Earnings Gaps for Conspicuous Characteristics: Evidence from Indonesia*

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Abstract

Recent research has begun to analyze the effects of height on earnings in Indonesia, a developing country with a large population. Little has been done on the potential effects of weight and general health status on earnings. Carefully accounting for selection into the workforce and the potential endogeneity of our health variables, we use a sample of individuals between the ages of 25 and 55 from the Indonesian Family Longitudinal Survey (IFLS) to identify this effect and conduct Oaxaca-Blinder decompositions to identify possible discrimination. We compare these results to those using less conspicuous health measures such as blood pressure, cholesterol, and chest pain. Endogeneity of our health measures is subsequently addressed using several econometric methodologies. Results suggest that overweight males in Indonesia earn an income premium, while underweight females are subject to an income penalty.

KEYWORDS: Earnings gaps, Oaxaca-Blinder decomposition, Health in a Developing Country

JEL CLASS: I1

I. INTRODUCTION

Discrimination can be prevalent in the labor market and can take different forms (statistical, overt, and so forth), particularly if it is the consumers who are discriminating. Discrimination occurs "when there are different earnings and employment opportunities across equally skilled workers employed in the same job because of workers' race, gender, national origin, sexual orientation, age, religion, 'beauty' etc" (Borjas 2012). In Becker's "taste discrimination" model, employers will act as if the cost of hiring, for example, visibly unhealthy workers (assuming here that health is uncorrelated with productivity or sick days) is (w+d), where w is wage (equal to the value of the marginal product of labor, or VMPL) and d is a discrimination coefficient. The source of the prejudice could come from the employer, employee, or customer.

Hamermesh and Biddle's (1994) research on beauty in the labor market finds a beauty premium in the labor market that is mostly independent of occupation. Averett and Korenman (1996) confirm this finding using the body mass index (BMI) as a proxy for beauty. Mocan and Tekin (2010) find that being attractive reduces a young adult's propensity to engage in criminal activities. In line with Averett and Korenman, we focus on measures of health in identifying wage premiums.

Following Averett and Korenman, there have been several studies on the effect of obesity on labor market outcomes in the United States (among others, Sabia and Rees 2012; Han et al. 2011; Wada and Tekin 2010; Cawley et al. 2009), and Europe (Caliendo and Lee 2013; Bozoyan and Wolbring 2011; Lindeboom et al. 2010; Johansson et al. 2009; Atella et al. 2008; Greve 2008; Brunello and D'Hombres 2007; Paraponaris et al. 2005). Relatively little, however, has been done in developing countries, where cultural norms and laws protecting workers often differ substantially. An example is Colchero and Bishai's (2012) paper, where they find that overweight women do not earn less than those of normal weight in the Philippines. Sohn (2015) finds that taller individuals in Indonesia earn more. Our study employs 1993-2014 data from the IFLS, with an initial focus on the more comprehensive health information available in 2007 (Wave 4 out of the five waves currently available).

II. DATA

The Indonesian Family Life Survey (IFLS) is an on-going longitudinal survey in Indonesia. So far five waves were conducted in 1993, 1997, 2000, 2007 and 2015. The sampled population at the time of first wave represented 83 percent of the population living in the 13 out of 26 provinces. The map below, reproduced from the RAND website, identifies the 13 IFLS provinces in the IFLS.

About 22,000 individuals from 7,224 households were interviewed in the IFLS1 (the first wave). Both the number of respondents and households grew in the following waves, as new members joined the household through marriage or birth, and split in the households. The IFLS has been successful in tracking the households and its members which resulted in a very low attrition of the original sample. The re-contact rates in the second, third, fourth and fifth waves are 94.4, 95.3, 93.6 and 92 percent respectively (Strauss et al. 2016). The low attrition feature makes the data particularly useful for the longitudinal study.

Another appealing feature of the IFLS is that it provides rich set of data on individual health, education, employment, marriage, and fertility outcomes—particularly useful for our study. Unfortunately, the availability of health measures differs across waves and age groups. For example, the information about cholesterol is only available for the fourth wave and for individuals who are 40 years and older in 2007. We use the fourth wave of the IFLS for our primary analysis, as it offers the most diverse set of health measures.

We analyze the effects of both conspicuous (weight, height), less conspicuous (general health status), and inconspicuous (blood pressure, cholesterol, chest pain) health measures on income and parse out explained and unexplained portions using Oaxaca-Blinder decompositions. We subsequently compare conspicuous and inconspicuous in a difference-in-differences (DD) framework and conduct several robustness checks. Finally, we employ all five waves of our panel data and run individual fixed effects models.

Other studies that have employed the IFLS in analyzing health include those by Witoelar et al. (2009), Sohn (2015), Kim (2015), Kim et al. (2017), and Sohn (2017).

III. ECONOMETRIC METHODOLOGY

Inputs in a typical earnings function include both human capital (Mincer 1958) and health capital. Individuals have an incentive to invest in their health, which can be viewed as both an investment good and a consumption good (Grossman 1972). Our empirical methodology begins with the following specification for predicting income:

$$(1) \qquad Ln(Real\ Income)_{it} = \alpha_0 + \alpha_1\ Health_{it} + \alpha_2 X_{it} + \mu_i + \varepsilon_{1it}$$

Where *X* is a vector of individual-level variables pertaining to age, education, marital status; μ_i represent individual fixed effects used in panel data models, and ε_{1it} is an error term. The *health* variable of interest is one of the following: underweight (dichotomous variable =1 if individual has a body mass index less than 18.5 kg/m^2), overweight (=1 if individual has a body mass index greater than or equal to 25 kg/m^2), height above average[3] (=1 if individual's height is above the average in the sample for that individual's gender), high blood pressure (=1 if diastolic blood pressure >=90 mm Hg or systolic blood pressure >=140 mm Hg), high cholesterol (=1 if total cholesterol greater than or equal to 240 mg/dL, asked of individuals 40 years of age and older), chest pain (=1 if pain on left side of chest, only asked of individuals 50 years of age and older), and good health (=1 if the individual is reported as being in excellent, very good, good, or above average health, as evaluated by a nurse). The above specification is employed for our panel data analyses (preliminary results of which are in Appendix Table 2), yet we begin with Wave 4 (2007), which contains more comprehensive information on our health variables. (In particular, information on cholesterol is only available in Wave 4.) We start by estimating OLS and Heckman (1976) selection models.

Endogeneity can arise in this context due to reverse causality (structural endogeneity) or unobserved heterogeneity (statistical endogeneity). One can apply the occupational crowding hypothesis, which usually refers to the segregation of women into occupations where the return on investment is lower (Borjas 2012), to this context. In other words, individuals in Indonesia who are underweight, for example, may select into occupations with a lower rate of return. Accounting for this type of selection and endogeneity is what we attempt to do next.

[3] Height values over six standard deviations from the mean were deemed unrealistic and changed to missing (Freedman et al. 2015).

The following methods are employed as robustness checks: (1) difference-in-differences (DD) estimation, (2) stepwise estimation, in which covariates are gradually added to the baseline model, (3) propensity score matching, (4) instrumental variables (employing internal instruments à la Lewbel 2012), and (5) individual fixed effects models, which address unobserved heterogeneity but have the potential to eliminate much variation.

Ordinary Least Squares (OLS) and Heckman Selection

We begin by running simple OLS models predicting income. In order to account for selection into the labor force, two-step Heckman (1976) selection models are also run, where variables pertaining to age, religion, and marital status are used to predict work status. (Unpaid workers are coded as zero since they are not working for pay.) Results for these models are shown in Table 2.

Oaxaca-Blinder Decomposition

For our decomposition (Blinder 1973; Oaxaca 1973), we have (Wagstaff et al. 2007):

$$y^{healthy} - y^{unhealthy} = \Delta x \beta^{unhealthy} + \Delta \beta x^{unhealthy} + \Delta x \Delta \beta$$

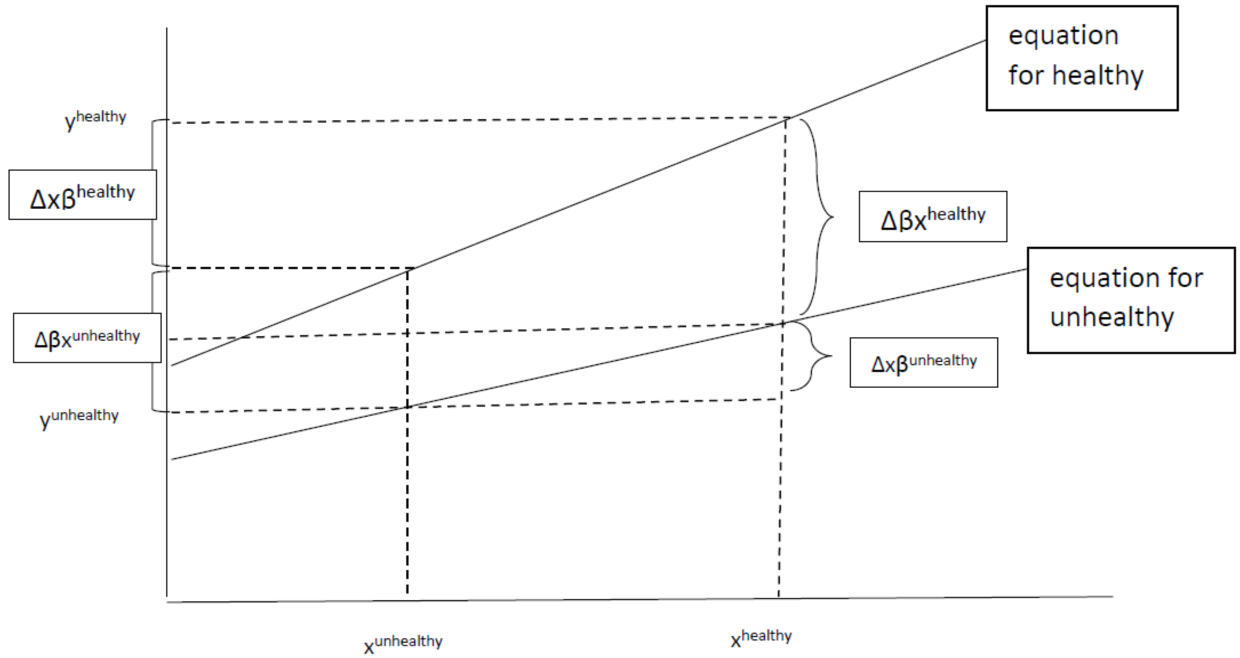
Observed change = Δendowments (E) + Δcoefficients (C)+ Δinteraction (CE)

The observed change in income is due to differences in endowments (E), differences in coefficients (C), and their interaction (CE). If we pool C and CE, we have:

$$y^{healthy} - y^{unhealthy} = \Delta x \beta^{unhealthy} + \Delta \beta x^{healthy}$$

Observed change = E + (C + CE) (in our model, = "unexplained")

This can be seen in the following figure:



We should be cautious in interpreting the unexplained portion as discrimination since factors determining wages such as quality of education and motivation are not controlled for. That being said, if there is discrimination prior to entrance into the labor market that affects these factors, then the discrimination interpretation may be the accurate one. Results for the Oaxaca-Blinder models are shown in Table 3.

Difference-in-Differences

In our difference-in-differences (DD) estimation, we compare groups with the same inconspicuous characteristics (high blood pressure, high cholesterol, chest pain) who have differing conspicuous characteristics (underweight, overweight, height above average). We assume that, conditional on conspicuous health characteristics, inconspicuous health characteristics have no significant effect on the outcome. This is confirmed by the insignificance of the coefficients on the inconspicuous health characteristics in these models. We have the following equation:

$$(2) \qquad Ln(Real\ Income)_{it} = \beta_0 + \beta_1\ Underweight_i + \beta_2\ HBP_i + \beta_3\ Underweight_i{*}HBP_i$$

	Coefficient	**Difference within groups**	**Difference-in-differences**
Underweight=0, High blood pressure=0	β_0	$(\beta_0 + \beta_2) - \beta_0 = \beta_2$	
Underweight=0, High blood pressure=1	$\beta_0 + \beta_2$		$(\beta_2 + \beta_3) - \beta_2 = \boldsymbol{\beta_3}$
Underweight=1, High blood pressure=0	$\beta_0 + \beta_1$	$(\beta_0 + \beta_1 + \beta_2 + \beta_3) - (\beta_0 + \beta_1) = \beta_2 + \beta_3$	
Underweight=1, High blood pressure=1	$\beta_0 + \beta_1 + \beta_2 + \beta_3$		

Results for these models are shown in columns 1-3 of Table 4.

Stepwise Estimation

To test the sensitivity of the coefficient on health, gradually adding covariates is an appropriate empirical strategy. Should the inclusion of individual characteristics substantially reduce the relationship between health and labor market outcomes, we can infer that these characteristics may be driving the observed correlations. Three steps are estimated: (1) health only, (2) health + a limited set of covariates, and (3) health + an extended set of covariates. Results for these models are shown in columns 4-6 of Table 4.

Propensity Score Analysis

Propensity score matching may be used to determine the average effect of the treatment (measures of health status) on the treated. The assumption that the effect of unobservable characteristics on the propensity score is the same as that of observable characteristics is made. This is estimated as:

$$\tau \equiv E\{I_1 - I_0 | H = 1\}$$

$$= E\{E\{I_1 - I_0 | H = 1, p(W)\}\}$$

$$= E\{E\{I_1 | H = 1, p(W)\} - E\{I_0 | H = 0, p(W) | H = 1\},$$

Where τ is the average effect of the treatment on the treated (ATT), H is a binary variable representing health status, I represents real income, and W is a vector of pretreatment characteristics. The propensity score, $p(W)$, is defined as the probability of being in good health given pretreatment characteristics (W). These covariates satisfy the balancing property in all bloacks. Mahalanobis matching is employed (Leuven and Sianesi 2003; Mahalanobis 1936).[4] Note that the propensity score matching approach assumes that there is no other confounding factor after many covariates are controlled for (Rosenbaum and Rubin, 1983), a strong assumption. These results should therefore be interpreted in conjunction with several estimation strategies, such as the ones employed in this paper. Results for these models are shown in column 7 of Table 4.

Instrumental Variables

Lewbel (2012) has devised a technique whereby internal instruments are generated when external instruments are weak or unavailable. In this context, it is difficult to find external instruments that pass the necessary tests. The technique put forth by Lewbel (2012) relies on higher order variation as reflected by the presence of heteroscedasticity in the error term of the first-stage equation, which is tested using a Breusch-Pagan (1979) test. The Lewbel IV procedure uses the deviations from the means of the independent variables multiplied by the predicted residuals from the first-stage regression as instrumental variables. In other words, it

[4] Results are not sensitive to the choice of matching method and are robust to other methods such as Kernel (with alternative bandwidths) and radius matching.

employs $(X - \bar{X}) * \varepsilon_{1idt}$ as identifying instruments, where X is a vector of all independent variables or a subset of them and ε_1 is the predicted residual from the first-stage (health status) regression. Researchers that have successfully used this technique find the Lewbel IV results to be more plausible than ones using questionable external instruments (Sabia 2007; Kelly and Markowitz 2009; Belfield and Kelly 2012; Kelly forthcoming). In this context, the variability in health status among certain groups can be greater than that in other groups. As a result, the heteroskedasticity that arises due to these differences provides a source of identification that can capture an unobserved inclination toward being healthy. Results for these models are shown in column 8 of Table 4.

IV. RESULTS

We begin our analysis using the 2007 IFLS data (Wave 4), which has the most comprehensive information for our variables of interest. In the Appendix, we include results using all five available waves.[5] Table 1 shows weighted summary statistics. Although a slightly higher percentage of males is underweight (10.4% versus 8.4% of females), substantially more females are overweight (38.6% versus 20.7% of males). For less conspicuous health characteristics, approximately 25% of the sample has high blood pressure, 15% has high cholesterol, and 12% has experienced chest pain. Approximately 70% of individuals in the sample are in "above average" health, as evaluated by a nurse. This is unsurprising given that the sample consists of individuals 25 to 55 years of age who are working for pay. Most individuals in the sample are married (86%) and Muslim (93%).

[5] Since we are parsing out potential discrimination across individuals and wish to include time-invariant characteristics in order to avoid omitted variables bias, Oaxaca decomposition is not deemed suitable for fixed effects panel data analyses. (See, for example, discussions at: http://detachers.tistory.com/m/entry/Oaxaca-Decomposition-problem-when-panel-data-is-used and http://faculty.arts.ubc.ca/nfortin/econ351/Oaxaca1.PDF.)

Results from OLS models and models accounting for selection are reported in Table 2. These models control for age, religion, education, marital status, type of worker (self-employed, government worker, or private worker), and health insurance status. Panel A reveals that underweight males and females earn *less* than their fuller counterparts, a finding that contrasts with that found in most developed countries but which is in line with cultural differences in weight perception (CITE). In particular, males on average earn 18.56-19.84% less, and females earn 21.94-25.06% less, holding other factors constant. In a similar vein, overweight individuals earn *more*, with males earning 33.53-34.94% more on average and females earning a lower premium of 12.45-15.73%. In line with Sohn's (2015) findings, we see in Panel C of Table 2 that taller individuals also earn a wage premium.

Turning to less conspicuous health characteristics, we find in Table 2 that high blood pressure has a *positive* effect on wages for males but not females, suggesting that there may be unaccounted for unobserved heterogeneity. Similar effects can be found for both high cholesterol and good health but not for chest pain. Tests for differences in coefficients between OLS and selection models suggest that accounting for selection into the labor force is appropriate.

Oaxaca-Blinder decomposition results are shown in Tables 3a and 3b for conspicuous and inconspicuous characteristics, respectively. Preferred models that account for selection are shown in Columns (2) and (4) for males and females, respectively. The largest predicted income difference can be seen for overweight males, who earn 57.06% *more* than males who are not overweight (Table 3a, Panel B). Moreover, (34.94/57.06 =) 61.23% of this difference is unexplained,[6] possibly suggesting that males who are not overweight are unfairly penalized. Overweight females earn a much lower premium of 18.91%, with (12.45/18.91 =) 65.84% of this difference unexplained (Table 3a, Panel A). Underweight individuals face an income penalty, earning 29.39% and 33.33% less for males and females, respectively. A large portion of this (25.06/33.33 =) 75.19% is unexplained for females in particular. While taller individuals earn more, a smaller percentage of this difference is unexplained when compared to weight.

Interestingly, males with high blood pressure earn 20.67% *more* (Table 3b, Panel A) – a surprising result – whereas females with high blood pressure earn 12.22% *less*. It is therefore unsurprising that most of this difference is unexplained for males yet explained for females. The unexplained portion continues to be significant for males for high cholesterol and good health status, but not for females. The unexplained portion for chest pain is insignificant and relatively low in magnitude for both genders.

V. ROBUSTNESS CHECKS

Turning to Tables 4a and 4b for males and females, respectively, the most consistent findings once the endogeneity of the conspicuous health variable is addressed using various econometric methodologies are as follows: Overweight males earn significantly 11.22-57.45% *more* (Table 4a, Panel B, columns 1, 4-8), while underweight females earn significantly 21.06-32.84% *less* (Table 4b, Panel A, columns 1, 4-8). The difference-in-differences models suggest that high blood pressure is the most appropriate comparison group. Results from individual fixed effects models using all waves (Appendix Table 2) confirm these results.

VI. DISCUSSION AND CONCLUSIONS

[6] Note that the unexplained portion in the pooled Oaxaca models is simply the negative of the coefficient on the health variable shown in Table 2.

In this paper, we decompose differences in earned income for a sample of 25-55 year olds in Indonesia in order to see if individuals who are visibly healthy earn a wage premium. Results were somewhat striking. We find that individuals who are overweight consistently earn a wage premium that is not necessarily explained, pointing to possible discrimination against underweight individuals and those of normal weight. These results survive several robustness checks.

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Table 1
Weighted Means, IFLS Wave 4 (2007)

Variable	Mean (StDev)	Mean (StDev)	Mean (StDev)
Dependent Variable	***Pooled***	***Males***	***Females***
Real income (in thousands of Rupiah)	5009.401 (604376.800)	7006.866 (755927.400)	1470.031 (2511.625)
Health Variables			
Conspicuous			
Underweight	0.098	0.104	0.084
	(0.297)	(0.306)	(0.278)
Overweight	0.271	0.207	0.386
	(0.445)	(0.405)	(0.487)
Height above average	0.533	0.533	0.531
	(0.499)	(0.499)	(0.499)
Inconspicuous			
High blood pressure	0.245	0.235	0.263
	(0.430)	(0.424)	(0.440)
High cholesterol	0.147	0.125	0.187
	(0.354)	(0.331)	(0.390)
Chest pain	0.123	0.118	0.133
	(0.328)	(0.323)	(0.340)
Grey area			
Good health	0.697	0.719	0.664
	(0.460)	(0.449)	(0.473)
Demographic Characteristics			
Male	0.639	1.000	0.000
	(0.480)	(0.000)	(0.000)
Age	39.814	39.660	40.139
	(8.652)	(8.743)	(8.460)
Muslim	0.931	0.933	0.925
	(0.254)	(0.250)	(0.263)
Christian	0.045	0.045	0.049
	(0.208)	(0.206)	(0.216)
Hindu	0.022	0.021	0.025
	(0.147)	(0.143)	(0.155)
Other religion	0.002	0.002	0.001
	(0.040)	(0.041)	(0.037)
Less than primary school	0.250	0.220	0.302
	(0.433)	(0.414)	(0.459)
Primary school	0.236	0.231	0.244
	(0.425)	(0.422)	(0.429)

Some middle school	0.029	0.031	0.023
	(0.167)	(0.175)	(0.151)
Middle school	0.341	0.380	0.271
	(0.474)	(0.485)	(0.444)
Some secondary school	0.017	0.021	0.011
	(0.131)	(0.144)	(0.103)
Secondary school	0.004	0.005	0.005
	(0.067)	(0.069)	(0.068)
Some college	0.051	0.043	0.067
	(0.220)	(0.202)	(0.249)
College plus	0.071	0.069	0.078
	(0.258)	(0.253)	(0.268)
Single	0.064	0.067	0.060
	(0.245)	(0.250)	(0.237)
Married	0.863	0.906	0.786
	(0.344)	(0.292)	(0.411)
Divorced	0.035	0.018	0.066
	(0.184)	(0.132)	(0.249)
Widowed	0.038	0.009	0.088
	(0.190)	(0.094)	(0.284)
Self-employed	0.465	0.458	0.483
	(0.499)	(0.498)	(0.500)
Government worker	0.094	0.092	0.096
	(0.292)	(0.290)	(0.295)
Private worker	0.441	0.450	0.421
	(0.497)	(0.498)	(0.494)
Health insurance	0.298	0.287	0.318
	(0.457)	(0.452)	(0.466)

Notes: Sample size is 12,056. Sample consists of individuals between the ages of 25 and 55 working for pay.

Table 2
Dependent Variable: Natural Log of Income
Ordinary Least Squares and Heckman Selection, Wave 4

	OLS	SELECTION	OLS	SELECTION
VARIABLES	**Males**		**Females**	
Underweight	-0.1856***	-0.1984***	-0.2194***	-0.2506***
	(0.036)	(0.035)	(0.051)	(0.051)
Observations	7,658	7,658	4,289	4,289
ChiSq for Difference Bet OLS and Heckman		8.337		9.245
PVal for Difference Bet OLS and Heckman		0.004		0.002
Overweight	0.3353***	0.3494***	0.1245***	0.1573***
	(0.028)	(0.028)	(0.032)	(0.032)
Observations	7,658	7,658	4,289	4,289
ChiSq for Difference Bet OLS and Heckman		8.980		24.970
PVal for Difference Bet OLS and Heckman		0.003		0.000
Height above average	0.1710***	0.1554***	0.1232***	0.1067***
	(0.023)	(0.022)	(0.031)	(0.031)
Observations	7,664	7,664	4,296	4,296
ChiSq for Difference Bet OLS and Heckman		17.760		10.370
PVal for Difference Bet OLS and Heckman		0.000		0.001
High blood pressure	0.1261***	0.1561***	-0.0483	0.0078
	(0.027)	(0.027)	(0.038)	(0.036)
Observations	7,697	7,697	4,288	4,288
ChiSq for Difference Bet OLS and Heckman		21.260		23.480
PVal for Difference Bet OLS and Heckman		0.000		0.000
High cholesterol	0.1622***	0.1695***	0.1132*	0.0919
	(0.054)	(0.054)	(0.058)	(0.058)
Observations	2,912	2,912	1,819	1,819
ChiSq for Difference Bet OLS and Heckman		1.228		4.997
PVal for Difference Bet OLS and Heckman		0.268		0.0254
Chest pain	-0.0265	-0.0248	-0.0455	-0.0440
	(0.053)	(0.054)	(0.063)	(0.062)

Observations	3,003	3,003	1,875	1,875
ChiSq for Difference Bet OLS and Heckman		0.081		0.046
PVal for Difference Bet OLS and Heckman		0.776		0.830
Good health	0.0530**	0.0525**	0.0251	0.0274
	(0.024)	(0.024)	(0.032)	(0.032)
Observations	7,725	7,725	4,313	4,313
ChiSq for Difference Bet OLS and Heckman		0.024		0.220
PVal for Difference Bet OLS and Heckman		0.877		0.639

Notes: Models include controls for age, age squared, religion, education, marital status, self-employed, government worker, private worker, and health insurance. For Heckman selection models, the selection equation employs controls for age, religion, and marital status. High cholesterol is only asked of individuals 40 years of age and older. Chest pain is only asked of individuals 50 years of age and older. Robust standard errors, accounting for clustering at the household level, are reported in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 3a

Dependent Variable: Natural Log of Income

Oaxaca-Blinder Decompositions, Conspicuous Characteristics

VARIABLES	OAXACA	OAXACA SELECTION	OAXACA	OAXACA SELECTION
	Males		***Females***	
Panel A: Underweight				
Prediction_1	7.2520***	7.2520***	6.8044***	6.8044***
	(0.013)	(0.013)	(0.018)	(0.018)
Prediction_2	6.9581***	6.9581***	6.4711***	6.4711***
	(0.035)	(0.035)	(0.055)	(0.055)
Difference	0.2939***	0.2939***	0.3333***	0.3333***
	(0.037)	(0.037)	(0.058)	(0.058)
Explained	0.1082***	0.0955***	0.1139***	0.0827***
	(0.016)	(0.015)	(0.031)	(0.030)
Unexplained	0.1856***	0.1984***	0.2194***	0.2506***
	(0.036)	(0.035)	(0.051)	(0.050)
Observations	7,658	7,658	4,289	4,289
Panel B: Overweight				
Prediction_1	7.1003***	7.1003***	6.7051***	6.7051***
	(0.014)	(0.014)	(0.022)	(0.022)
Prediction_2	7.6709***	7.6709***	6.8942***	6.8942***
	(0.026)	(0.026)	(0.029)	(0.029)
Difference	-0.5706***	-0.5706***	-0.1891***	-0.1891***
	(0.029)	(0.029)	(0.036)	(0.036)
Explained	-0.2352***	-0.2211***	-0.0645***	-0.0318*
	(0.015)	(0.014)	(0.020)	(0.018)
Unexplained	-0.3353***	-0.3494***	-0.1245***	-0.1573***
	(0.028)	(0.028)	(0.032)	(0.032)
Observations	7,658	7,658	4,289	4,289
Panel C: Height above average				
Prediction_1	7.0620***	7.0620***	6.6353***	6.6353***
	(0.018)	(0.018)	(0.025)	(0.025)
Prediction_2	7.3464***	7.3464***	6.8913***	6.8913***
	(0.017)	(0.017)	(0.024)	(0.024)
Difference	-0.2843***	-0.2843***	-0.2560***	-0.2560***
	(0.024)	(0.024)	(0.035)	(0.035)
Explained	-0.1133***	-0.1289***	-0.1328***	-0.1493***
	(0.012)	(0.011)	(0.018)	(0.017)
Unexplained	-0.1710***	-0.1554***	-0.1232***	-0.1067***
	(0.023)	(0.022)	(0.031)	(0.031)
Observations	7,664	7,664	4,296	4,296

Notes: Models include controls for age, age squared, religion, education, marital status, self-employed, government worker, private worker, and health insurance. For Heckman selection models, the selection equation employs controls for age, religion, and marital status. Robust standard errors, accounting for clustering at the household level, are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 3b

Dependent Variable: Natural Log of Income

Oaxaca-Blinder Decompositions, Less Conspicuous Characteristics

VARIABLES	OAXACA *Males*	OAXACA SELECTION *Males*	OAXACA *Females*	OAXACA SELECTION *Females*
Panel A: High blood pressure				
Prediction_1	7.1743***	7.1743***	6.8025***	6.8025***
	(0.014)	(0.014)	(0.020)	(0.020)
Prediction_2	7.3810***	7.3810***	6.6804***	6.6804***
	(0.027)	(0.027)	(0.035)	(0.035)
Difference	-0.2067***	-0.2067***	0.1222***	0.1222***
	(0.030)	(0.030)	(0.040)	(0.040)
Explained	-0.0806***	-0.0506***	0.0738***	0.1299***
	(0.015)	(0.014)	(0.025)	(0.022)
Unexplained	-0.1261***	-0.1561***	0.0483	-0.0078
	(0.027)	(0.027)	(0.038)	(0.036)
Observations	7,697	7,697	4,288	4,288
Panel B: High cholesterol				
Prediction_1	7.2122***	7.2122***	6.7372***	6.7372***
	(0.022)	(0.022)	(0.028)	(0.028)
Prediction_2	7.5326***	7.5326***	6.8865***	6.8865***
	(0.057)	(0.057)	(0.063)	(0.063)
Difference	-0.3204***	-0.3204***	-0.1492**	-0.1492**
	(0.061)	(0.061)	(0.069)	(0.069)
Explained	-0.1582***	-0.1509***	-0.0361	-0.0574
	(0.033)	(0.032)	(0.040)	(0.039)
Unexplained	-0.1622***	-0.1695***	-0.1132*	-0.0919
	(0.054)	(0.054)	(0.058)	(0.058)
Observations	2,912	2,912	1,819	1,819
Panel C: Chest pain				
Prediction_1	7.2629***	7.2629***	6.8008***	6.8008***
	(0.022)	(0.022)	(0.028)	(0.028)
Prediction_2	7.2182***	7.2182***	6.6592***	6.6592***
	(0.058)	(0.058)	(0.069)	(0.069)
Difference	0.0447	0.0447	0.1416*	0.1416*
	(0.061)	(0.061)	(0.074)	(0.074)
Explained	0.0181	0.0199	0.0961**	0.0975**
	(0.030)	(0.030)	(0.039)	(0.039)
Unexplained	0.0265	0.0248	0.0455	0.0440
	(0.053)	(0.054)	(0.062)	(0.062)
Observations	3,003	3,003	1,875	1,875

Panel D: Good health

Prediction_1	7.1186***	7.1186***	6.6797***	6.6797***
	(0.022)	(0.022)	(0.030)	(0.030)
Prediction_2	7.2575***	7.2575***	6.8205***	6.8205***
	(0.015)	(0.015)	(0.022)	(0.022)
Difference	-0.1388***	-0.1388***	-0.1408***	-0.1408***
	(0.026)	(0.026)	(0.037)	(0.037)
Explained	-0.0859***	-0.0864***	-0.1157***	-0.1134***
	(0.012)	(0.012)	(0.020)	(0.019)
Unexplained	-0.0530**	-0.0525**	-0.0251	-0.0274
	(0.024)	(0.024)	(0.032)	(0.032)
Observations	7,725	7,725	4,313	4,313

Notes: Models include controls for age, age squared, religion, education, marital status, self-employed, government worker, private worker, and health insurance. For Heckman selection models, the selection equation employs controls for age, religion, and marital status. High cholesterol is only asked of individuals 40 years of age and older. Chest pain is only asked of individuals 50 years of age and older. Robust standard errors, accounting for clustering at the household level, are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 4a
Dependent Variable: Natural Log of Income
Robustness Checks, Males

VARIABLES	DD Health *High blood press	DD Health *High cholesterol	DD Health *Chest pain	STEP1 Health Only	STEP2 Limited	STEP3 Extended	PSCORE	Lewbel IV
Underweight	-0.1674***	-0.2489***	-0.2549***	-0.2938***	-0.2735***	-0.1856***	-0.2022	-0.0351
	(0.037)	(0.062)	(0.064)	(0.037)	(0.038)	(0.036)	(0.159)	(0.070)
High blood press/chol/chest	0.1165***	0.1399**	-0.0344					
	(0.028)	(0.056)	(0.057)					
Interaction	-0.0452	0.1192	-0.0416					
	(0.126)	(0.227)	(0.160)					
Observations	7,633	2,889	2,933	7,662	7,662	7,658	7,646	7,658
F-stat								172.3
Overid pval								0.466
Overweight	0.2832***	0.4193***	0.3844***	0.5714***	0.5585***	0.3353***	0.5745***	0.2990***
	(0.034)	(0.045)	(0.044)	(0.029)	(0.030)	(0.028)	(0.142)	(0.088)
High blood press/chol/chest	0.0320	0.1440**	-0.0703					
	(0.033)	(0.064)	(0.062)					
Interaction	0.1122*	-0.1057	0.1566					
	(0.059)	(0.115)	(0.114)					
Observations	7,633	2,889	2,933	7,662	7,662	7,658	7,662	7,658
F-stat								50.72
Overid pval								0.000963
Height above average	0.1652***	0.1555***	0.1748***	0.2849***	0.2993***	0.1710***	0.3793**	-0.5698
	(0.025)	(0.039)	(0.038)	(0.024)	(0.025)	(0.023)	(0.154)	(0.422)
High blood press/chol/chest	0.1104***	0.1552**	0.0218					
	(0.040)	(0.071)	(0.070)					
Interaction	0.0212	0.0078	-0.1129					
	(0.053)	(0.108)	(0.110)					
Observations	7,637	2,892	2,936	7,668	7,668	7,664	7,668	7,664
F-stat								1.849
Overid pval								0.693

Notes: Models include controls for age, age squared, religion, education, marital status, self-employed, government worker, private worker, and health insurance. For Heckman selection models, the selection equation employs controls for age, religion, and marital status. High cholesterol is only asked of individuals 40 years of age and older. Chest pain is only asked of individuals 50 years of age and older. Robust standard errors, accounting for clustering at the household level, are reported in parentheses. Standard errors in propensity score models are bootstrapped. *** p<0.01, ** p<0.05, * p<0.1.

Table 4b
Dependent Variable: Natural Log of Income
Robustness Checks, Females

VARIABLES	DD Health *High blood press	DD Health *High cholesterol	DD Health *Chest pain	STEP1 Health Only	STEP2 Limited	STEP3 Extended	PSCORE	Lewbel IV
Underweight	-0.1877***	-0.4341***	-0.4140***	-0.3284***	-0.3168***	-0.2194***	-0.6119**	-0.2386**
	(0.058)	(0.076)	(0.079)	(0.058)	(0.058)	(0.051)	(0.258)	(0.094)
High blood press/chol/chest	-0.0413	0.0818	-0.0434					
	(0.039)	(0.060)	(0.066)					
Interaction	-0.2106*	0.3260	-0.0368					
	(0.112)	(0.244)	(0.192)					
Observations	4,262	1,809	1,844	4,296	4,296	4,289	4,288	4,289
F-stat								104.6
Overid pval								0.0874
Overweight	0.1468***	0.1952***	0.2344***	0.1894***	0.1944***	0.1245***	-0.1100	0.4620**
	(0.038)	(0.049)	(0.048)	(0.036)	(0.036)	(0.032)	(0.192)	(0.229)
High blood press/chol/chest	-0.0500	0.1666**	0.1273					
	(0.053)	(0.085)	(0.079)					
Interaction	-0.0520	-0.1373	-0.3934***					
	(0.072)	(0.116)	(0.127)					
Observations	4,262	1,809	1,844	4,296	4,296	4,289	4,296	4,289
F-stat								5.796
Overid pval								0.0627
Height above average	0.1477***	0.1128**	0.0733	0.2567***	0.2563***	0.1232***	0.1303	-0.1118
	(0.035)	(0.048)	(0.047)	(0.034)	(0.035)	(0.031)	(0.189)	(0.441)
High blood press/chol/chest	0.0115	0.1922**	-0.0998					
	(0.052)	(0.083)	(0.086)					
Interaction	-0.1164*	-0.1491	0.1048					
	(0.071)	(0.115)	(0.124)					
Observations	4,267	1,811	1,846	4,303	4,303	4,296	4,303	4,296
F-stat								1.214
Overid pval								0.395

Notes: Models include controls for age, age squared, religion, education, marital status, self-employed, government worker, private worker, and health insurance. High cholesterol is only asked of individuals 40 years of age and older. Chest pain is only asked of individuals 50 years of age and older. Robust standard errors, accounting for clustering at the household level, are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Appendix Table 1
Weighted Means for Health Variables, IFLS, All Waves

	Mean (StDev)
Underweight	0.10
	(0.31)
Overweight	0.22
	(0.42)
Height above average	0.49
	(0.50)
High blood pressure	0.59
	(0.49)
High cholesterol	0.13
	(0.34)
Chest pain	0.15
	(0.36)
Good health	0.77
	(0.42)

Notes: Sample for all waves (person-year observations) is 18,432. Waves included: Wave 1 (1993), Wave 2 (1997), Wave 3 (2000), Wave 4 (2007), and Wave 5 (2014).

Appendix Table 2

Dependent Variable: Natural Log of Income

Panel Regressions (Individual Fixed Effects Models), All Waves

	(1)	(2)
VARIABLES	***Males***	***Females***
Underweight	-0.0536	-0.1423***
	(0.034)	(0.048)
Observations	26,364	16,199
Number of pid	14,015	9,812
Overweight	0.1326***	0.0432
	(0.028)	(0.030)
Observations	26,364	16,199
Number of pid	14,015	9,812
Height above average	0.0050	0.0231
	(0.032)	(0.044)
Observations	26,410	16,232
Number of pid	14,029	9,831
High blood pressure	0.0879***	0.0492*
	(0.020)	(0.026)
Observations	26,402	16,150
Number of pid	14,013	9,788
Chest pain	0.0220	-0.1488*
	(0.058)	(0.077)
Observations	8,121	5,130
Number of pid	6,325	4,166
Good health	0.0530***	0.0259
	(0.019)	(0.023)
Observations	26,491	16,261
Number of pid	14,049	9,840

Notes: Models include controls for age, age squared, religion, education, marital status, self-employed, government worker, private worker, and health insurance. Chest pain is only asked of individuals 50 years of age and older. Questions on cholesterol are only asked in

Wave 4 and therefore not included. Standard errors are reported in parentheses. Waves included: Wave 2 (1997), Wave 3 (2000), Wave 4 (2007), and Wave 5 (2014). Wave 1 (1993) is also included for underweight, overweight, and height above average variables. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.