	0.603	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	
IT	0.397	.	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	
FR	**0.000**	**0.000**	.	0.640	0.945	0.914	0.960	0.983	1.000	1.000	1.000	1.000	1.000	1.000	
DE	**0.000**	**0.000**	0.360	.	0.770	0.909	0.999	1.000	1.000	1.000	1.000	1.000	1.000	1.000	
BE	**0.000**	**0.000**	0.055	0.230	.	0.717	0.870	0.940	1.000	0.999	1.000	1.000	1.000	1.000	
LU	**0.000**	**0.000**	0.086	0.091	0.283	.	0.692	0.841	0.995	0.996	1.000	1.000	1.000	1.000	
ES	**0.000**	**0.000**	**0.040**	**0.001**	0.130	0.308	.	0.839	0.996	1.000	1.000	1.000	1.000	1.000	
CZ	**0.000**	**0.000**	**0.017**	**0.000**	0.060	0.159	0.161	.	0.959	0.999	1.000	1.000	1.000	1.000	
CH	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.005**	**0.004**	**0.041**	.	0.618	0.933	0.952	0.987	0.996	
AT	**0.000**	**0.000**	**0.000**	**0.000**	**0.001**	**0.004**	**0.000**	**0.001**	0.382	.	0.889	0.954	0.998	1.000	
NL	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	0.067	0.111	.	0.665	0.916	0.979	
SI	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.048**	**0.046**	0.335	.	0.837	0.963	
SE	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.013**	**0.002**	0.084	0.163	.	0.886	
DK	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.004**	**0.000**	**0.021**	**0.037**	0.114	.	
k															

Note: Countries in columns are ordered by the magnitude of DU in Figure 4.

J Marginal effects estimated by country: control approach

Outcome: *Access*	EE		IT		DE		FR		BE		ES		CZ	
Age	0.004**	(0.001)	0.004**	(0.001)	0.001**	(0.000)	0.002**	(0.000)	0.002**	(0.000)	0.001**	(0.000)	0.001**	(0.000)
Female	-0.019	(0.010)	-0.045**	(0.009)	-0.019**	(0.006)	-0.031**	(0.006)	-0.013*	(0.005)	-0.010+	(0.004)	-0.013*	(0.005)
Mother's edu= Primary	0.025	(0.023)	0.050**	(0.013)	-0.002	(0.015)	0.002	(0.008)	0.018+	(0.009)	-0.002	(0.009)	0.016	(0.016)
= Secondary	0.010	(0.026)	0.027	(0.032)	-0.018	(0.016)	-0.003	(0.012)	0.020	(0.011)	0.026**	(0.006)	0.017	(0.016)
Father's edu= Primary	0.027	(0.027)	0.011	(0.013)	0.063	(0.041)	0.002	(0.008)	-0.005	(0.007)	0.011	(0.006)	0.015	(0.018)
= Secondary	0.028	(0.029)	0.036	(0.025)	0.076	(0.041)	0.002	(0.011)	-0.023+	(0.009)	-0.024	(0.020)	0.034+	(0.017)
Height decile	0.007**	(0.002)	0.002	(0.002)	0.001	(0.001)	-0.001	(0.001)	0.001	(0.001)	0.001	(0.001)	0.001	(0.001)
Years of schooling	0.009**	(0.002)	0.012**	(0.001)	0.001	(0.001)	0.004**	(0.001)	0.003**	(0.001)	0.002*	(0.001)	0.003*	(0.001)
Correlation coefficients of pairs of error terms														
Access—Income	0.170**	(0.023)	0.134**	(0.026)	0.218**	(0.035)	0.225**	(0.039)	0.094*	(0.036)	0.104**	(0.031)	0.109*	(0.036)
Access—Health	0.190**	(0.032)	0.364**	(0.035)	0.229**	(0.042)	0.241**	(0.047)	0.394**	(0.048)	0.277**	(0.043)	0.245**	(0.046)
Access—Insurance	-0.050	(0.065)	0.031	(0.059)	0.105+	(0.044)	0.252**	(0.066)	0.357**	(0.048)	0.083	(0.061)	-0.005	(0.080)
Income—Health	0.159**	(0.020)	0.095**	(0.020)	0.141**	(0.018)	0.132**	(0.021)	0.065**	(0.019)	0.100**	(0.017)	0.140**	(0.018)
Income—Insurance	0.062	(0.040)	0.174**	(0.031)	0.137**	(0.019)	0.126**	(0.034)	0.095**	(0.021)	0.211**	(0.023)	0.166**	(0.031)
Health—Insurance	0.083	(0.059)	-0.032	(0.042)	0.141**	(0.025)	0.139*	(0.045)	0.105**	(0.028)	0.099*	(0.030)	0.007	(0.042)

Note: A reference category of parental education is "less than primary education". $+p < 0.05$ $*p < 0.01$ $**p < 0.001$

K Marginal effects estimated by country: preference approach

Outcome: *Unmet need*	EE		IT		DE		FR		BE		ES		CZ	
Age	0.005**	(0.001)	0.006**	(0.001)	0.001+	(0.001)	0.001**	(0.000)	0.002	(0.015)	0.002	(0.001)	0.002+	(0.001)
Female	-0.021	(0.011)	-0.039**	(0.010)	-0.020	(0.013)	-0.031*	(0.010)	-0.013	(0.069)	-0.008	(0.006)	-0.014	(0.013)
Mother's edu= Primary	0.027	(0.024)	0.047**	(0.013)	-0.001	(0.018)	-0.001	(0.010)	0.014	(0.070)	-0.002	(0.010)	0.047	(0.028)
= Secondary	-0.004	(0.030)	0.011	(0.034)	-0.017	(0.018)	-0.005	(0.013)	0.018	(0.127)	0.033	(0.024)	0.056	(0.030)
Father's edu= Primary	0.016	(0.034)	0.003	(0.012)	0.071	(0.079)	-0.001	(0.009)	-0.005	(0.011)	0.012	(0.015)	0.028	(0.028)
= Secondary	0.010	(0.043)	0.033	(0.025)	0.086	(0.098)	-0.003	(0.014)	-0.023	(0.073)	-0.026	(0.028)	0.075*	(0.028)
Height decile	0.006+	(0.002)	0.001	(0.002)	0.001	(0.002)	-0.001	(0.001)	0.001	(0.016)	0.001	(0.001)	0.004+	(0.002)
Years of schooling	0.004	(0.006)	0.009**	(0.002)	0.001	(0.004)	0.002	(0.002)	0.003	(0.039)	0.002	(0.002)	0.014**	(0.004)
Log income	0.084	(0.172)	0.026*	(0.009)	-0.015	(0.126)	0.030	(0.066)	-0.016	(0.819)	-0.021	(0.071)	-0.368+	(0.147)
Health	0.085	(0.055)	0.112	(0.059)	0.006	(0.044)	0.001	(0.027)	0.020	(0.149)	0.048	(0.039)	0.082	(0.049)
Insurance	0.104+	(0.049)	-0.041	(0.128)	-0.002	(0.031)	0.012	(0.054)	0.039	(0.234)	0.025	(0.023)	0.011	(0.065)
Correlation coefficients of pairs of error terms														
Access—Income	-0.086	(0.466)	0.000	(0.043)	0.326	(0.829)	-0.025	(0.489)	0.246	(7.612)	0.256	(0.530)	1.413*	(0.532)
Access—Health	-0.090	(0.162)	-0.033	(0.187)	0.202	(0.258)	0.205	(0.186)	0.223	(0.299)	-0.063	(0.209)	0.024	(0.127)
Access—Insurance	-0.365	(0.227)	0.112	(0.274)	0.121	(0.191)	0.164	(0.267)	0.103	(0.397)	-0.115	(0.206)	0.024	(0.127)
Income—Health	0.153**	(0.020)	0.091**	(0.020)	0.138**	(0.018)	0.123**	(0.021)	0.063*	(0.019)	0.099**	(0.017)	0.139**	(0.018)
Income—Insurance	0.062	(0.039)	0.173**	(0.032)	0.136**	(0.019)	0.120**	(0.034)	0.093**	(0.021)	0.203**	(0.023)	0.164**	(0.031)
Health—Insurance	0.083	(0.059)	-0.032	(0.043)	0.127**	(0.025)	0.132*	(0.045)	0.103**	(0.028)	0.098*	(0.031)	0.002	(0.042)

Note: A reference category of parental education is "less than primary education". $+p < 0.05$ $*p < 0.01$ $**p < 0.001$

L Policy simulation: control approach

		EE	IT	DE	FR	LU	BE	ES
Unconditional	I^B	0.093**	0.089**	0.043**	0.042**	0.036**	0.035**	0.034**
		(0.005)	(0.006)	(0.003)	(0.003)	(0.005)	(0.003)	(0.003)
	I^C	0.091**	0.079**	0.038**	0.037**	0.027**	0.029**	0.029**
		(0.005)	(0.005)	(0.003)	(0.003)	(0.004)	(0.003)	(0.002)
Conditional on *inc*	I^B	0.090**	0.080**	0.041**	0.038**	0.031**	0.031**	0.029**
		(0.005)	(0.006)	(0.003)	(0.003)	(0.004)	(0.003)	(0.002)
	I^C	0.088**	0.071**	0.035**	0.033**	0.023**	0.026**	0.025**
		(0.005)	(0.005)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)
Conditional on *health*	I^B	0.084**	0.081**	0.040**	0.039**	0.029**	0.035**	0.030**
		(0.005)	(0.005)	(0.003)	(0.003)	(0.004)	(0.003)	(0.002)
	I^C	0.084**	0.076**	0.037**	0.037**	0.024**	0.032**	0.027**
		(0.005)	(0.005)	(0.003)	(0.003)	(0.004)	(0.003)	(0.002)
Conditional on *pi*	I^B	0.069**	0.063**	0.035**	0.047**	0.032**	0.034**	0.023**
		(0.006)	(0.006)	(0.003)	(0.004)	(0.004)	(0.003)	(0.003)
	I^C	0.068**	0.057**	0.031**	0.043**	0.025**	0.029**	0.020**
		(0.005)	(0.005)	(0.003)	(0.004)	(0.004)	(0.003)	(0.002)
		CZ	AT	CH	SI	NL	SE	DK
Unconditional	I^B	0.031**	0.019**	0.017**	0.014**	0.013**	0.010**	0.007**
		(0.003)	(0.002)	(0.003)	(0.002)	(0.002)	(0.001)	(0.002)
	I^C	0.028**	0.015**	0.012**	0.012**	0.011**	0.009**	0.005**
		(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)
Conditional on *inc*	I^B	0.030**	0.017**	0.015**	0.012**	0.012**	0.009**	0.006**
		(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)
	I^C	0.026**	0.014**	0.011**	0.010**	0.010**	0.007**	0.005**
		(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Conditional on *health*	I^B	0.028**	0.018**	0.018**	0.011**	0.013**	0.010**	0.007**
		(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.001)	(0.002)
	I^C	0.026**	0.015**	0.015**	0.010**	0.012**	0.009**	0.006**
		(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)
Conditional on *pi*	I^B	0.020**	0.014**	0.016**	0.013**	0.013**	0.007**	0.005**
		(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)
	I^C	0.018**	0.011**	0.012**	0.011**	0.012**	0.006**	0.004**
		(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)

Note: Unconditional I^B corresponds to IOp in Figure 3.

M Policy simulation: preference approach

		EE	IT	FR	DE	BE	ES	LU
Unconditional	I^B	0.115**	0.114**	0.068**	0.065**	0.060**	0.055**	0.051**
		(0.009)	(0.010)	(0.014)	(0.010)	(0.014)	(0.013)	(0.010)
	I^C	0.115**	0.107**	0.064**	0.060**	0.055**	0.046**	0.047**
		(0.009)	(0.010)	(0.015)	(0.010)	(0.014)	(0.012)	(0.010)
Conditional	I^B	0.115**	0.106**	0.064**	0.064**	0.057**	0.050**	0.046**
on *inc*		(0.012)	(0.015)	(0.014)	(0.010)	(0.013)	(0.012)	(0.010)
	I^C	0.114**	0.100**	0.060**	0.058**	0.051**	0.042**	0.042**
		(0.009)	(0.015)	(0.014)	(0.008)	(0.012)	(0.010)	(0.010)
Conditional	I^B	0.116**	0.114**	0.069**	0.066**	0.062**	0.055**	0.051**
on *health*		(0.009)	(0.010)	(0.015)	(0.011)	(0.014)	(0.013)	(0.011)
	I^C	0.116**	0.109**	0.066**	0.062**	0.057**	0.047**	0.048**
		(0.009)	(0.010)	(0.015)	(0.011)	(0.014)	(0.013)	(0.011)
Conditional	I^B	0.100**	0.097**	0.075**	0.059**	0.062**	0.053**	0.042**
on *pi*		(0.012)	(0.013)	(0.015)	(0.011)	(0.014)	(0.013)	(0.010)
	I^C	0.101**	0.089**	0.073**	0.057**	0.058**	0.046**	0.037**
		(0.012)	(0.013)	(0.015)	(0.011)	(0.014)	(0.012)	(0.010)
		CZ	CH	AT	NL	SI	SE	DK
Unconditional	I^B	0.046**	0.035*	0.032**	0.026*	0.024+	0.019+	0.014
		(0.009)	(0.012)	(0.009)	(0.010)	(0.010)	(0.008)	(0.007)
	I^C	0.043**	0.028+	0.028*	0.024+	0.022+	0.017+	0.012
		(0.009)	(0.011)	(0.009)	(0.010)	(0.010)	(0.007)	(0.007)
Conditional	I^B	0.046**	0.031*	0.030**	0.025**	0.022*	0.018**	0.013*
on *inc*		(0.009)	(0.010)	(0.006)	(0.007)	(0.007)	(0.005)	(0.005)
	I^C	0.042**	0.025*	0.026**	0.022*	0.020*	0.016**	0.011*
		(0.006)	(0.008)	(0.005)	(0.007)	(0.007)	(0.004)	(0.004)
Conditional	I^B	0.047**	0.036*	0.033**	0.027+	0.024+	0.020+	0.015
on *health*		(0.010)	(0.013)	(0.010)	(0.010)	(0.010)	(0.008)	(0.008)
	I^C	0.044**	0.030+	0.029*	0.025+	0.022+	0.018+	0.013
		(0.010)	(0.012)	(0.010)	(0.010)	(0.010)	(0.008)	(0.008)
Conditional	I^B	0.037**	0.034*	0.028*	0.027*	0.024+	0.015+	0.013
on *pi*		(0.009)	(0.012)	(0.009)	(0.010)	(0.010)	(0.007)	(0.007)
	I^C	0.035**	0.026+	0.023*	0.026+	0.022+	0.015+	0.011
		(0.009)	(0.011)	(0.008)	(0.010)	(0.010)	(0.007)	(0.007)

Note: Unconditional I^B corresponds to IOp in Figure 4.

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