Int J Health Econ Manag (2015) 15:29–51
DOI 10.1007/s10754-014-9157-6

RESEARCH ARTICLE

Have health insurance reforms in Tunisia attained their intended objectives?

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Received: 16 March 2013 / Accepted: 24 November 2014 / Published online: 3 December 2014

Abstract A growing number of developing countries are currently promoting health system reforms with the aim of attaining ‘ universal health coverage’ (UHC). In Tunisia, several reforms have been undertaken over the last two decades to attain UHC with the goals of ensuring *financial protection in health* and *enhancing access to healthcare*. The first of these goals has recently been addressed in a companion paper by Abu-Zaineh et al. (Int J Health Care Financ Econ 13(1):73–93, 2013). The present paper seeks to assess *whether these reforms have in fact enhanced access to healthcare*. The average treatment effects of two insurance schemes, *formal-mandatory* (MHI) and *state-subsidized* (MAS) insurance, on the utilization of outpatient and inpatient healthcare are estimated using *propensity score matching*. Results support the hypothesis that both schemes (MHI and MAS) increase the utilization of healthcare. However, significant variations in the average effect of these schemes are observed across services and areas. For all the matching methods used and compared with those the excluded from cover, the increase in outpatient and inpatient services for the MHI enrollees was at least 19 and 26 %, respectively, in urban areas, while for MAS beneficiaries this increase was even more pronounced (28 and 75 % in the urban areas compared with 27 and 46 % in the rural areas for outpatient and inpatient services, respectively). One important conclusion that emerges is that the current health insurance schemes, despite improving

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accessibility to healthcare services, are nevertheless incapable of achieving *effective coverage* of the whole population for all services. Attaining the latter goal requires a strategy that targets the “trees” not the “forest”.

Keywords Universal health coverage · State-subsidized insurance · Healthcare utilization · Propensity score matching · Developing countries · Tunisia

JEL Classification C31 · C53 · I 12 · I 13 · I 14

Introduction

The goal of ‘universal health coverage’ (UHC) has been pursued for many decades (e.g., WHO’s constitution of 1948 and the Alma-Ata declaration of 1978). Interest in UHC has continued to grow, especially in recent years. At the 2005 World Health Assembly, all WHO Member States adopted a resolution committing themselves to achieving UHC, and a growing number of developing countries are currently promoting healthcare reforms with UHC as an explicit aim (WHO 2010; Giedion et al. 2013). Moreover, it is very likely that UHC will be adopted by the United Nations as one of the main post-2015 development goals (O’Connell et al. 2014). Interestingly, the latest World Health Report (2013) has emphasized the role of ‘research’ in defining and measuring progress towards achieving the UHC goals of ensuring that all people have access to the health services they need and protecting households against the risk of financial hardship linked to paying for care (WHO 2013). This study seeks to address some of the key questions about achieving UHC using the current context of Tunisia, a country characterized by rapid demographic, epidemiological and political transitions coupled with the presence of a large informal sector, structural unemployment and sluggish economic growth (World Bank 2011; NIS 2011). Several health sector reforms have been undertaken in Tunisia over the last two decades with the aims of achieving UHC and reducing the financial burden on the government budget through increased involvement of insurance funds in the financing of health expenditures (Ministry of Public Health 2009; World Bank 2006). Initial attempts to reform health insurance schemes—constituting the so-called ‘large-scale reform’—were undertaken in 1996 (Achour 2011; Arfa and Achouri 2008). This reform intended to improve coverage and accessibility to healthcare mainly through: (i) the implementation of a basic, mandatory, unified insurance scheme (merging several insurance plans covering different professional groups under the Social Security Fund); (ii) extending the benefit package to include services provided by accredited suppliers in the private health delivery sector, and (iii) introducing an optional complementary health insurance scheme managed by mutual health insurance companies (Arfa and Achouri 2008). In addition, special efforts were made to extend coverage through different forms of state-subsidized health insurance schemes—the ‘Medical Assistance Schemes’ (MAS)—embodied in the law n° 91-63 of July 29, 1991 and two decrees endorsed in 1998. Such schemes are typically used by developing countries both to provide healthcare services to the poor and excluded segments of the population, and to protect households from the financial repercussions of illness (Trujillo et al. 2005). A more recent 2004 reform, directly inspired by the French Sickness Fund, mandated the creation of a single agency entitled ‘Caisse Nationale d’Assurance Maladie’ (CNAM). Besides pursuing the implementation of previous reforms and coordinating between all insurance schemes, in late 2007 CNAM introduced new procedures mainly concerning reimbursement mechanisms for healthcare expenditures (details are provided in the following section).

Yet, despite the remarkable progress achieved in expanding the breadth of health coverage, a recent report (Ministry of Social Affairs 2012) indicates that, in practice, a significant proportion of the active population remains uncovered. In addition, a recent study (Arfa et al. 2008) indicates that the Tunisian healthcare system is still largely funded through private sources (where direct out-of-pocket payments alone represent approximately 48.1 % of the total health expenditure). In general (WHO 2010; Nishtar 2010) and in the specific case of Tunisia (Abu-Zaineh et al. 2014), out-of-pocket payments have been shown to compromise equity in healthcare delivery and to induce the risk of 'catastrophic' and 'impoverishing' effects on households' standards of living (Abu-Zaineh et al. 2013). As elsewhere, ensuring access to healthcare in Tunisia has become a major issue, especially, following the implementation of the structural adjustment programs in the 1990s which resulted in a shift in the structure of the healthcare financing-mix from public to private sources. The extent to which the Tunisian health system has succeeded in protecting people against the financial consequences of ill-health has been addressed in a companion paper (Abu-Zaineh et al. 2013). To date however, no empirical evidence exists about *whether or not the current insurance schemes have achieved their intended objectives in terms of enhancing access to healthcare services in Tunisia*. Furthermore, empirical studies undertaken elsewhere to evaluate the impact of similar schemes have provided somewhat mixed evidence (Acharya et al. 2012).

This study, therefore, attempts to provide policy-makers with some insights into the impact of the current health insurance coverage strategy (consisting of two main insurance schemes: formal mandatory health insurance (MHI) and the state-subsidized medical assistance scheme (MAS)) on the utilization of two types of healthcare: outpatient and inpatient care. In the absence of experimental data, the net effect of either health insurance scheme on the utilization of healthcare is typically approximated using the cross-sectional propensity score matching (PSM) approach (Rubin 1974; Rosenbaum and Rubin 1983). This allows the scheme effect to be estimated by comparing the observed characteristics of insured (treated) and uninsured (control) groups while controlling for different types of selection biases arising from unobserved characteristics (Sianesi 2004). The PSM approach has gained great popularity and is widely applied as an evaluation tool for the impact of different social programs (Sianesi 2004). It has also been employed to assess the impact of specific health insurance schemes on access to, and utilization of, healthcare (e.g., Robyn et al. 2012; Thanh et al. 2010; Koch and Alaba 2010; Gnawali et al. 2009; Wagstaff and Yu 2007; Trujillo et al. 2005). However, the main added-value of this paper, when compared with previous research (e.g., Trujillo et al. 2005), is that it conducts PSM separately, comparing three groups belonging to the same population but distinguished from one another according to their health insurance status as follows: formal insurance enrollees, state-subsidized beneficiaries, and those excluded from any health insurance coverage. The study makes use of nationally representative data taken from the Tunisian HealthCare Utilization and Morbidity Survey (THCUMS-2007). The paper is organized as follows. "Institutional background: the Tunisian National Health Insurance System" section presents the main institutional characteristics of the current health insurance system. "Empirical strategy" section presents the methodology and the data used in the econometric analysis. "Empirical findings" and "Discussion" sections present and discuss the study results. The paper concludes with some recommendations in "Conclusion" section.

Institutional background: the Tunisian National Health Insurance System

Since its establishment in 1951, the Tunisian health insurance system has undergone several reforms and expansions. The country's main health insurance scheme is the formal

MHI—currently run by the National Health Insurance Fund (CNAM). The MHI covers two categories of the population based on their professional status (public and private sector employees and self-employed workers) (World Bank 2006; Arfa and Elgazzar 2013). Those ineligible for the MHI scheme are, in principle, entitled to the state-subsidized health scheme, MAS, which is a *means-tested benefit*. MAS comprises two schemes: (i) the "Free Medical Cards" scheme whereby eligible households, defined according to the local official poverty line, are exempted from healthcare fees, and (ii) the 'Reduced-Fee Plan' whereby eligible populations (defined as those receiving the official minimum wage rate), receive care at greatly reduced fees. In both MAS schemes, regional quotas are applied to determine the number of beneficiaries. Furthermore, both MAS schemes are publicly funded and managed by the Ministry of Social Affairs. They offer beneficiaries access to public sector healthcare services.

In terms of coverage, the Tunisian HealthCare Utilization and Morbidity Survey (THCUMS-2007) indicated that about 22 % of the population benefit from MAS while about 66 % are covered by MHI. Accordingly, about 12 % of the population remains without any health insurance coverage either because they work in the informal sector or are unemployed (National Institute of Public Health 2008). This indicates that a significant number of low-income households remain excluded from the MAS subsidized regime. Additional coverage by complementary private insurance schemes (e.g., *mutuelle de santé* or *assurance groupe*), which have developed in recent years, remains limited to those who can afford the relatively high *risk-adjusted premia* (about 9 % of the total population) (Abu-Zaineh et al. 2013).

The latest reform undertaken by the CNAM (initially founded in 2004), introduced new directives (effective since late 2007) under which MHI enrollees (except formal enrollees affiliated under a special regime implemented in 2002 to cover low-income workers) are offered two options: the 'single-provider scheme' and the 'two-sector (or reimbursement) scheme'. In the former, beneficiaries must choose care delivered either by public or private sector health facilities. Incentives to choose the public single-provider scheme include, among other things, direct access to all public services and a cap on the required annual co-payments (representing approximately one and half month of patients' salaries) above which additional costs are borne by the CNAM. By contrast, for the private single-provider scheme, service cost containment mechanisms are imposed whereby beneficiaries (about 10.2 % of the total MHI enrollees in 2010) are required to choose a general practitioner who serves as a gatekeeper to specialist care services. Furthermore, co-payments and fees are higher (although CNAM-regulated) than those paid under the public sector single-provider scheme. In the second option, entitled the *two-sector (or reimbursement) scheme*, beneficiaries (approximately 14 % of the total MHI enrollees in 2010) can obtain care from any public or private provider. However, with this option, they are required to first pay the full regulated-tariff of the care service provided at the point of consumption, and then request reimbursement from the CNAM (NHIF 2012; decree n° 2007-1367 of June 11, 2007). It should be noted that although the latest reform undertaken by the CNAM did not change the eligibility enrollment criteria in MHI (i.e. declaring to exercise a professional activity), MHI coverage increased by 16 % between 2008 and 2011 mainly due to the expansion of eligible groups (NHIF 2012; Ministry of Social Affairs 2012). More detailed information on the characteristics of the Tunisian Healthcare system is provided in a companion paper (Abu-Zaineh et al. 2013).

Empirical strategy

Specification of the propensity score function

Given that subscription to the formal MHI in Tunisia is only possible for the those working in the formal sector, while others are either entitled to the state-subsidized scheme (MAS) or excluded, direct assessment of the *expected effect* of the insurance scheme (i.e. *the average treatment*) on the outcome variable of interest (in our case utilization of healthcare) is not possible due to the *selection problems* potentially present in cross-sectional non-experimental data. This difficulty may arise from the fact that the utilization of healthcare is not only determined by insurance coverage, but also by other observable and non-observable individual characteristics (Bonjour et al. 2002). One way to overcome such a measurement problem is to use the Propensity Score Matching (PSM) approach, which was first introduced by Rubin (1974), and then elaborated by Rosenbaum and Rubin (1983) to study the efficiency of treatments on patients. The *average treatment effect* (ATE) on those treated can therefore be regarded as the *counterfactual effect*; i.e., the level of healthcare utilization that would have been used by an insured individual had s/he not had any insurance coverage.

PSM enables the comparison of those treated (participants) with those controlled (non-participants), while controlling for their observable characteristics (Bonjour et al. 2002; Burtless 1995; Heckman et al. 1999). The Propensity Score (PS) is defined as the conditional probability that an individual is treated, given a set of individual observable characteristics (Caliendo and Kopeinig 2008). Since PS is a conditional probability in the comparator (i.e., the non-covered group, also called the control group or the non-treated group), its value ranges between 0 and 1 for all the values of propensity scores in the covered group (treated), so $0 < \Pr(Y = 1|X) < 1$. The characteristics observed for each individual can be simplified to a single PS (Caliendo and Kopeinig 2008) and computed as follows (Rosenbaum and Rubin 1985):

$$e(X) = \Pr\left(Y = \frac{1}{X}\right) = E\left(Y\,|X\right) \tag{1}$$

where X is a vector of observed covariates for a given individual, and Y is a dependent binary variable taking the value of 1 if the individual is insured over a given period of time, and zero otherwise. Accordingly, both insured and uninsured individuals with the same probability of treatment have the same distribution of X. Formally X and Y are conditionally independent given $e(X)$ (Robyn et al. 2012; Rosenbaum and Rubin 1985).

The matching focuses on the observable similar characteristics between the group benefiting from the program and the group excluded from it. Basically, for every individual in the insured group the PSM approach identifies an uninsured individual who is in some way similar. The uninsured individual becomes the *counterfactual* of the insured individual. If we consider that insured and uninsured individuals with similar propensity scores are the individuals with the most similar observable characteristics, the PSM approach can be considered *a quasi-experimental approach* (Bonjour et al. 2002). This similarity between the propensity scores allows us to estimate the *net effect* of health insurance on the decision to use healthcare services on the one hand, and on the other hand, to isolate the *systematic effect* of the individual characteristics (Bonjour et al. 2002). By then comparing the average effect on healthcare utilization of the treated group with the average effect of the non-treated *matched* group, an estimation of the health insurance scheme effect on healthcare utilization (i.e., the ATE) can be obtained (Rosenbaum and Rubin 1983).

We used the PSM approach to obtain three comparable (matched and homogenous) groups from the same data. We separately computed three PSM, isolating in each case two matched groups to compare: (i) the MHI enrollees with the excluded (control group); (ii) the MAS beneficiaries with the excluded (control group), and (iii) the beneficiaries of MAS with the MHI enrollees (control group). The latter allowed the comparison of the ATE of the 'free' insurance scheme with that of the formal MHI scheme.

Healthcare utilization estimates

In the present study, utilization of healthcare was measured by the number of physical units of two types of services: (i) outpatient care was defined as the total number of consultations/visits to a health facility during the previous 3 months, and (ii) inpatient care was defined as the number of days of hospitalization during the previous 12 months. As mentioned above, in Tunisia, enrollment in the MHI is mandatory for individuals exercising a declared professional activity while eligibility for MAS is determined according to whether the individual is earning the minimum wage rate and the local poverty line. This helps minimize self-selection bias but not the heterogeneity between the insured and uninsured groups. In line with other studies (e.g., Robyn et al. 2012; Gnawali et al. 2009) a set of individual, household and community characteristics were taken into account to compare the insured and uninsured groups. Individual characteristics included age, gender, marital status, income, educational level, employment, and health status. Given that enrollment in the current insurance schemes occurs at the household level (i.e., all household members are covered), a set of household characteristics (including household size, type of housing, health expenditure, number of rooms, car possession, personal computer possession, internet availability) were included in the analysis. Accessibility to healthcare services can also be affected by other factors, such as availability of healthcare infrastructure. Using the available data, two specific community characteristics (place of residence: urban vs. rural and distance in km to the nearest healthcare center) were included in the analysis to capture geographical accessibility (detailed descriptive statistics on these variables are provided in Table 1).

Two types of variables derived from self-reported health status (SRH) and the presence of an illness episode (IE) were employed to control for individual's health status. Given the multidimensionality of health, simple self-reported measures of health may not fully capture the complex character of an individual's health status and there is some evidence (Benyamini 2008; Abu-Zaineh et al. 2009) that in comparison with diagnostics and objective measures of health, such self-reported measures do not fully reflect the direct utilization of healthcare. This independence is quite necessary, given that our main dependent variable is healthcare utilization. Descriptive statistics on the distribution of the two measures of health status in pre- and post-matching are reported in Table 4.

Analysis involved several steps. First, we assumed that there were inherent differences—unobservable characteristics—between both groups (i.e., the treated and control groups). These unobservable characteristics are difficult to measure so we further assumed that the observable characteristics captured all the differences—observable and unobservable—between both groups. Moreover we assumed that these differences determine an individual's decision to use healthcare services or not (Caliendo and Kopeinig 2008). This implies that the estimated probability of an individual benefiting from health insurance coverage makes the characteristics of both groups homogeneous. The propensity scores are then estimated in our case for the above three matching using three dichotomous models. The PS can be estimated by a probit or logit model (Robyn et al. 2012). For the case of a *unique treatment* (such as health coverage), probit or logit model provide similar results, and thus the choice

Table 1 Descriptive statistics for three separate matching

Groups of three separate matching		Matching I		Matching II		Matching III	
		MHI vs. excluded		MAS vs. excluded		MAS vs. MHI	
		Treatment 1 (MHI) n = 3,513	Control (Excluded) n = 732	Treatment 2 (MAS) n = 1,736	Control (Excluded) n = 732	Treatment 3 (MAS) n = 1,736	Control (MHI) n = 3,513
Outcome variables	Definition	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)
Outpatient care	= number of consultations during last three months	0.717 (1.391)	0.483 (1.001)	0.741 (1.341)	0.483 (1.001)	0.741 (1.341)	0.717 (1.391)
Inpatient care	= number of days hospitalisation during the last 12 months	0.609 (3.700)	0.367 (2.853)	1.119 (6.912)	0.367 (2.853)	1.119 (6.912)	0.609 (3.700)
Household head's characteristics							
Male	= 1 if male, 0 if female	0.454 (0.498)	0.405 (0.491)	0.370 (0.483)	.405 (0.491)	0.370 (0.483)	0.454 (0.498)
Age group (35–70)	= individual's age (in years)	49.228 (9.551)	48.854 (9.682)	50.747 (9.996)	48.854 (9.682)	50.747 (9.996)	49.228 (9.551)
Married	= 1 if married, 0 otherwise	0.906 (0.291)	0.826 (0.378)	0.828 (0.377)	0.826 (0.378)	0.828 (.377)	0.906 (.291)
Self reported health status: SRH and IE (are reported in Table 4 pre and post matching)							
Income	= average monthly income (in DT)	433.927 (371.238)	347.474 (322.872)	191.994 (160.011)	347.474 (322.872)	191.994 (160.011)	433.927 (371.238)

Table 1 continued

Groups of three separate matching		Matching I		Matching II		Matching III	
		MHI vs. excluded		MAS vs. excluded		MAS vs. MHI	
		Treatment 1 (MHI) n = 3,513	Control (Excluded) n = 732	Treatment 2 (MAS) n = 1,736	Control (Excluded) n = 732	Treatment 3 (MAS) n = 1,736	Control (MHI) n = 3,513
Outcome variables	Definition	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)
Education							
Higher education	= 1 higher education, 0 otherwise	0.100 (0.301)	0.053 (0.224)	0.007 (0.086)	0.053 (0.224)	0.007 (0.086)	0.100 (0.301)
Secondary	= 1 college school, 0 otherwise	0.229 (0.420)	0.153 (0.360)	0.066 (0.249)	0.153 (0.360)	0.066 (0.249)	0.229 (0.420)
Elementary	= 1 primary school, 0 otherwise	0.376 (0.484)	0.372 (0.483)	0.338 (0.473)	0.372 (0.483)	0.338 (0.473)	0.376 (0.484)
Illiterate	= 1 no schooling, 0 otherwise	0.292 (0.455)	0.420 (0.494)	0.586 (0.492)	0.420 (0.494)	0.586 (0.492)	0.292 (0.455)
		Mean (SE)	Mean (SE)	Mean (SE)	Mean (SE)	Mean (SE)	Mean (SE)
Employment[a]	= 1 working more than 3 days per week, 0 otherwise	0.509 (0.499)	0.406 (0.491)	0.307(0.461)	0.406 (0.491)	0.307 (0.461)	0.509 (0.499)
	= 1 working at least 1 day per week, 0 otherwise	0.513 (0.499)	0.420 (0.494)	0.316 (0.465)	0.420 (0.494)	0.316 (0.465)	0.513 (0.499)

Table 1 continued

Groups of three separate matching		Matching I		Matching II		Matching III	
		MHI vs. excluded		MAS vs. excluded		MAS vs. MHI	
		Treatment 1 (MHI) n = 3,513	Control (Excluded) n = 732	Treatment 2 (MAS) n = 1,736	Control (Excluded) n = 732	Treatment 3 (MAS) n = 1,736	Control (MHI) n = 3,513
Outcome variables	Definition	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)
Household characteristics							
Household size	= number of household members	5.400 (2.020)	5.260 (2.286)	5.720 (2.337)	5.260 (2.286)	5.720 (2.337)	5.400 (2.020)
Healthcare expenditures	= Household monthly mean	23.118 (39.279)	25.058 (40.630)	13.853 (24.940)	25.058(40.630)	13.853 (24.940)	23.118 (39.279)
House							
Traditional house	= 1 living in Traditional house, 0 otherwise	0.522 (0.499)	0.625 (0.484)	0.868 (0.338)	0.625 (0.484)	0.868 (0.338)	0.522 (0.499)
Villa	= 1 living in villa, 0 otherwise	0.423 (0.494)	0.326 (0.469)	0.116 (0.320)	0.326 (0.469)	0.116 (0.320)	0.423 (0.494)
Apartment	= 1 living in Apartment, 0 otherwise	0.048 (0.215)	0.038 (0.191)	0.006 (0.079)	0.038 (0.191)	0.006 (0.079)	0.048 (0.215)
Rudimentary house	= 1 living in Rudiment. house, 0 otherwise	0.003 (0.058)	0.006 (0.082)	0.007 (0.086)	0.006 (0.082)	0.007 (0.086)	0.003 (0.058)
Rooms	= number of rooms	3.22 (1.123)	2.998 (1.223)	2.556 (1.029)	2.998 (1.223)	2.556 (1.029)	3.225 (1.123)

Table 1 continued

Groups of three separate matching		Matching I		Matching II		Matching III	
		MHI vs. excluded		MAS vs. excluded		MAS vs. MHI	
		Treatment 1 (MHI) n = 3,513	Control (Excluded) n = 732	Treatment 2 (MAS) n = 1,736	Control (Excluded) n = 732	Treatment 3 (MAS) n = 1,736	Control (MHI) n = 3,513
Outcome variables	Definition	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)
Car	= 1 having a car, 0 otherwise	0.258 (.438)	0.233 (0.423)	0.074 (0.263)	0.233 (0.423)	0.074 (0.263)	0.258 (0.438)
Internet connection	= 1 having internet, 0 otherwise	0.046 (0.211)	0.017 (0.132)	0.005 (0.075)	0.017 (0.132)	0.005 (0.075)	0.046 (0.211)
Personal Computer	= 1 having PC, 0 otherwise	0.138 (0.345)	0.079 (0.270)	0.012 (0.109)	0.079 (0.270)	0.012 (0.109)	0.138 (0.345)
Community characteristics							
Urban	= 1 living in urban area, 0 Rural	0.642 (0.479)	0.502 (0.500)	0.331 (0.470)	0.502 (0.500)	0.331 (0.470)	0.642 (0.479)
Distance from healthcare center	= distance in km	4.268 (10.871)	8.409 (22.654)	4.585 (13.145)	8.409 (22.654)	4.585 (13.145)	4.268 (10.871)

Heterogeneous sample: Sample size = 6,538 households head composed from pure MHI (n = 3,513) + pure MAS (n = 1,736) + pure excluded (n = 732) + heterogeneous group of MAS and MHI at the same time dropped (n = 429) + missing relevant information deleted (n = 128).

[a] MAS and excluded employment: Number of MAS working > 3 days per week = n = 526; number of MAS working 1 day at least per week = n = 550

Number of excluded working > 3 days per week = n = 291; number of excluded working 1 day at least per week = n = 308 between both models is not critical (Bryson et al. 2002). Like others (Gregg and Wadsworth 1996; White et al. 1997; Bonjour et al. 2002; Dorsett 2004), we estimated a multivariate logit model to examine the characteristics associated with each matching.

By matching the PS of two homogeneous groups, the common support region can be estimated. In order to estimate the probability of observing two units with exactly the same PS value, various methods have been proposed in the literature (Becker and Ichino 2002). The most widely used are the Nearest Neighbor, Radius, Kernel and Stratification Matching methods. The quality of the matches of each of these can be improved by imposing a *common support restriction* (Becker and Ichino 2002). Given that no one of these methods is superior to another, we use all four to assess the sensitivity of our results by estimating the lower and upper bounds of the ATE. Insured individuals with extreme values of propensity scores were eliminated to avoid misrepresentation of the distribution. Three separate matchings provided us with three comparable groups—MHI enrollees, MAS beneficiaries and those excluded. Accordingly, we were able to estimate the effect of both MHI and MAS schemes on healthcare utilization. All statistical analyses were conducted using STATA 12.1 and algorithms elaborated by Leuven and Sianesi (2003) and Caliendo and Kopeinig (2008).

Data description and computation procedures

This study is based on the Tunisian HealthCare Utilization and Morbidity Survey (THCUMS-2007) conducted by the Tunisian National Institute of Public Health between June 2005 and April 2007. The survey was carried out on a random national sample and included all members aged between 35 and 70 years of 6,538 households. It provides detailed information on healthcare utilization, expenditure and health status for the country's seven regions. Data were weighted to compensate for missing cases and to ensure the representativeness of the sample as per the 2004 Tunisian Population Census.

For the purpose of this analysis three heterogeneous groups were constructed in the pre-matching phase: (i) MHI enrollees; (ii) beneficiaries of the state-subsidized MAS scheme, and (iii) excluded households without any health coverage. The separate matchings were made for three treatment variables: Treatment I for MHI vs. Excluded (control group); Treatment II for MAS vs. Excluded (control group), and Treatment III for MAS vs. MHI (control group). In the matching phase of analysis three homogeneous groups were constructed and compared using a common set of covariate variables. After the matching phase, the outcome variables - outpatient and inpatient care—were included in the estimates of healthcare use equations. This allowed us to estimate the ATE for each matching. Table 1 provides detailed descriptive statistics of the common and outcome variables used in the analysis for the three separate matchings.

Table 1 also provides descriptive statistics about informal work and the pre-matching heterogeneous groups consisting of MHI and MAS beneficiaries, as well as those excluded. It is worth noting that the total number of households belonging to these three groups (6967 observations) is greater than our total population consisting of 6538 observations. This indicates that our groups were not mutually exclusive. For instance, of those who were reported to benefit from MAS, approximately 19.81 % [= 429/(429 + 1,736)] were also found to be affiliated to MHI. To ensure the construction of mutually exclusive groups, it was necessary to filter the two heterogeneous groups. Table 1 presents the number of pure treated and control pre-matching groups for each treatment. Table 1 also highlights that approximately 11.19 % [= 732/6538] of the interviewed Tunisian households were not covered by either of the above schemes.

Empirical findings

Probabilities of enrolment

Results based on the logistic regression analysis and computed separately for each matching are presented in Table 2. Results for Matching I (MHI vs. excluded) reveal the characteristics

Table 2 Statistics of the logistic regression for the three separate matching

Variables	Treatment = 1	Matching I	Matching II	Matching III
		MHI vs. excluded	MAS vs. excluded	MAS vs. MHI
		Coefficient (SE)	Coefficient (SE)	Coefficient (SE)
Household head's characteristics				
Male		−0.187 (0.139)	0.178 (0.144)	0.298 (0.108)**
Age group (35–70)		0.015 (0.005)**	0.012 (0.005)**	−0.004 (0.004)
Married		0.605 (0.127)***	−0.003 (0.140)	−0.498 (0.109)***
Self reported health status	IE	0.268 (0.121)**	0.250 (0.132)**	−0.040 (0.098)
	SRH	0.017 (0.089)	0.126 (0.102)	0.093 (0.072)
Income		0.000 (0.000)	−0.002 (0.000)***	−0.003 (0.000)***
Education (b)				
Secondary		−0.104 (0.225)	−0.015 (0.431)	−0.423 (0.125)**
Elementary		−0.419 (0.223)*	0.340 (0.412)	(a)
Illiterate		−0.784 (0.234)**	0.460 (0.416)	0.486 (0.084)***
Employment		0.399 (0.139)**	−0.269 (0.144)*	−0.560 (0.108)***
Household characteristics				
Household size		0.027 (0.022)	0.157 (0.025)***	0.122 (0.017)***
Healthcare expenditures		−0.002 (0.001)**	−0.006 (0.001)***	−0.004 (0.001)**
House				
Traditional house		1.307 (0.948)	0.669 (0.996)	−1.037 (1.117)
Villa		1.394 (0.950)	0.075 (1.000)	−1.721 (1.119)
Apartment		1.243 (0.971)	−0.490 (1.071)	−1.891 (1.163)
Rudimentary house		1.206 (1.097)	0.224 (1.129)	−1.469 (1.194)
Car		−0.283 (0.115)**	−0.528 (0.156)**	−0.184 (0.120)
Rooms		0.104 (0.044)**	−0.155 (0.050)**	(a)
PC		−0.004 (0.182)	−0.723 (0.332)**	−0.931 (0.263)***
Internet connection		0.678 (0.340)**	0.559 (0.642)	−0.262 (0.408)
Community characteristics				
Urban		0.330 (0.094)***	(a)	−0.498 (0.074)***
Distance from health center		−0.015 (0.002)***	(a)	0.004 (0.003)
Constant		−1.679 (1.015)	−0.576 (1.134)	2.446 (1.140)
LR Chi square		231.84***	434.20***	1630.32***
Pseudo R2		0.0619	0.1476	0.2497
N		4118	2427	5130

*** Significant at $p < 0.001$, ** at $p < 0.05$, * at $p < 0.10$. The propensity score function included the same set of variables for the three matching. (a) For the specific matching, variable not included in PSM Function because not balanced. (b) Reference group: Higher education of those excluded (uninsured) individuals who would have had a greater probability of being covered by MHI. Among these characteristics were: marital status (being married), education level (having a higher educational level), health status (having poor health), housing (having many rooms, internet) and place of residence (living in an urban area). Interestingly, when adjusting for these characteristics, employment status (being employed) appeared to be significantly ($p < 0.05$) related to the probability of being an MHI enrollee. Unfortunately, we did not have direct information on the type of professional activity exercised by these individuals. However, since these employed individuals were uninsured there are reasons to think that they were working in the informal sector.

Turning to the characteristics of those excluded, who were more likely to benefit from MAS, results on Matching II indicate that those individuals tended to have a low level of income, lived in a house with fewer rooms and no computer, had larger family sizes, and had poor health. Controlling for household wealth and all these aforementioned characteristics, it appeared less likely that employed individuals benefitted from MAS. This is logical given the rules of entitlement to this scheme, which are based on the local poverty line and the minimum wage rate. Thus, results suggest that among the uninsured, the individuals who were employed were more likely to be enrolled in the MHI and less likely to benefit from MAS. Results from Matching III highlight the characteristics of MHI enrollees who were more likely to benefit from MAS: males, those with larger family sizes, those with low levels of education, of income and wealth, and those living in rural areas. After controlling for all these characteristics, unemployment status emerged, once again, as a significant factor of MHI enrollees' entitlement to MAS ($p < 0.001$).

Propensity scores estimation

Table 3 summarizes the main characteristics of the estimated propensity score functions (e(x)) for each matching. It is interesting to note first that the test of balancing is almost satisfied at a high significance level ($p < 0.001$). In effect, we were able to calibrate, for all three matchings, the function e(x), until the balancing property was satisfied for a significance level of $p < 0.001$. The mean of each estimated function varied from 0.667 to 0.831 for the three matchings. The regions of common support (i.e., the similar propensity scores) between the treated and control groups were high, ranging from 84.9 % for Matching I (MHI vs. excluded) to 87.3 % for Matching II (MAS vs. excluded) and 89.7 % for Matching III (MAS vs. MHI). Given the size of the available data, we were able to compute at least 8 blocks for Matching I, 10 for Matching II and 9 for Matching III. This ensured the minimum number of blocks that satisfied the balancing property and the same mean of PS for treated and control groups in each block. For each of the three matchings, the propensity score function was estimated using the same variables. These variables captured the main factors (e.g., individual, household, and community characteristics) which influenced the individual's probability of being covered by the scheme. A complete list of the variables is provided in Table 3.

Health status amongst treated and controls

The self-reported health status measures reported in Table 4 provide some insights into the effect of health insurance status on healthcare utilization controlling for individual health status among treated and control groups. With the exception of the non-significant differences in post-matching I (MHI enrollees vs. the excluded), all differences in the post-matching means of self-reported health status (SRH) were significant: MAS beneficiaries appeared

Table 3 Propensity score matching function e(x)

	Matching I		Matching II (b)		Matching III (c)	
	MHI vs. excluded		MAS vs. excluded		MAS vs. MHI	
	Treatment 1 (MHI)		Treatment 2 (MAS)		Treatment 3 (MAS)	
Region of common support	[0.1316, 0.9804]		[0.0837, 0.9568]		[0.0041, 0.9011]	
Mean	0.8314		0.7163		0.3475	
Std. Deviation	0.0872		0.1746		0.2447	
Significance of balancing	0.001		0.001		0.001	
Number of blocks	8		10		10	
Observations per-block (a)	Excluded	MHI	Excluded	MAS	MHI	MAS
	1	2	8	2	663	20
	2	2	31	6	375	29
	13	3	48	16	589	103
	32	28	48	19	414	118
	67	150	54	63	340	205
	210	645	85	83	333	243
	307	1,818	104	187	253	316
	60	771	152	535	174	346
			138	720	89	266
			8	81	11	63

For each matching: the propensity score function included the following variables: treatment, Male, Age, Married, Self reported health status, Income, Higher education, Secondary, Elementary, Illiterate, Employment, Household size, Health Expenditures, Traditional House, Villa, Apartment, Rudimentary house, Car, Rooms, PC, Internet, Urban, Distance from healthcare center. (a) Number of blocks ensures that the mean propensity score is not different for treated and controls in each block. (b) For matching II variables Distance from healthcare center and Urban were not included in PSM Function because not balanced. (c) For matching III, variables Elementary and Rooms were not included in PSM Function because not balanced

to report better SRH compared with both excluded (a significant difference of 0.071 at $p < 0.001$) and MHI enrollees (a significant difference of 0.064 at $p < 0.001$), although these beneficiaries appeared to have more episodes of illness (EI) when compared with those excluded (a significant difference of 0.032 at $p < 0.10$) but not with MHI enrollees (a non-significant difference).

Although significant differences in the means of health between the MAS beneficiaries and those excluded were identified, comparisons with the means of health of the MHI enrollees may reflect reporting bias. Indeed, SRH has been shown (Van Doorslaer and Jones 2003; Subramanian et al. 2009) to be rather less informative in the context of developing countries and may even reflect the opposite socio-economic gradient (i.e. the poor reporting better health status than the better off). Reporting bias may be due to 'peer effect' and/or 'constrained access' (Sen 2002; Abu-Zaineh et al. 2011). This is reflected in our self-reported measures, where the economically 'worse-off' MAS beneficiaries reported better SRH compared with the 'better-off' MHI enrollees but not with those excluded, who we expected to be even more economically worse-off. However, it is important to note that the higher healthcare utilization of MAS beneficiaries (reported in Table 1) compared with MHI enrollees may reflect greater medical needs of the former group despite their higher SRH.

Table 4 Distribution of illness by matching groups

Groups of matching		Matching I		Matching II		Matching III	
		MHI vs. excluded		MAS vs. excluded		MAS vs. MHI	
		Treatment1 (MHI) n = 3,513	Control (Excluded) n = 732	Treatment 2 (MAS) n = 1,736	Control (Excluded) n = 732	Treatment 3 (MAS) n = 1,736	Control (MHI) n = 3,513
		Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)
Self reported health status							
Variables	*Definition*	*Pre-matching*					
SRH	= 1 if self-reported health status is excellent or very good or good, 0 otherwise	0.396 (0.489)	0.397 (0.489)	0.461 (0.498)	0.397 (0.489)	0.461 (0.498)	0.396 (0.489)
		Difference = −0.001		Difference = 0.064**		Difference = 0.065***	
IE	= 1 if no illness episode during last 15 days, 0 otherwise	0. 802 (0. 397)	0. 819 (0. 384)	0. 785 (0.410)	0. 819 (0. 384)	0. 785 (0. 410)	0. 802 (0. 397)
		Difference = −0.017		Difference = −0.034*		Difference = −0.017	
Post-matching							
SRH		0.396 (0.489)	0.402 (0.490)	0.462 (0.498)	0.391 (0.488)	0.463 (0.498)	0.399 (.489)
		Difference = −0.006		Difference = 0.071***		Difference = 0.064***	
IE		0. 801 (0. 399)	0. 821 (0. 383)	0. 786 (0.410)	0. 818 (0.385)	0. 785 (0. 410)	0.800 (0. 400)
		Difference = −0.02		Difference = −0.032*		Difference = −0.015	

*** Significant at $p < 0.001$, ** at $p < 0.05$, * at $p < 0.10$

Healthcare utilization given health coverage

The ATE of the two health insurance schemes (MHI and MAS) is presented in Table 5 for the two types of care under consideration (outpatient vs. inpatient). Estimates of ATE are presented separately for the urban and rural areas based on four different PSM methods. In addition, the bootstrapped standard errors are reported in parentheses. The statistically significant estimates of the lower and upper bounds of the insurance scheme effect are reported in the last row of each panel.

As can be seen, the four matching methods exhibit fairly similar trends for each of the three matching groups. However, with the exception of Matching III (MAS vs. MHI), there are significant variations in the estimates of the ATE between urban and rural areas. For Matching I (MHI vs. excluded), the ATE of the MHI appears to be more pronounced in the urban areas especially in the case of inpatient care. For instance, given illness amongst the MHI enrollees, the increases in outpatient and inpatient care range from 18.8 to 21.4 % point and from 25.8 to 38 % point, respectively, compared with a significant increase in outpatient of about 15 % point in the rural areas and no significant increase in inpatient care.

The differences in the ATE are even more noticeable in the case of Matching II (MAS vs. excluded) with the gains always significantly higher in urban areas compared with rural areas, and for inpatient compared with outpatient care, regardless of the matching method used. As shown in the fourth column of Table 5, the ATE in urban areas varied from 28.3 to 39.0 % points percentage points and from 75.1 to 86.1 % points for outpatient and inpatient care, respectively, while in the rural areas it ranged from 27.5 to 29.0 % points for outpatient care and from 46.5 to 73.8 % points for inpatient care.

Matching I and II show that the excluded households used both types of healthcare (outpatient and inpatient) services significantly less, although they incurred higher healthcare expenditure costs compared with those enrolled in MHI and MAS. Indeed, as Table 1 shows, the excluded households appeared to spend almost twice as much on healthcare as the MAS beneficiaries (25.1 for the excluded vs. 13.85 for MAS beneficiaries), while their average healthcare expenditure appeared to be slightly higher than that of the MHI enrollees (25.1 for the excluded vs. 23.1 for the MHI). This means that excluded households with at least one ill member incurred a heavy burden of direct expenditure on healthcare compared with insured households. Interestingly, this indicates that although MHI seems to have an effect on the use of healthcare, its effect on healthcare expenditures appears to be rather modest, as it does not significantly reduce healthcare expenditure of insured beneficiaries compared with excluded individuals and MAS beneficiaries.

Finally, by considering Matching III, no significant differences in the ATE between the MHI enrollees and MAS beneficiaries are observed (the fifth column of Table 5) between the urban and rural areas, except for the use of outpatient care, where a significant increase of about 9 and 14 % points is found in the former and latter, respectively. This indicates that both schemes tend to have similar effects on access to healthcare services.

Discussion

This study attempted to assess the impact of health insurance schemes (both the extended formal-mandatory and the state-subsidized schemes) on the utilization of two types of healthcare services in Tunisia (inpatient and outpatient services). As is standard practice in impact evaluation literature, the 'average treatment effect' on the 'treated' was estimated using propensity score matching. This allowed us to minimize heterogeneity in the observed

Table 5 Propensity score matching estimates on average insurance effect (ATE) on healthcare utilization

Matching method	Outcome variables	Matching I	Matching II	Matching III
		MHI vs. excluded	MAS vs. excluded	MAS vs. MHI
		Observed coefficient (ATE)	Observed coefficient (ATE)	Observed coefficient (ATE)
Urban				
Nearest neighbor	Outpatient care	0.214 (0.059)***	0.320 (0.069)***	0.092 (0.062)
	Inpatient care	0.276 (0.109)**	0.841 (0.211)***	0.414 (0.263)
Radius	Outpatient care	0.188 (0.081)**	0.390 (0.124)**	−0.025 (0.104)
	Inpatient care	0.380 (0.196)*	0.861 (0.478)*	0.344 (0.387)
Kernel	Outpatient care	0.211 (0.046)***	0.294 (0.062)***	0.089 (0.050)*
	Inpatient care	0.258 (0.113)**	0.803 (0.188)***	0.337 (0.232)
Stratification	Outpatient care	0.205 (0.046)***	0.283 (0.053)***	0.083 (0.053)
	Inpatient care	0.260 (0.118)**	0.751 (0.203)***	0.297 (0.178)
Lower and Upper Bounds (at $p < 0.10$)	Outpatient care	[0.188, 0.214]	[0.283, 0.390]	0.089
	Inpatient care	[0.258, 0.380]	[0.751, 0.861]	–
Rural				
Nearest neighbor	Outpatient care	0.125 (0.108)	0.290 (0.080)***	0.136 (0.074)*
	Inpatient care	0.236 (0.191)	0.465 (0.221)**	0.097 (0.326)
Radius	Outpatient care	0.137 (0.178)	0.186 (0.164)	0.084 (0.175)
	Inpatient care	0.870 (0.539)	0.634 (0.330)*	0.124 (0.678)
Kernel	Outpatient care	0.146 (0.070)**	0.275 (0.063)***	0.111 (0.066)
	Inpatient care	0.171 (0.169)	0.738 (0.193)***	0.315 (0.213)
Stratification	Outpatient care	0.105 (0.115)	0.290 (0.078)***	0.102 (0.065)
	Inpatient care	0.076 (0.212)	0.571 (0.277)**	0.227 (0.181)
Lower and Upper Bounds (at $p < 0.10$)	Outpatient care	0.146	[0.275, 0.290]	0.136
	Inpatient care	–	[0.465, 0.738]	–

*** *t* value significant at $p < 0.001$, ** at $p < 0.05$, * at $p < 0.10$
Bootstrapped Standard Errors in parenthesis. The common support condition was imposed in all estimations
In Radius method, the size of the radius is 0.0001. The Nearest Neighbour method is random draw version
Kernel method refers to the Gaussian Kernel

characteristics of the treatment and control groups, thereby reducing the potential effect of selection bias. Unlike most previous studies (e.g., Trujillo et al. 2005), where only one scheme was subject to matching, the present analysis considered the co-existence of two *non-universal* insurance schemes (MHI and MAS). A simultaneous assessment of the net effect of the two schemes therefore necessitated the construction of three matching groups whereby the effect of each treatment was estimated in comparison with the control group (those uninsured) while a third matching allowed us to assess the *differential effect* of MAS compared with MHI (control group).

Several key points emerging from our analysis merit discussion, in light of previous findings reported in the literature, and the specific features of the Tunisian healthcare system. The present study brings new evidence from Tunisia, while confirming some of the findings reported in previous studies conducted in the context of other low- and middle-income countries (e.g., Gnawali et al. 2009; Mensah et al. 2010; Robyn et al. 2012). It has been argued (Hadley 2003; Sinha et al. 2006; Galárraga et al. 2010; Acharya et al. 2012) that in contexts where universal health coverage for the whole population has not yet been achieved, some forms of state-subsidized or community-based schemes may facilitate healthcare accessibility for those not covered by formal, mandatory risk-pooling mechanisms. The purpose of this paper was to evaluate whether or not Tunisian efforts to improve access to healthcare services through either an extension of the formal health insurance scheme or of a state-subsidized insurance program targeting the poor, have met their intended objectives.

Generally, our results support the hypothesis that both insurance schemes (the formal MHI and the state-subsidized MAS schemes) increase enrollee utilization of healthcare. Indeed, comparing all the matching methods used with those excluded from cover, the net increase in outpatient and inpatient services in the MHI group was at least 19 and 26 %, respectively, in urban areas, while in the case of MAS, the increase in utilization was even more pronounced (approximately 28 and 75 % in urban areas, and 27 and 46 % in the rural areas, for outpatient and inpatient services, respectively).

Quite interestingly, important variations in the magnitude of ATE of MHI and MAS were observed between the different matching methods: ranging from approximately 26 % using the *Kernel* method to 38 % using the *Radius* method for the MHI group, and from 75 % using the *Stratification* method to 86 % using the *Radius* method, for the MAS group. Nonetheless, no significant differential effects on the utilization of both services between MAS and MHI insured were found. A notable exception was the significant increase in outpatient utilization by MAS beneficiaries (approximately 9 % in urban areas using the *Kernel* method and approximately 14 % in rural areas using the Nearest Neighbor method).

In technical terms, all the matching methods mentioned above are based on a trade-off between the quality and quantity of the matches, and that the differences in the estimated ATE are due to the number of observations being excluded from the common support region (Becker and Ichino 2002). For instance, although none of the matching methods in the literature have proven to be *a priori* superior (Becker and Ichino 2002), in Matching I and II of the present study the *Radius* method yielded the highest ATE for inpatient care, albeit at a relatively loose standard ($p < 0.10$). This result was mainly due to the length of the radius used (0.0001), which is considered restrictive, resulting in the exclusion of many observations from the common support region (Trujillo et al. 2005). In fact, given the common support condition and the fact that the same significance level was used in all three matchings, results obtained by the Nearest Neighbor, Kernel and Stratification matching methods are quite similar. Taken together, they provide evidence for a positive ATE in the range of 21–28 and 26–75 % associated with outpatient and inpatient care, respectively.

A closer look at the detailed results reveals that the increase in inpatient care was always higher than that of outpatient care, regardless of matching method and group. Indeed, compared with those excluded from insurance cover, the ATE on inpatient use was at least 7 and 47 % higher than that of outpatient use in the MHI and MAS groups, respectively. Given that inpatient care is costly, these findings indicate that both MHI and MAS improve accessibility to this type of care and protect households from the associated heavy financial burden. However, the shielding role of MHI was modest in terms of reducing healthcare expenditures, especially when compared with MAS. This result may reflect variations in the type of benefit package offered for each insured group, including the type of services and providers.

Indeed, unlike the MAS scheme, where beneficiaries are only entitled to health services provided by the public sector, the MHI scheme offers enrollees a wider benefit package with the possibility of using private provider facilities. This, however, entails higher copayments and fees than those paid at public sector facilities. It is important to note that the public sector facilities were under-funded and several medical examinations and medications were unavailable (Abu-Zaineh et al. 2014). MAS beneficiaries belong to the general population's most disadvantaged groups and might be unable to afford services in the private sector. Consequently, they may either forgo further treatment due to financial limitations, or run the risk of catastrophic health expenditures if they choose to have private treatment.

A recent study conducted in Tunisia (Abu-Zaineh et al. 2013) has already identified the relative weakness in current insurance mechanisms in preventing the risk of catastrophic health expenditures. Indeed, being covered by a health insurance scheme would appear to only halve the probability of incurring such expenditure when compared with those excluded from cover (Abu-Zaineh et al. 2013). However, financial burden is only one of the factors explaining variations in healthcare utilization. The latter can also be explained by other important factors such as geographical accessibility, especially in rural areas. The role of two variables (place of residence and distance from the nearest healthcare centre) are highlighted by our results. In line with previous studies (e.g., Hartley et al. 1994; Ensor 2008; Wagstaff 2010) our findings indicate that households living in rural areas and those far from healthcare centers were more likely to be covered by MAS. The significant positive effect of MAS in rural areas indicates that this subsidized scheme helped improve access to healthcare amongst the rural segments of the population. However, this finding does not necessarily reflect improved geographical accessibility to healthcare services, as the gains in rural areas were significantly smaller than those in urban areas (especially for inpatient care where the ATE was 21 % higher for MAS beneficiaries).

The aim of health insurance reforms in Tunisia is not only to improve utilization of healthcare, but also to achieve universal coverage for all segments of the population. A major finding of our results is that these reforms have not yet fully achieved this second objective, since a significant proportion of the population is excluded from receiving any kind of healthcare insurance and uses healthcare significantly less frequently than those insured. Approximately 42 % of the excluded group exercise a professional activity but in the informal sector. These individuals constitute a leakage from the current risk-pooling schemes whose revenue collection mechanisms are based on payroll deductions of a declared professional activity. In the Tunisian context, these deductions include all forms of individuals' contributions to the broader social security system (e.g., pension funds, social allowances, employment insurance benefits, etc.). A previous qualitative research study (De Allegri et al. 2006) identified a variety of reasons for people being excluded from insurance schemes. Some deliberately failed to meet their social security liabilities while others reported failure to meet the current premium level (unaffordability). Nevertheless, some of those excluded from cover expressed their willingness to enroll in a health insurance plan provided that their contributions would be in line with how much they could afford to pay and that these contributions would not incur further payments to other types of social security contributions (De Allegri et al. 2006). Moreover, our results revealed that about 20 % of household heads who reported benefiting from MAS were also enrolled in MHI. This reflects the lack of effective monitoring to ensure proper identification of the targeted groups according to the *means-benefits principle*. Tunisian legislation stipulates that any non-declared professional work is considered informal, therefore not entitled to formal insurance coverage. Moreover, those who are ineligible for MHI can benefit from the state-subsidized scheme (MAS) if they meet one of the two established criteria: earning the minimum wage rate and living on the poverty line.

Although the analysis undertaken in this study used recent methodological developments in the field of impact evaluation, some practical limitations must be mentioned. Firstly, as is common in impact evaluation literature (Hartley et al. 1994; Smolderen et al. 2013), the effect of the insurance scheme on the 'treated' (i.e., the average treatment effect—ATE—on the treated) was interpreted in terms of the additional healthcare utilization of the treatment group 'the insured' compared with the control group 'the uninsured'. However, it is not unlikely that part of the 'extra care' was induced by changes in individuals' behaviors *ex post*, thereby giving rise to the problem of *moral hazard* (i.e., being insured reduces the patient's price of healthcare which in turn leads to increased demand). This type of 'extra care' was however shown to have no impact on health outcomes (Nyman 2004). Acknowledging that our results could not provide any traction to the potential moral hazard, two observations are worth highlighting. First, the moral hazard effect has been shown (Pauly et al. 2006) to be greater in the case of private voluntary health insurance coverage. By contrast, our paper deals with public coverage. Second, it has been shown (Jütting 2005; Nyman 2003) that in the case of public insurance coverage in developing countries, the risk of moral hazard is 'minimal', given the under-utilization of healthcare and the high number of medical needs which are not met, especially for the poor and rural segments of the population. Under such conditions, an increase in the utilization of care may be considered a 'welfare gain' rather than a 'moral hazard' (Nyman 2003). The question of whether or not any 'extra care' due to health insurance can be considered a moral hazard however remains a potential limitation of our assessment of the impact of health insurance on changes in utilization. Future research providing additional data on the appropriateness of utilization *vis-à-vis* medical needs shall address the potential effect of moral hazard.

Second, one of the main objectives of the health insurance reforms in Tunisia has been to ensure access to healthcare services that people need. As is common practice in the literature (O'Donnell et al. 2007), our analysis evaluated access to care in terms of the 'effective-utilization' (using the number of consultations and hospitalization days) whereas 'need' was captured using self-reported health measures. This clearly involves an implicit assumption that after adjustment for health status, 'more utilization' reflects 'improved access' to services that people need. However, to the extent that these reforms measures diverge, an over- or under-estimations of the impact of insurance might have occurred. Finally, although the data used in the present analysis provided us with the opportunity to study the impact of health insurance reforms in Tunisia, some of the reform's decisions were only implemented in late 2007, after data from the Tunisian HealthCare Utilization and Morbidity Survey became available. However, these reforms primarily concerned reimbursement mechanisms and choice of providers for only a part of the MHI enrollees (noting that formal enrollees affiliated under a special regime implemented in 2002 to cover low-income workers and the MAS beneficiaries were excluded from these measures (NHIF 2012; Arfa and Elgazzar 2013). Future research shall assess the impact of these additional measures for reimbursement mechanisms and the choice of providers on healthcare behavior.

Conclusion

As noted at the outset, in recent years international organizations and policy-makers have become increasingly interested in 'universal health coverage' (UHC) (WHO 2013). However, remarkably little is known about the impact of health insurance reforms already in place in developing countries, in particular regarding key goals such as ensuring access to healthcare without the risk of incurring financial hardship. The Tunisian health insurance system, which has implemented several reforms since the early 1990s—with a view to achieving UHC, provided us with an opportunity to explore the hitherto unstudied impact of health insurance reforms. Lessons drawn from the Tunisian experience may therefore help inform ongoing policy development towards achieving UHC. Overall, results reported in this study indicate some evidence in favor of scaling up coverage via some form of *state-subsidized schemes* as a means of promoting health coverage and utilization among the poorer segments of the population, in addition to risk-pooling mechanisms based on the population participating in the formal sector of the economy.

An important conclusion that emerges is that current health insurance schemes, despite improved accessibility to healthcare services, are nevertheless incapable of achieving *effective* coverage of the whole population for all services. Achieving effective UHC in the local context is a challenge given the presence of a large informal sector, a spiraling rate of structural unemployment, and the emergence of non-communicable diseases. Achieving the goal of UHC may therefore require targeting the "trees" not the "forest". This can be achieved through improved design of health insurance schemes, which take into account the current socio-economic, socio-demographic and epidemiological profile of the Tunisian population, while reinforcing the financial and supply capacity of the health insurance system.

Acknowledgments We would like to thank The *French National Research Agency (ANR)* for its financial support to the research project (*INEGSANTE-Les Suds-Aujourd'hui II-2010*). This work has been completed thanks to the support of the A*MIDEX project (no. ANR-11-IDEX-0001-02) funded by the "Investissements d'Avenir" French Government program, managed by the French National Research Agency (ANR). Thanks are also due to Professor Jean-Paul Moatti, Professor Pedro P. Barros and two anonymous reviewers for helpful comments and suggestions.

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