Primary Care Utilisation and Workers' Opportunity Costs. Evidence from Italy

De Luca, Giuliana and Ponzo, Michela

Department of Economics and Statistics, University of Calabria (Italy)

2009

Primary Care Utilisation and Workers' Opportunity Costs. Evidence from Italy

Giuliana De Luca, Michela Ponzo*

Working Paper Version
Forthcoming in Empirical Economics Letters, 2010

Abstract: *This paper analyses the effects of employment condition and work hours on the utilisation of primary care services in Italy. Although the Italian NHS provides free and equitable access to primary care, type of occupation and labour contracts may still deter workers to attend medical appointments. The hypothesis is that the higher the workers' opportunity cost in terms of earning forgone, the less the demand for General Practitioner (GP) visits. Using survey data provided by the Italian National Institute of Statistics (ISTAT), we estimate a negative binomial model of GP visits as a function of employment related variables, individual characteristics, supply factors and geographical effects. We find that self-employed workers, managers and cadres have relatively low demand compared to white and blue collars. We conclude that the former, bearing higher opportunity costs, suffer more from the loss of earnings related to the absence from work than the latter.*

Keywords. Opportunity cost, hours of work, utilisation of GP, employment status.
JEL classifications: J20, I10, I18, J21.

* Corresponding author: michela.ponzo@unical.it. Department of Economics and Statistics, University of Calabria (Italy). We gratefully acknowledge award of a fellowship from the Department of Economics and Statistics, University of Calabria. We would like to thank Vincenzo Scoppa, the editor and two anonymous referees for useful comments and suggestions. The usual disclaimers apply.

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 an actual 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; Phelps et al., 1974; Acton, 1975; Grossman, 1982]. For example, it is likely that employees who are entitled to receive sickness subsidy have a lower time price compared to self-employed who are not insured against earning losses. Moreover, other contractual conditions such as performance-related pay mechanisms and promotion systems may carry out additional opportunity costs for taking time off to attend medical appointments. Therefore, the more costly is in terms of earning losses the absence from work due to illness the less likely the recourse to the GP services.

Little evidence exists about this issue compared to the amount of research focusing on individual (demographic, socio-economic characteristics, health status) and system (geographic location, waiting times, supply) determinants of utilisation across different health care systems [Andersen, 1995; Wagstaff et al, 2000; Gravelle et al., 2003; Fernández-Olano et al., 2006]. This abundant strand of literature finds that income is the main determinant of utilisation to private health care systems after controlling for need. However, it does not appear to play a role in publicly founded health care system [Van Doorsaler et al, 2004].

Most of studies focusing on the effect of non-monetary factors investigate the ‘time required’ on the use of primary care services, including travelling, waiting and treatment [Janssen, 1992; Boaz et al., 1989 among others]. By contrast, few studies focus on the ‘value of time’ allocated to obtaining medical care [Wellstood et al., 2006; Fell et al., 2007; Economou et al., 2008]. Rachel et al. (1989) find that retirement increases the number of physician visits compared with full-time self-employed. Among the most recent studies, Fell et al. (2007) show that individuals with long work hours have significantly lower GP utilisation rates compared with full-time workers. Furthermore, white collar workers with long work hours seem to visit a GP significantly less often than white collar workers with regular hours. Economou et al. (2008) find that the unemployed and individuals out of the labour force visit the GP more often and that individuals working overtime exhibit a lower likelihood of attending medical appointments in comparison with their unemployed counterparts.

In this paper we study the effect of employment status and work hours on the demand for GP visits in Italy. The underlying hypothesis is that utilisation (U) depends on health status (H), occupational status (E), work hours (W) and other variables (X): $U = f(H, E, W, X)$. Different types of occupation and the related contractual conditions may lead to different effects on the demand for GP visits made by self-employed and employees.

Specifically, we expect to find that workers who bear higher opportunity costs in terms of earning losses, visit the GP less compared to other categories that are unlikely to lose earnings being fully protected by the sickness security law. Furthermore, we expect that the higher the total number of work hours, the stronger the disutility of visiting the GP suffered from workers who have a greater value of time.

We find that self-employed, managers and cadres (upper white collars), bearing higher opportunity costs, have a relatively low demand for primary care services compared to the white and blue collars. Specifically, self-employed workers, being the “residual claimants” of the produced output, fully internalise the costs of being absent from work. Similarly, managers and cadres response to performance related pay schemes, leads to a reduction in the number of working hours lost in order to minimize their income losses.

The paper is organized as follows. Section 2 presents the ISTAT dataset we use and provides descriptive statistics. In section 3 we undertake empirical verification by estimating different specifications explaining the effects of employment conditions and work hours on the demand of GP visits. Section 4 offers some concluding remarks.

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 the most recent available 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 utilisation. Regional supply-side variables extracted from the "Health for All" dataset provided by ISTAT are also used. We restrict the sample to working-age individuals (aged 15-65). This leaves 86,185 observations used in the first step of the analysis to assess the effect of employment status on the GP utilization. Afterwards, we further restrict the sample to the employed, ending up with a total of 49,536 individuals, to test the hypothesis that a higher opportunity cost of time measured by work hours reduces the demand for primary care services.

The dependent variable is the total count of GP visits occurred in the latest four weeks immediately prior to the interview (Table 1). It is worthwhile to note that, with data at hand, we expect that a higher number of respondents have no utilisation. Mean values of GP visits in the overall sample and in the sub-sample are 0.21 (not shown) and 0.18, respectively. The distribution of the number of visits reveals a large proportion of zeros 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, 1986] and/or temporal dependency.

[INSERT TABLE 1]

The highly skewed nature of the data (Figure 1) makes traditional OLS estimators inappropriate to model medical visits [Cameron et al, 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 [Grossman, 1982; Duan et al., 1983; Cameron et al., 1988] and the agency approaches [Manning et al., 1981; Pohlmeier et al., 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 - even though they did not use primary care during the survey period - or do not use the service at all. As regards the econometric models, the negative binomial (NB) model accounts for the fact that all patients have a positive probability of visiting a doctor. By contrast, the zero-inflated models differentiate between the true no-participants (structural zeros) and potential participants who did not visit the GP during the survey period (sampling zeros). Finally, hurdle models assume that excess of zeros is due to sampling zeros [Mullhay, 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 participants; 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. Notwithstanding some relevant information are lost following this approach, this measure might be more reliable if respondents find it easier to remember if they have consumed primary care services but have difficulties to remember the precise number of time in which they demanded for GP visits.

Formally, the NB regression 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 $x_{\boldsymbol{i}}^{'}$:

$$E\left[v_i \mid x_i, \varepsilon_i\right] = \exp\left(\alpha + x_i^{'}\beta + \varepsilon_i\right) = \lambda_i \delta_i$$

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

The density for δ_i is given by:

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

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

$$\Pr\left[V = v_i \mid x_i^{'}\right] = \frac{\Gamma\left(v_i + \theta\right) r_i^{\theta} \left(1 - r_i\right)^{v_i}}{\Gamma\left(1 + v_i\right)\Gamma\left(\theta\right)}$$

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

The unobservable heterogeneity produces overdispersion while preserving the conditional mean:

$$E\left[v_i \mid x_i^{'}\right] = \lambda_i$$

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

where $k = \left[Var\left(\delta_i\right)\right]$

Maximum likelihood estimation of the parameters is straightforward [Greene, 2008].

The main variable of interest is the employment status (employed versus not-unemployed individuals) that is used in the first step of the analysis. In the second step, we investigate the effect of the total number of work hours per week to measure the opportunity costs of visiting the GP among workers. The total number of the employed workers is 57%. Among them 26% are self-employed and 7% are managers and cadres (Table 2). The average of work hours per week is roughly 40 (SD=12). The percentage of workers who work overtime (>=50 hours) is around 10.

Table 2 presents summary statistics for the whole sample and the sub-sample. Several variables that influence GP visits and may also be associated with variables of interest are used as controls in regressions to limit the omitted variable problem. If workers with different health conditions self-select in different type of occupations and jobs, estimations might be biased. To attenuate this kind of problem, following the existing literature, we 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 wealth[1] and supply side variables. Controlling in particular for health status, age and a measure of wealth, we try to reduce biases deriving from omitted variables problem.

The two samples differ in the proportion of females (lower in the sub-sample (40%) respect to the whole sample (51%)) and in the proportion of smokers (greater in the sub-sample (52%) than in the whole sample (45%)). The population under study is predominantly married[2], aged about 41 years, high school educated[3].

[INSERT TABLE 2]

3. Results

Table 3 shows the main results from six specifications. Columns give the metric coefficients. They are quite stable across all specifications, both in sign and in order of magnitude. Table 4 reports marginal effects. Columns 1-2 of each table report estimates from the whole sample while columns 3-6 show findings from the sub-sample. Standard errors are adjusted for clustering within households. Dummies for each Italian macro geographical areas are also controlled for to account for territorial and environmental effects and other area-specific unobservable factors[4]. 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 (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. For this reason, in Coloumn 2 we separately consider self-employed and employees. It emerges 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).

It is likely that being self-employed workers in positions of personal responsibility, their opportunity costs, in terms of the reduction in earnings due 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 for the employees income losses due to illness are predominantly borne by their employer or by the Social Security system thanks to the sickness security law. By contrast, the not-employed 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 work hours 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 utilisation of GP services (Column 3 in Table 3). For a standard deviation increase in the mean work hours, 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 work hours and the self-employed status to test whether the effect of work hours on utilisation interacts with the type of professional condition (Column 4 in Tables 3 and 4). The negative coefficient 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 Tables 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 work hours 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 Tables 3 and 4). It is estimated that 10 hours increase in time work per week decreases the expected number of visits per month by 1.0%.

The 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 et al, 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 managers and cadres may also be explained through the relatively widespread adoption of performance related pay (PRP) used to raise motivational and effort levels by linking wage or promotions to workers' output. Self-employed workers have similar incentives, since they are the "residual claimants" of the produced output. Under these circumstances, it becomes more costly for this type of workers to be absent from the workplace.

These findings are related to the evidence emerging in an Italian study on workers' absenteeism and incentives showing that contractual arrangements affect worker's behaviour (Scoppa, 2010). In particular, the author finds that self-employed workers, who fully internalise the costs of the absenteeism, tend to be less absent than public and private employees.

In line with the literature, being female and married is associated with higher demand of GP visits. The effect of age is related to the dependent variable through a quadratic patterns showing that as age increases, the expected number of primary care demand rises. The U-shaped patter 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. 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 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. Finally, we find that wealthier individuals make fewer visits to the GP than less wealthy individuals and this is likely due to 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 utilisation across macro geographical areas may reflect differences 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 paper has attempted to investigate the empirical relationship between the opportunity cost of time and the demand for primary care services in Italy.

After controlling for individual characteristics, social-economic variables, health status and supply factors, we find a significant trade-off between time spent in working activities and utilisation of primary care services depending on the type of occupation and related labour contracts. 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). It might be that self-employed workers being the residual claimants of the produced output tend to reduce the number of working hours lost. Similarly, it is likely that individual performance related pay schemes rise work attendance among managers and cadres even thought they are fully insured against sickness losses.

We conclude that in a publicly founded regime, such as Italy, where there exist no financial barriers to the utilisation of primary care, type of occupation and time of work may still affect the demand of GP visits. Paid sick leave and other contractual conditions such as performance-related pay mechanisms and promotion systems are all possible explanations of these findings.

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.

References

Acton, G., 1975, Non-monetary factors in the demand for medical services: some empirical evidence, *Journal of Political Economy*, **83**, 549-614.

Ai, C. and Norton E.C., 2003, Interaction terms in logit and probit models, *Economics Letters*, **80**, 123–129.

Andersen, R.M., 1995, Revisiting the behavioural model and access to medical care: does it matters?, *Journal of Health Socioeconomics Behaviour*, **36**, 1-10.

Becker, G., 1965, A theory of the allocation of time, *Economic Journal,* **75**, 493-517.

Boaz, R. and Muller, C., 1989, Does having more time after retirement change the demand for physician services?, *Medical Care*, **21**, 1-15.

Cameron, A.C., Trivedi, P.K., Milne F. and Piggott J., 1988, A microeconometric model of the demand for health care and health insurance in Australia, *Review of Economic Studies*, **55**, 85-106.

Cameron, A.C. and Trivedi P.K., 1998, *Regression Analysis of Count Data*, Cambridge University Press, Cambridge.

Duan, N., Manning, W.G., Morris, C.N. and Newhouse J.P., 1983, A comparison of alternative models for the demand for medical care, *Journal of Business and Economic Statistics*, **2**, 115-126.

Economou, A., Nikolaou, A. and Theodossiou, I., 2008, Socioeconomic status and healthandcare utilization: a study of the effects of low income, unemployment and hours of work on the demand for health care in the European Union, *Health Services Management Research*, **21**, 40-59.

Fell, B., Kephart, G ., Curtis, J., Bower, K., Muhajarine, N., Reid, R. and Roos, L., 2007, The Relationship between Work Hours and Utilization of General Practitioners in Four Canadian Provinces, *Health Services Research*, **42** , 1483-1498.

Fernández-Olano, C., Hidalgo, R.J., Cerdá-Díaz, R., Requena-Gallego, M., Sánchez-Castaño, C., Urbistondo-Cascales, L., Otero-Puime, A., 2006, Factors associated with health care utilization by the elderly in a public health care system, *Health Policy*, **75**, 131-139.

Gravelle, H., Sutton, M., Morris, S., Windmeijer, F., Leyland, A., Dibben, C. and Muirhead, M., 2003, Modelling supply and demand influences on the use of health care: implications for deriving a needs-based capitation formula, *Health Economics*, **12**, 985-1004.

Greene, W., 2008, Functional forms for the negative binomial model for count data, *Economics Letters*, **99**, 585-590.

Grossman, M., 1982, The demand for health after a decade, *Journal of Health Economics*, **1**, 1-3.

Janssen, R., 1992, Time prices and the demand for GP services, *Social Science & Medicine*, **34**, 725-733.

Manning, W.G., Morris, C.N., Newhouse, J.P. *et al.,* 1981, A two-part model of the demand for medical care: preliminary study from the health insurance study, in *Health, Economics, and Health Economics,* Ed) Sheffler R.M. and Rossiter, L.F., Amsterdam, North-Holland, 103-123.

Mullahy, J., 1986, Specification and testing of some modified count data models, *Journal of Econometrics*, **33**, 341-365.

Mullahy, J., 1997, Heterogeneity, excess zeros, and the structure of count data models, *Journal of Applied Econometrics,* **12**, 337-350.

Phelps, C. and Newhouse, J., 1974) Coinsurance, the price of time and the demand for medical services, *Review of Economic and Statistics*, **56**, 334-342.

Pohlmeier, W. and Ulrich, V., 1995, An econometric model of the two-part decision making process in the demand for health care, *Journal of Human Resources*, **30**, 339-361.

Scoppa, V., 2010, Worker Absenteeism and Incentives: Evidence from Italy, *Managerial and Decision Economics*, forthcoming.

Van Doorslaer, E., Koolman, X. and Jones A.M., 2004, Explaining income-related inequalities in doctor utilisation in Europe, *Health Economics*, **13**, 629-647.

Wagstaff, A. and Van Doorslaer, E., 2000, Equity in health care finance and delivery, in *Handbook of Health Economics*, Eds.) Culyer A.J. and Newhouse J.P., Amsterdam, The Netherlands: Elsevier, 1803-1910.

Wellstood, K., Wilson, K. and Eyles, J., 2006, Reasonable access to primary care: assessing the role of individual and system characteristics, *Health and Place*, **12**, 121-130.

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

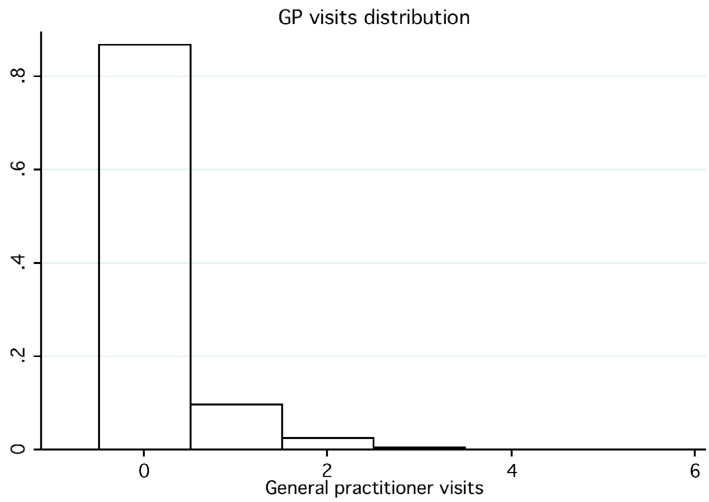

Table 2. Descriptive statistics for the whole sample and for sub-sample of workers.

	N=86,185				n=49,536			
Variables	Mean	Standard Deviation	Min	Max	Mean	Standard Deviation	Min	Max
Dependent variable								
Number of GP visits	0.21	0.64	0	25	0.18	0.56	0	20
Demographic								
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
Socio-economic characteristics								
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
Need								
Very good health	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
Lifestyle								
Smoker	0.45	0.50	0	1	0.52	0.50	0	1
Supply-side								
Diagnostic centers	55.92	15.11	26.72	87.06	56.96	14.81	26.72	87.06
GP Density x100,000	0.82	0.06	0.66	0.94	0.82	0.06	0.66	0.94
Prevention	89.96	15.49	40	100	90.11	15.44	40	100
Geographical effects								
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
Centre	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 Models.

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

Diagnostic centers	-0.002*	-0.002*	-0.004***	-0.004***	-0.004***	-0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
GP Density x *100,000*	0.475*	0.467*	0.102	0.080	0.096	0.089
	(0.267)	(0.267)	(0.338)	(0.337)	(0.338)	(0.338)
Prevention department	0.000	0.000	-0.000	-0.000	-0.000	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
North-East	0.235***	0.238***	0.216***	0.215***	0.216***	0.215***
	(0.036)	(0.036)	(0.045)	(0.045)	(0.045)	(0.045)
Centre	0.122***	0.125***	0.121**	0.122**	0.120**	0.121**
	(0.038)	(0.038)	(0.049)	(0.048)	(0.049)	(0.049)
South	0.165***	0.169***	0.110***	0.110***	0.103**	0.105**
	(0.031)	(0.031)	(0.041)	(0.041)	(0.041)	(0.041)
Islands	0.224***	0.230***	0.088	0.089	0.082	0.084
	(0.053)	(0.053)	(0.073)	(0.073)	(0.073)	(0.073)
Alpha	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)
Constant	-3.122***	-3.107***	-2.027***	-2.013***	-2.062***	-2.066***
	(0.263)	(0.262)	(0.355)	(0.355)	(0.355)	(0.356)
Observations	86185	86185	49536	49536	49536	49536
Pseudo R-squared	-43379.50	-43346.07	-23041.12	-23037.26	-23026.33	-23027.51

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-collars employees (columns 5-6) in the sub-sample.

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

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

	(0.014)	(0.014)	(0.025)	(0.025)	(0.025)	(0.025)
Smoker	0.002	0.001	0.002	0.001	0.001	0.001
	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)
Diagnostic centers	-0.000*	-0.000*	-0.001***	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
GP Density x100,000	0.077*	0.075*	0.015	0.012	0.014	0.013
	(0.043)	(0.043)	(0.050)	(0.049)	(0.049)	(0.049)
Prevention department	0.000	0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
North-East	0.041***	0.041***	0.034***	0.034***	0.034***	0.034***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Centre	0.020***	0.021***	0.018**	0.019**	0.018**	0.018**
	(0.007)	(0.007)	(0.008)	(0.008)	(0.008)	(0.008)
South	0.028***	0.028***	0.017***	0.017***	0.015**	0.016**
	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)	(0.006)
Islands	0.040***	0.040***	0.013	0.014	0.012	0.013
	(0.010)	(0.010)	(0.012)	(0.012)	(0.011)	(0.011)
Observations	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).

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

Observations	49536
Pseudo R-squared	-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)

[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.

[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.