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May 2009

Online at <https://mpra.ub.uni-muenchen.de/15479/>

MPRA Paper No. 15479, posted 03 Jun 2009 00:12 UTC

Access to primary care and workers' opportunity costs. Evidence from Italy

Giuliana De Luca* and Michela Ponzo*

Abstract

This paper explores whether and to which extent employment condition and working hours influence individuals' decision process in consuming primary care. The hypothesis is that the higher the workers' opportunity cost in terms of earning forgone, the less the demand for General Practitioner (GP) visits.

Data used in the analysis come from the 2004/2005 "Health conditions and recourse to health services" survey provided by the Italian National Institute of Statistics (ISTAT). We apply a negative binomial regression to model the relationship between the number of GP visits and employment related variables, controlling for a rich set of individual demographic characteristics, socio-economic variables, health status, supply and geographical factors.

We show that self-employed workers, managers and cadres use significantly less primary care services notwithstanding the access is free. We interpret these findings as being due to the fact that these type of workers have higher opportunity costs than white and blue collars, since they suffer more from the loss of earnings related to the absence from work

Keywords. Opportunity cost, hours of work, utilisation of GP, labour market.

JEL classifications: J20, I10, I18, J21.

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1. Introduction

The Italian National Health system (NHS) provides free and equitable access to primary care at the point of delivery to all residents. Resources are allocated in relation to need, and GPs are paid according to a capitation fee. Although financial- and need- related factors do not represent a real individual constraint to the consumption of health care, some non-financial factors, such as occupational status and time work, may still discourage the use of GP services in the absence of out-of-pocket prices. In fact, workers whose time is most valuable may use medical services less because of higher opportunity costs (Becker, 1965; Acton, 1975; Grossman, 1982; Phelps and Newhouse, 1974). That means the more costly is in terms of earning losses the absences from work (i.e. for self-employed and upper-white collars) the less likely the recourse to the GP services.

There exists little evidence on this issue compared to the amount of research published on individual (demographic, socio-economic characteristics, health status) and system (geographic location, wait times, supply) determinants of access across different health care systems (Andersen, 1995; Wagstaff and Van Doorsaler, 2000; Gravelle *et al.*, 2003; Fernández-Olano *et al.*, 2006). This abundant strand of literature finds that income, after controlling for need, is the main determinant of access to private health care systems although it does not appear to play a role in countries where a universal health coverage exists (Van Doorslaer *et al.*, 2004).

Among those authors who studied the effect of non-monetary factors on utilization of care services, most of them focuses on the 'time required' to visit the GP, including travelling, waiting and treatment as a measure of the time price (among others Janssen, 1992; Boaz and Muller, 1989). By contrast, a few studies explain the barrier to access through the intrinsic value of time given by the opportunity cost of spending it in alternative activities (Economou *et al.*, 2008; Fell *et al.*, 2007; Wellstood *et al.*, 2006).

In this paper we study the effect of employment status and work hours on the demand for GP visits. The underlying hypothesis is that use or access (U) depends on health status (H), occupational status (E), hours worked (W) and other variables (X) as follows:

$$U = f(H, E, W, X)$$

We expect to find that workers who borne higher opportunity costs in terms of earning losses (self-employed workers and upper-white collars) visit the GP less compared to other categories (white and blue collars) who are unlikely to lose earnings being protected by the sickness security law. Furthermore, we expect that the higher the total number of hours worked the stronger the disutility connected to visiting the GP suffered from those workers who have a greater value of time.

2. Data and methodology

The data used in this study come from the 2004/2005 Italian Survey on “Health conditions and recourse to health services” provided by ISTAT. This is a survey based on a representative sample drawn in two stages, including 50,474 households for a total of 128,040 individuals. The survey collects a wide range of information on both demographic and socio-economic characteristics of individuals and households, as well as variables on health conditions and health care utilization. Regional supply-side variables extracted from “Health for All” dataset provided by ISTAT are also used. We restrict the sample to working-age individuals (age 15 through 65). This leaves 86,185 observations used in the first step of the analysis to assess whether and to which extent the employment status influences the GP utilization compared to the condition of not-employed, including the inactive and the unemployed. Afterwards, we further restrict the sample to the employed ending up with a total of 49,536 individuals. This sub-sample is used to test the hypothesis that a higher opportunity cost measured by working hours reduces the number of GP visits.

The dependent variable is the total count of GP visits occurred in the latest four weeks immediately prior to the interview (tables 1). The mean number of GP visits in the overall sample is 0.21 (not shown) whereas in the sub-sample is 0.18. The distribution of the number of visits reveals a large proportion of zero observations in the sub-sample (85%) and a small proportion of individuals who use the GP more frequently. The sample variance (0.31) is greater than the sample mean indicating that the data exhibit overdispersion. This characteristic may be due to excess zeros, unexplained heterogeneity (Mullahy, 1997) and/or temporal dependency.

[INSERT TABLE 1]

The highly skewed nature of the data (figures 1) makes traditional OLS estimators inappropriate to model medical visits (Cameron and Trivedi, 1998).

To overcome this problem, two main traditions of econometric modelling use either one-step (Negative Binomial, Zero-Inflated models) or two-step estimators (hurdle-models) depending on the theoretical approaches they are based upon, namely the Grossman approach (Grossman, 1982; Duan *et al.*, 1983; Cameron *et al.*, 1988) and the agency one (Manning *et al.*, 1981; Phlmeier-Ulrich, 1995). The former assumes that utilisation is mainly patient determined, although conditioned by the health-care delivery system. The latter emphasises the role played by the GP in deciding the frequency of treatment (frequency decision) though is the patient to initiate the visit (contact decision).

[INSERT FIGURE 1]

The large proportion of zeros, in turn, may be interpreted as individuals who either are potential users but not during the survey period or do not use the service at all. The negative binomial (NB) model accounts for the fact that all patients have a positive probability of visiting a doctor ignoring the difference between diverse sources of zero observations, i.e. the true no-participant (structural zeros) are undistinguishable from potential participants who did not visit the GP during the survey period (sampling zeros). By contrast, the zero-inflated models do differentiate between the two types of zeros. Finally, hurdle models assume that excess of zeros is due to sampling zeros (Mullahy, 1986) and, accordingly, model the patient decision of contacting the doctor separately from the GP decision on the number of future encounters.

In the analysis we apply NB regression to model the number of GP visits, v_i . We assume that all zero observations observed in the last four weeks represent potential patients; therefore, the existence of unobservable heterogeneity is sufficient to explain excess zeros without recurring to different specifications such as zero inflated and hurdle models. As a robustness check we also estimate the probability of visiting the GP with a Probit model.

Formally, the NBR accounts for unobservable heterogeneity by adding in the conditional mean of the Poisson model an error term, $\varepsilon \sim G(\theta, \theta)$, with mean 1 and variance $1/\theta$ that is assumed to be uncorrelated with the observed \mathbf{x}_i :

$$E[v_i | x_i, \varepsilon_i] = \exp(\alpha + x_i' \beta + \varepsilon_i) = \lambda_i \delta_i$$

where x_i' is a vector of regressors, $\lambda_i = \exp(\alpha + x_i' \beta)$ and $\delta_i = \exp(\varepsilon_i)$.

The density for δ_i is given by:

$$f(\delta_i) = \frac{\theta^\theta}{\Gamma(\theta)} \exp(-\theta \delta_i) \delta_i^{\theta-1}, \quad \delta_i \geq 0, \quad \theta > 0$$

After integrating δ_i out of the joint distribution, the marginal negative binomial distribution is obtained (Greene, 2008):

$$\Pr[V = v_i | x_i', \delta_i] = \Gamma \frac{(v_i + \theta) r_i^\theta (1 - r_i)^{v_i}}{\Gamma(1 + v_i) \Gamma(\theta)}$$

where $r_i = \frac{\theta}{(\theta + \lambda_i)}$.

The unobservable heterogeneity produces overdispersion while preserving the conditional mean:

$$E[v_i | x_i'] = \lambda_i$$

$$\text{Var}[v_i | x_i'] = \lambda_i \left[1 + \frac{1}{\theta} \lambda_i \right] = \lambda_i [1 + \kappa \lambda_i]$$

where $k = [\text{Var}(\delta_i)]$

Maximum likelihood estimation of the parameters is straightforward (Greene, 2008).

One variable of interest is the employment status (employed versus not-unemployed individuals). This is used in the first step of our analysis. Subsequently, to measure the opportunity costs of visiting the GP among

workers, we introduce in the second part of our analysis the total number of worked hours per week. The employed workers in the population under study are 57% and among them 26% are self-employed; the manager and cadres account for 7% among the overall sample population (Table 2). The average of hours worked per week is roughly 40 (SD=12). The percent of workers who work overtime (≥ 50) is around 10%.

Table 2 presents summary statistics for the whole sample and for the sub-sample consisting of employed subjects. Several variables, that influence GP visits and may also be associated with our variables of interest, emerging from the literature, are used as controls in our regressions to limit the omitted variable problem. These include demographic and socio-economic characteristics; several measures of health need (self-reported health status, chronic diseases and disability); a lifestyle measure (smoker status); self-reported wealth¹ and supply side variables. Since we are controlling for a wide range of characteristics, in particular for health status, age and a measure of wealth, we suppose that selection bias is not a relevant problem in our analysis focusing on employment status.

The two samples do not differ much between each other but the proportion of female that is lower in the sub-sample (40%) than in the whole sample (51%) and the proportion of smokers who show a greater proportion in the sub-sample (52%). The population under study is predominantly married², aged about 41 years, high school educated³.

[INSERT TABLE 2]

¹ *Wealth* categories are defined as follows: 1 for the wealthier wealth status; 2 for middle wealth status; 3 for bad wealth status; 4 for poorer wealth status.

² *Married* is set to zero if the individual has never got married, is widowed, separated or divorced.

³ *Education* is set at zero for no educational qualification; 5 for elementary school; 8 for middle school; 11 for some high school; 13 for high school; 18 for university; 20 for postgraduate qualification.

3. Results

Table 3 shows the main results from six specifications. The columns give the metric coefficients. They are quite stable for the six specifications, both in sign and in order of magnitude. Table 4 reports the marginal effects. Columns 1-2 of each table report estimates from the overall sample while column 3-6 show findings related to the sub-sample of employed. Standard errors are adjusted for clustering within households. Dummies for each Italian territorial areas are also controlled for to account for geographical and environmental aspects and other area-specific unobservable factors⁴. In all specifications the alpha parameter is significantly different from zero (test not shown) confirming the presence of data over-dispersion.

[INSERT TABLES 3, 4]

The main findings can be summarised as follows. Employment status has a negative (-0.2%) but not statistically significant effect (z-score of -0.59) on GP visits with respect to the not-employed one (Column 1 in Table 2)⁵. This unexpected result may be due to the fact that the variable “employed” captures the effect of two categories of workers who behave differently compared to each other. In fact, it emerges from Column 2 that self-employed visit the GP significantly less than the not-employed (-3.2%, z-score of -6.03) while the employees are not different from not-employed (0.6%, z-score of 1.57).

A likely explanation may be that being the former in positions of personal responsibility, their opportunity costs, in terms of the reduction in earnings due

⁴ *North-West* includes the following regions: Piedmont, Valle d'Aosta, Lombardy, Liguria; *North-East* includes Veneto, Trentino Alto Adige, Friuli Venezia Giulia, Emilia Romagna; *Centre* includes Tuscany, Lazio, Marche, Umbria; *South* includes Abruzzi, Campania, Apulia, Molise, Basilicata, Calabria; *Islands* include Sicily and Sardinia.

⁵ In a previous specification (not shown) including only the unemployed as a reference group, we do not find a statistically significant difference between the individuals out of the labour force and the unemployed.

to the loss of time from workplace, is higher. On the other hand, it is reasonable to believe that both employees and not-employed are unlikely to lose earnings due to GP visits. This may be explained by the fact that the employees income losses due to illness are predominantly borne by the employer or by the Social Security system thanks to the sickness security law while the latter can manage their available time without specific time work constraints.

To further confirm this explanation using the available data, we assume that the total number of hours worked per week may represent an adequate approximation of the opportunity cost of visiting the GP. We find that there exists an inverse association between work hours and utilization of GP services (Column 3 in Table 3). For a standard deviation increase in the mean hours worked, roughly 12, the expected number of visits per month decreases by a factor of $\exp(-0.005*12)=-0.94$, holding all other variables constant.

Moreover, we include an interaction term between hours worked and the self-employed status to test whether the effect of hours worked on access interacts with the type of professional condition (Column 4 in Table 3 and 4). The negative coefficient effect of the interaction term indicates a significant lower recourse of GP visits by the self-employed compared to the overall category of employees.

Finally, among the category of employees we distinguish managers and cadres (upper-white collars) from white and blue collars (the remaining employees) to check whether the former behave similarly to self-employed. We find evidence that both the upper-white collars and the self-employed have a bigger negative effect on GP utilisation compared to the white and blue collars (Column 5 in Table 3 and 4). Since the effects estimated are not so different between each other, we unify the two categories (self-employed/managers/cadres). The negative marginal effect of the interaction term indicates that the slope for hour worked is greater for self-employed/managers/cadres category compared to the white and blue-collars, implying a higher opportunity cost of the time for the former (Column 6 in Table 3 and 4). This means that 10 hours increase in time work per week decreases the expected number of visits per month by 1.0%.

Our main results are confirmed using a Probit model. We define a dummy variable (*Visits*) that takes value one if employed see their GP one or more times and zero otherwise (in the last four weeks). Table 5 shows the results from the last and most informative specification. The results show that for self-employed/managers/cadres category the probability of visiting the GP decreases by 0.08%. It can be argued that for non-linear models the interaction effect cannot be evaluated simply by looking at the sign, magnitude, or statistical significance of the coefficient on the interaction term (Ai and Norton, 2003). To this purpose we use both linear probability model and the procedure suggested by Ai and Norton (2003) and implemented in STATA software to estimate significance of interaction terms and examine the “correct” direction of changes. The estimated effect is confirmed in sign, magnitude whereas statistical significance reduces from 1% to 5% (Table 6).

The increase in the opportunity cost of GP visits for self-employed, managers and cadres may also be explained through the widespread adoption of performance related pay (PRP) used to raise motivational and effort levels by linking the wage level or promotions to workers’ output. Under these circumstances, it becomes more costly for these type of workers to lose time at workplace.

In line with the literature, being female and married is associated with higher demand of GP visits than males and single. The effect of individual’s age is related to the dependent variable through a quadratic patterns showing that as age increases, the expected number of primary care demand raise. The U-shaped patten exhibits a minimum at 42 years. Also the number of children in the household shows a non-linear shape with a maximum at 1.37. Fewer GP visits are associated with a higher education level, showing that individuals more educated are more efficient producers of health. The contact visits are clearly responsive to need proxied by morbidity and the self reported health status. Specifically, individuals reporting “fair” or “bad” health status are respectively

associated with a higher number of contact visits compared to those claiming that their health is excellent (all the estimated effects are significant at the 1% level). In addition, individuals reporting chronic conditions use much more GP services compared to the reference category (subjects with no chronic condition). Surprisingly, being a smoker is not significantly associated with GP use. It was important to control for several measures of need to prevent any bias that may occur if workers with different health conditions self-select in different type of occupations. Finally, we find that wealthier individuals make fewer visits to the GP than less wealthy individuals and this can be due to the fact that they have a more salubrious lifestyle. It was important to control for several measures of need to prevent any bias that may occur if workers with different health conditions self-select in different type of occupations.

Among aggregate variables used to correct for a possible supply-side effect a higher percentage of diagnostic centres is negatively and significantly associated with GP visits implying a substitution effects. Doctor density and the presence of prevention department do not have any relevant effect. Finally, differences in access across territorial areas may reflect difference in the organisational local health system. In fact, when controlling for regional dummies effects (not shown) excluding supply-side variables we still found significant differences across Italian Regions.

4. Conclusion

This work finds that there is a significant trade-off between time spent in working activities and utilisation of primary care services and that it differs by type of occupation. Self-employed, managers and cadres who devote much more time at workplace have a lower expected number of visits to GP compared to the employees (white and blue collars). We conclude that in a publicly founded

regime, such as Italy, where there exist no financial barriers to the utilization of primary care, type of occupation and time of work may still affect the demand of GP visits.

From a policy perspective, it is desirable to improve access to primary care by extending GP out-of-work hours (enabling workers to be seen after work and at weekends) or/and reducing GP waiting times (by extending the practice of scheduling appointments). More generally, the health care system should be aware of any hidden cost imposed to the patients in terms of time lost at work and, consequently, should count the opportunity cost of patient's time as part of the total cost of health care.

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APPENDIX

Table 1 - Tabulation of GP visits, n=49,536

GP Visits			
	Freq.	Percent	Cum.
0	43,114	87.04	87.04
1	4,870	9.83	96.87
2	1,144	2.31	99.18
3	238	0.48	99.66
4	108	0.22	99.87
≥5	62	0.13	100.00
Total	49,536	100.00	
Mean	0.18		
Variance	0.31		

Figure 1 GP visits distribution, n=49,536

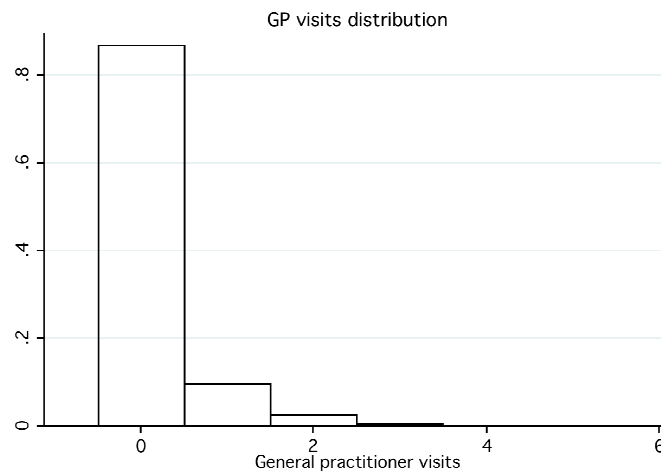


Table 2 Descriptive statistics for the whole sample and for sub-sample of workers.

<i>Variables</i>	N=86,185				n=49,536			
	Mean	Standard Deviation	Min	Max	Mean	Standard Deviation	Min	Max
<i>Dependent variable</i>								
Number of GP visits	0.21	0.64	0	25	0.18	0.56	0	20
<i>Demographic</i>								
Female	0.51	0.50	0	1	0.40	0.49	0	1
Age (yrs)	40.49	13.86	15	65	40.48	10.77	15	65
Married	0.64	0.48	0	1	0.68	0.47	0	1
Children (#)	0.52	0.81	0	7	0.58	0.83	0	7
<i>Socio-economic characteristics</i>								
Education (yrs)	12.74	3.15	0	21	12.89	3.03	0	21
Employed	0.58	0.49	0	1	-	-	-	-
Not employed	0.42	0.49	0	1	-	-	-	-
Employees	0.43	0.49	0	1	0.74	0.44	0	1
Self-employed	0.15	0.35	0	1	0.26	0.44	0	1
Managers/cadres	0.04	0.20	0	1	0.07	0.26	0	1
Hours of work	22.87	21.65	0	99	39.80	11.92	0.5	99
Wealth 1	0.04	0.19	0	1	0.04	0.20	0	1
Wealth 2	0.67	0.47	0	1	0.72	0.45	0	1
Wealth 3	0.25	0.43	0	1	0.21	0.41	0	1
Wealth 4	0.05	0.21	0	1	0.03	0.17	0	1
<i>Need</i>								
Very good health status	0.22	0.42	0	1	0.22	0.41	0	1
Good health status	0.48	0.50	0	1	0.53	0.50	0	1
Fair health status	0.26	0.44	0	1	0.24	0.43	0	1
Bad health status	0.03	0.16	0	1	0.01	0.12	0	1
Very bad health status	0.00	0.07	0	1	0.00	0.04	0	1
Chronic diseases	0.46	0.50	0	1	0.44	0.50	0	1
Disability	0.01	0.11	0	1	0.00	0.06	0	1
<i>Lifestyle</i>								
Smoker	0.45	0.50	0	1	0.52	0.50	0	1
<i>Supply-side</i>								
Diagnostic centers (%)	55.92	15.11	26.72	87.06	56.96	14.81	26.72	87.06
GP Density x100,000 pop.	0.82	0.06	0.66	0.94	0.82	0.06	0.66	0.94
Prevention departments	89.96	15.49	40	100	90.11	15.44	40	100
<i>Geographical effects</i>								
North-West	0.20	0.40	0	1	0.22	0.41	0	1
North-East	0.17	0.38	0	1	0.20	0.40	0	1
Center	0.17	0.38	0	1	0.19	0.39	0	1
South	0.30	0.46	0	1	0.25	0.44	0	1
Islands	0.12	0.32	0	1	0.10	0.29	0	1

Table 3. Determinants of GP Visits. Negative Binomial Regression estimations.

<i>Variables</i>	Sample: Working age population			Sub-sample: Employed		
	(1)	(2)	(3)	(4)	(5)	(6)
<i>Employed</i>	-0.016 (0.026)					
<i>Self-employed</i>		-0.215*** (0.039)	-0.202*** (0.037)	-0.192*** (0.037)	-0.218*** (0.037)	
<i>Employees</i>		0.043 (0.027)				
<i>Hours of work</i> [†]			-0.005*** (0.001)	-0.002 (0.002)	-0.000 (0.002)	-0.000 (0.002)
<i>Self-employed*Hours of work</i>				-0.007*** (0.003)	-0.009*** (0.003)	
<i>Managers/cadres</i>					-0.214*** (0.063)	
<i>Managers/cadres*Hours of work</i>					-0.017***	
<i>Self-employed/managers/cadres</i>						-0.212*** (0.034)
<i>Self-employed/managers/cadres*Hours of work</i>						-0.010*** (0.002)
<i>Female</i>	0.215*** (0.022)	0.200*** (0.022)	0.212*** (0.030)	0.220*** (0.030)	0.216*** (0.031)	0.218*** (0.030)
<i>Age</i>	-0.013** (0.006)	-0.014** (0.006)	-0.035*** (0.010)	-0.035*** (0.010)	-0.034*** (0.010)	-0.034*** (0.010)
<i>Age Squared</i>	0.000** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)
<i>Married</i>	0.106*** (0.036)	0.111*** (0.036)	0.115*** (0.044)	0.116*** (0.044)	0.116*** (0.044)	0.116*** (0.044)
<i>Children (#)</i>	0.129*** (0.039)	0.130*** (0.039)	0.110** (0.050)	0.112** (0.050)	0.115** (0.050)	0.116** (0.050)
<i>Children Squared (#)</i>	-0.057*** (0.016)	-0.056*** (0.016)	-0.040** (0.020)	-0.041** (0.020)	-0.041** (0.020)	-0.041** (0.020)
<i>Education</i>	-0.005* (0.003)	-0.006* (0.003)	-0.011*** (0.004)	-0.011*** (0.004)	-0.008* (0.005)	-0.007* (0.004)
<i>Wealth status 2</i>	0.113* (0.060)	0.103* (0.060)	0.132* (0.078)	0.132* (0.078)	0.123 (0.078)	0.125 (0.078)
<i>Wealth status 3</i>	0.237*** (0.062)	0.221*** (0.062)	0.245*** (0.081)	0.245*** (0.081)	0.228*** (0.081)	0.229*** (0.081)
<i>Wealth status 4</i>	0.253*** (0.078)	0.237*** (0.078)	0.307*** (0.109)	0.306*** (0.109)	0.289*** (0.109)	0.289*** (0.109)
<i>Good health</i>	0.357*** (0.039)	0.354*** (0.039)	0.347*** (0.048)	0.348*** (0.048)	0.347*** (0.048)	0.347*** (0.048)
<i>Fair health</i>	0.945*** (0.042)	0.942*** (0.042)	0.928*** (0.052)	0.929*** (0.052)	0.924*** (0.052)	0.925*** (0.052)
<i>Bad health</i>	1.565*** (0.055)	1.561*** (0.055)	1.566*** (0.083)	1.570*** (0.083)	1.558*** (0.083)	1.562*** (0.083)
<i>Very bad health</i>	1.951*** (0.107)	1.953*** (0.108)	1.880*** (0.260)	1.868*** (0.257)	1.850*** (0.256)	1.848*** (0.255)
<i>Chronic diseases</i>	0.613*** (0.025)	0.612*** (0.025)	0.568*** (0.031)	0.568*** (0.031)	0.572*** (0.031)	0.572*** (0.031)
<i>Disability</i>	0.197*** (0.074)	0.191*** (0.074)	0.016 (0.170)	0.017 (0.170)	0.007 (0.170)	0.008 (0.170)
<i>Smoker</i>	0.009 (0.021)	0.008 (0.022)	0.010 (0.029)	0.009 (0.029)	0.006 (0.029)	0.007 (0.029)
<i>Diagnostic centers</i>	-0.002* (0.002)	-0.002* (0.002)	-0.004*** (0.002)	-0.004*** (0.002)	-0.004*** (0.002)	-0.004*** (0.002)

	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
<i>GP Density x 100,000</i>	0.475*	0.467*	0.102	0.080	0.096	0.089
	(0.267)	(0.267)	(0.338)	(0.337)	(0.338)	(0.338)
<i>Prevention department</i>	0.000	0.000	-0.000	-0.000	-0.000	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
<i>North-East</i>	0.235***	0.238***	0.216***	0.215***	0.216***	0.215***
	(0.036)	(0.036)	(0.045)	(0.045)	(0.045)	(0.045)
<i>Center</i>	0.122***	0.125***	0.121**	0.122**	0.120**	0.121**
	(0.038)	(0.038)	(0.049)	(0.048)	(0.049)	(0.049)
<i>South</i>	0.165***	0.169***	0.110***	0.110***	0.103**	0.105**
	(0.031)	(0.031)	(0.041)	(0.041)	(0.041)	(0.041)
<i>Islands</i>	0.224***	0.230***	0.088	0.089	0.082	0.084
	(0.053)	(0.053)	(0.073)	(0.073)	(0.073)	(0.073)
<i>Alpha</i>	2.263	2.251	2.265	2.260	2.254	2.254
	0.069	0.069	0.099	0.099	0.099	0.099
	(0.031)	(0.031)	(0.044)	(0.044)	(0.044)	(0.044)
<i>Constant</i>	-3.122***	-3.107***	-2.027***	-2.013***	-2.062***	-2.066***
	(0.263)	(0.262)	(0.355)	(0.355)	(0.355)	(0.356)
<i>Observations</i>	86185	86185	49536	49536	49536	49536
<i>Pseudo R-squared</i>	-43379.505	-43346.073	-23041.125	-23037.266	-23026.337	-23027.513

Notes Negative Binomial metric coefficients. The dependent variable is *GP Visits*. Clustered (at household level) and robust standard errors are reported in parentheses. The symbols ***, **, * indicate that coefficients are statistically significant, respectively, at the 1, 5, and 10 percent level.

† Hours worked variable is mean centered. The omitted categories are male, never married, very good health status, wealthier, no chronic diseases, no disabilities, no smoker in all regressions. As for the employment status, the omitted categories are: the not-employed in the overall sample; the employees (columns 3-4) and white and blue-collar employees (columns 5-6) in the sub-sample.

Table 4. Determinants of GP Visits. Negative Binomial Regression estimations (Marginal Effects).

<i>Variables</i>	Sample: Working age population			Sub-sample: Employed		
	(1)	(2)	(3)	(4)	(5)	(6)
<i>Employed</i>	-0.003 (0.004)					
<i>Self-employed</i>		-0.032*** (0.005)	-0.028*** (0.005)	-0.027*** (0.005)	-0.030*** (0.005)	
<i>Employees</i>		0.007 (0.004)				
<i>Hours of work[†]</i>			-0.001*** (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)
<i>Self-employed*Hours of work</i>				-0.001*** (0.000)	-0.001*** (0.000)	
<i>Managers/cadres</i>					-0.029*** (0.008)	
<i>Managers/cadres*Hours of work</i>					-0.002*** (0.001)	
<i>Self-employed/managers/cadres</i>						-0.030*** (0.005)
<i>Self-employed/managers/cadres*Hours of work</i>						-0.001*** (0.000)
<i>Female</i>	0.035*** (0.004)	0.032*** (0.004)	0.032*** (0.005)	0.033*** (0.005)	0.032*** (0.005)	0.033*** (0.005)
<i>Age</i>	-0.002** (0.001)	-0.002** (0.001)	-0.005*** (0.001)	-0.005*** (0.001)	-0.005*** (0.001)	-0.005*** (0.001)
<i>Age Squared</i>	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)
<i>Married</i>	0.017*** (0.006)	0.018*** (0.006)	0.017*** (0.006)	0.017*** (0.006)	0.017*** (0.006)	0.017*** (0.006)
<i>Children (#)</i>	0.021*** (0.006)	0.021*** (0.006)	0.016** (0.007)	0.016** (0.007)	0.017** (0.007)	0.017** (0.007)
<i>Children Squared (#)</i>	-0.009*** (0.003)	-0.009*** (0.002)	-0.006** (0.003)	-0.006** (0.003)	-0.006** (0.003)	-0.006** (0.003)
<i>Education</i>	-0.001* (0.000)	-0.001* (0.000)	-0.002*** (0.001)	-0.002*** (0.001)	-0.001* (0.001)	-0.001* (0.001)
<i>Wealth status 2</i>	0.018* (0.009)	0.016* (0.009)	0.019* (0.011)	0.019* (0.011)	0.018 (0.011)	0.018 (0.011)
<i>Wealth status 3</i>	0.041*** (0.011)	0.038*** (0.011)	0.039*** (0.014)	0.039*** (0.014)	0.036*** (0.014)	0.036*** (0.014)
<i>Wealth status 4</i>	0.046*** (0.016)	0.043*** (0.016)	0.052** (0.021)	0.052** (0.021)	0.049** (0.021)	0.049** (0.021)
<i>Good health</i>	0.058*** (0.006)	0.058*** (0.006)	0.051*** (0.007)	0.051*** (0.007)	0.050*** (0.007)	0.050*** (0.007)
<i>Fair health</i>	0.198*** (0.011)	0.196*** (0.011)	0.180*** (0.013)	0.180*** (0.013)	0.178*** (0.013)	0.179*** (0.013)
<i>Bad health</i>	0.586*** (0.039)	0.581*** (0.039)	0.543*** (0.055)	0.545*** (0.055)	0.536*** (0.054)	0.539*** (0.055)
<i>Very bad health</i>	0.966*** (0.119)	0.965*** (0.120)	0.812*** (0.249)	0.800*** (0.242)	0.782*** (0.237)	0.780*** (0.236)
<i>Chronic diseases</i>	0.103*** (0.004)	0.102*** (0.004)	0.087*** (0.005)	0.087*** (0.005)	0.088*** (0.005)	0.088*** (0.005)
<i>Disability</i>	0.035** (0.014)	0.034** (0.014)	0.002 (0.025)	0.003 (0.025)	0.001 (0.025)	0.001 (0.025)
<i>Smoker</i>	0.002 (0.003)	0.001 (0.003)	0.002 (0.004)	0.001 (0.004)	0.001 (0.004)	0.001 (0.004)

<i>Diagnostic centers</i>	-0.000*	-0.000*	-0.001***	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
<i>GP Density x100,000</i>	0.077*	0.075*	0.015	0.012	0.014	0.013
	(0.043)	(0.043)	(0.050)	(0.049)	(0.049)	(0.049)
<i>Prevention department</i>	0.000	0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
<i>North-East</i>	0.041***	0.041***	0.034***	0.034***	0.034***	0.034***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
<i>Center</i>	0.020***	0.021***	0.018**	0.019**	0.018**	0.018**
	(0.007)	(0.007)	(0.008)	(0.008)	(0.008)	(0.008)
<i>South</i>	0.028***	0.028***	0.017***	0.017***	0.015**	0.016**
	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)	(0.006)
<i>Islands</i>	0.040***	0.040***	0.013	0.014	0.012	0.013
	(0.010)	(0.010)	(0.012)	(0.012)	(0.011)	(0.011)
<i>Observations</i>	86185	86185	49536	49536	49536	49536

Notes: The dependent variable is *GP Visits*. Cluster (at household level) and robust standard errors are reported in parentheses. The symbols ***, **, * indicate that coefficients are statistically significant, respectively, at the 1, 5, and 10 percent level.

† Hours worked variable is mean centered.

Table 5. Determinants of GP Visits. Probit estimates (Marginal Effects).

<i>Variables</i>	<i>Sub-sample: Employed</i>
<i>Self-employed/managers/cadres</i>	-0.024*** (0.003)
<i>Hours of work[‡]</i>	-0.000 (0.000)
<i>Self-employed/managers/cadres*Hours of work</i>	-0.001*** (0.000)
<i>Female</i>	0.022*** (0.003)
<i>Age</i>	-0.004*** (0.001)
<i>Age Squared</i>	0.000*** (0.000)
<i>Married</i>	0.015*** (0.004)
<i>Children (#)</i>	0.010** (0.005)
<i>Children Squared (#)</i>	-0.004* (0.002)
<i>Education</i>	-0.000 (0.000)
<i>Wealth status 2</i>	0.012 (0.008)
<i>Wealth status 3</i>	0.023** (0.009)
<i>Wealth status 4</i>	0.022 (0.013)
<i>Good Health</i>	0.038*** (0.004)
<i>Fair Health</i>	0.115*** (0.007)
<i>Bad Health</i>	0.265*** (0.021)
<i>Very bad Health</i>	0.233*** (0.057)
<i>Chronic diseases</i>	0.062*** (0.003)
<i>Disability</i>	0.005 (0.023)
<i>Smoker</i>	-0.000 (0.003)
<i>Diagnostic centers</i>	-0.000* (0.000)
<i>GP Density x100,000</i>	-0.017 (0.037)
<i>Prevention department</i>	0.000 (0.000)
<i>North-East</i>	0.024*** (0.005)
<i>Center</i>	0.011** (0.005)
<i>South</i>	-0.002 (0.004)
<i>Islands</i>	0.003 (0.008)

<i>Observations</i>	49536
<i>Pseudo R-squared</i>	-18074.604

Notes: The dependent variable is set to 1 if individuals visit the GP at least once, 0 otherwise. Cluster (at household level) and robust standard errors are reported in parentheses. The symbols ***, **, * indicate that coefficients are statistically significant, respectively, at the 1, 5, and 10 percent level.

† Hours worked variable is mean centered.

Table 6 Interaction effect, n=49,536.

		Mean	SE	Z-statistics
Probit	Marginal Effect	-0.001	0.000	-2.88
Ai and Norton procedure	Marginal Effect	-0.001	0.000	-2.51
Linear probability model (LPM)	Coefficient	-0.001	0.000	-2.22 (t-statistic)