

## ORIGINAL ARTICLE IN HEALTH ECONOMICS

### Testing the Dual-State-Process assumption in the preventive care services use

Dimitris Zavras<sup>1</sup>

*Affiliations:*

<sup>1</sup>Assistant Professor, University of West Attica, Athens, Greece

*Corresponding Author:*

Dimitris Zavras, Assistant Professor, University of West Attica, 196 Alexandras Avenue, 11521 Athens, Greece,

Email: dzavras@uniwa.gr

### Abstract

**Introduction:** Health services use is often measured as a count variable that is characterized by an excess of zeros. Zeros are generally considered to be generated from a dual-state process, i.e., sampling zeros concern a group of at-risk individuals, while structural zeros concern a group of not-at-risk individuals. However, in several studies, especially those regarding preventive services use, the dual-state-process assumption is questionable. In this sense, the objective of this paper is to investigate whether the dual-state-process assumption holds in the case of preventive services use.

**Methods:** For the purpose of this study, we analyzed data from a Panhellenic cross-sectional survey that was conducted in 2017. The survey used stratified random sampling, and the sample selection strata were defined by age, gender, urbanity status of permanent residence and prefecture. The sample consisted of 2003 adults. A computer-assisted telephone interviewing method was used for the data collection. Since the outcome variable was the number of times that preventive health services were used, the analysis was based on the comparison between a

zero-inflated negative binomial model and a standard negative binomial model through the corrected Vuong test. Several health, socioeconomic, demographic and structural factors of the Greek health care system were used as independent variables.

**Results:** According to the analysis, the dual-state-process assumption does not hold in the case of preventive services use and since the need for receiving preventive care exists in most age and gender groups, this is probably due to the fact that preventive services use is infrequent, meaning that the majority of zeros are sampling zeros.

**Discussion and Conclusion:** The results highlight the need for testing the assumption if zero-inflated count models are to be used.

**KEY WORDS:** Dual-state-process assumption; economics; Greece; preventive health services; sampling zeros, statistics; structural zeros, Vuong test; zero-inflated negative binomial model.

### **Riassunto**

**Introduzione:** L'uso dei servizi sanitari viene spesso misurato come una variabile numerica che è caratterizzata da un eccesso di zeri. Viene ritenuto che generalmente gli zeri vengano prodotti da un processo dualistico, ovvero gli zeri di campionamento riguardano un gruppo di soggetti a rischio, mentre gli zeri strutturali un gruppo di soggetti non a rischio. Tuttavia, in diversi studi, specialmente quelli riguardanti l'uso dei servizi preventivi, l'assunzione del processo dualistico è discutibile. In questo senso, l'obiettivo di questo studio è di indagare se l'assunzione dualistica del processo si mantiene quando si usano servizi preventivi.

**Metodi:** Per le finalità di questo studio, abbiamo analizzato i dati provenienti da uno studio trasversale panellenico condotto nel 2017. L'indagine si è basata su di un campionamento stratificato randomizzato, e la selezione degli strati di campionamento è stata definita in base

all'età, al sesso, allo stato di urbanità della residenza e della prefettura. Il campione era formato da 2003 adulti. Un metodo di intervista telefonica con il supporto del computer è stato utilizzato per la raccolta dei dati. Dal momento che la variabile esito era il numero di volte che i servizi di prevenzione sanitaria venivano usati, l'analisi si è basata sul confronto tra un modello binomiale negativo con eccesso di zeri ed un modello binomiale negativo standard attraverso il test di Vuong corretto. Diversi fattori sanitari, socio-economici, demografici e strutturali del servizio sanitario greco sono stati usati come variabili indipendenti.

**Risultati:** Secondo l'analisi, l'assunzione del processo dualistico non viene mantenuta nel caso di uso di servizi di prevenzione e dal momento che la necessità di ricevere cure preventive esiste in molte fasce d'età e di sesso, questo è probabilmente dovuto al fatto che l'uso dei servizi preventivi è infrequente, significando che la maggioranza degli zero sono zeri di campionamento.

**Discussione e Conclusione:** I risultati evidenziano la necessità di testare l'assunzione quando i modelli numerici con eccesso di zeri devono essere usati.

**TAKE-HOME MESSAGE:** When modeling health care use, especially that of preventive services, the categorization of individuals with zero utilization presents a methodological challenge. Zero utilization may be due to true non-use or to false non-use, i.e., the data-generating process can be interpreted as a mechanism that splits individuals between non-users and potential users. However, since the dual-state process assumption is questionable, it should be tested.

**Competing interests:** none declared

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## INTRODUCTION

In most studies, the use of health services is measured as a count variable that takes values greater than or equal to zero [1]. Health services use variables are characterized by an excess of zeros as well as a long right tail that corresponds to heavy health services users [2, 3]. Generally, zeros may represent either healthy individuals or those in need who, for whatever reason, did not satisfy their need [4]. However, illness is not the only reason for seeking health care [5]. Indeed, prevention is a core component of health care [6]. However, a substantial percentage of the population does not receive the recommended levels of preventive care [7]. In terms of count variables with an excess of zeros, one could consider that the zeros are either sampling or structural. Regarding health care use, structural zeros may represent true nonparticipants, whereas sampling zeros may represent potential participants who did not use health care services during the survey period, i.e., such zeros may be categorized based on the survey period [8]. On the other hand, sampling zeros may result from a group that produces a zero outcome due to sampling variability (i.e., a susceptible subpopulation of at-risk individuals), while structural zeros may result from a group that always produces a zero outcome in the count variable (i.e., a non-susceptible subpopulation of not-at-risk individuals) [9]. Since health needs are considered

as the most important cause of health services use [10], the general classification scheme, as mentioned above, is that structural zeros represent healthy people without a disease, while sampling zeros may represent those who have a disease [11].

However, the influence of several geographical, demographic, epidemiological, socioeconomic and structural factors of health care systems on health services use [12] complicates the distinction between at-risk and not-at-risk individuals. In this way, the distinction between structural zeros and sampling zeros is not obvious.

However, in several studies, the criteria on the basis of which the zeros are categorized are more evident. For example, in the study by Cançado et al. [13], the structural zeros represented patients who were not diagnosed with oral cancer, possibly due to a lack of insurance. Additionally, when measuring the number of inpatient days, structural zeros may correspond to patients who are in good health or can be treated through outpatient care, while sampling zeros may correspond to patients with more serious chronic conditions who, for whatever reason, had zero counts in a given period [14]. Furthermore, the criterion of distinction between structural zeros and sampling zeros may be the patients' eligibility for health services [15, 16]. Thus, based on the information mentioned above, structural zeros do not represent only healthy individuals.

Although the criteria on the basis of which the zeros are categorized are different in the abovementioned literature, some of these studies consider zeros to be generated from two processes; therefore, zero-inflated models could be applied. Since zero-inflated models assume that two types of zeros exist in the data (i.e., structural zeros and sampling zeros) [17, 18], they have been used in several studies of health services use [19–22]. Such models include zero-inflated Poisson models and zero-inflated negative models that extend the Poisson and negative

binomial models in such a way that they can handle the excess of zeros in the count response. Zero-inflated count models assume a degenerate distribution centered at 0 and describe a not-at-risk group of individuals [23].

A zero-inflated model is the proposed method of analysis when the status of the structural zeros is unknown, such as cases in which the structural zeros cannot be distinguished from the sampling zeros [24]. The basic assumption behind zero-inflated count models is that the data-generating process is that of a dual state, i.e., an observation belongs to either a perfect state that produces only zeros (structural zeros) or an imperfect state that produces both zero (sampling zeros) and non-zero counts [25, 26]. In other words, the data-generating process can be interpreted as a splitting mechanism [27].

However, in medical care, due to the uncertainty surrounding both the need for and the effectiveness of health care [28], it is questionable whether the dual-state-process assumption holds. This is especially true for preventive services use, which is something that has become obvious since the criteria on the basis of which the zeros are categorized are not always clear.

Consequently, since the distinction between non-users and potential users, does not suffice to justify the dual-state-process assumption, it should be evaluated whether it results from a splitting mechanism [29–31].

Moreover, although our choices are frequently built on our perception of risk, nothing can be absolutely free of risk [32]. As a result, risk alone cannot be considered as a criterion of the categorization of zeros, even if such a perception is considered as an important factor for preventive services use [33]. Furthermore, as in other kinds of medical care, uncertainty about health also plays an important role in using preventive services [34]. In addition, it is

questionable if the ‘need’ can be used as a criterion for the categorization of zeros. Indeed, since preventive services use does not concern only those individuals in need [35], studies on the relationship between self-perceived health and preventive services use have not provided definitive results [36]. From a consumption perspective, those in poor health are more likely to use preventive services, but healthy individuals and those who are future-oriented are also more likely to invest in their health and preventive care [37]. If health does not affect preventive health services use, as Lairson and Swint mentioned [38], it cannot be used as a criterion for the categorization of zeros.

In an attempt to extend the information described above, it should be mentioned that zeros may also be present in survey data for the following three additional reasons: a) consumers’ sensitivity to commodity prices given their preferences and income levels (zeros represent corner solutions), b) infrequency (the good is purchased infrequently), or c) abstention (the respondent would never purchase the good) [39–41].

As a result, the complicated nature of the above-described data calls into question the dual-state process assumption. At this point, since health care use can be viewed as the product of individual characteristics plus the health care provider and health care system attributes [42], the basic characteristics of the Greek primary health care (PHC) system should be presented.

The health care system in Greece is a mixed system in terms of both funding and provision. More specifically, a National Health System (ESY) is combined with a health insurance system, and health care services are also provided through the private sector [43]. Before 2010, PHC in Greece was delivered by a mix of public and private health care providers, mainly through the following four structures: a) rural health centers and their health surgeries, in addition to the

outpatient departments of public hospitals; b) PHC units owned and operated by social security funds; c) PHC offered through local authorities, such as clinics and welfare services offered by municipalities; and d) PHC provided by the private sector, such as private physicians, private diagnostic centers, and the outpatient departments of private hospitals [44, 45].

The establishment of the National Organization for the Provision of Health Services (EOPYY) in 2011 constituted a structural health care system reform since the four main social security funds (Social Security Institution (IKA), Insurance Organization for the Self Employed (OAEE), Agricultural Insurance Organization (OGA), Insurance Organization for Public Sector Employees (OPAD)) were merged into the EOPYY and, subsequently, almost all of the smaller social security funds were incorporated into this larger agency. Consequently, the PHC units of IKA came under the umbrella of the EOPYY [46].

Thus, in rural and semi-urban areas, public PHC was mostly provided by ESY health centers and their health surgeries, whereas in urban areas, PHC was mostly provided by a few urban health centers, the outpatient departments of public hospitals, and EOPYY units [47, 48].

Legislation passed in 2014 (4238/2014) aiming to develop a nationwide PHC service (PEDY) consisting of health centers, EOPYY units and contracted physicians [49]. According to law 4238/2014, all PHC facilities under the EOPYY and the rural and urban health centers under the ESY were organizationally unified [50]. Although it was conceptually on the right path, the reform encountered several problems during its implementation [51].

As a result, a new PHC reform was introduced in 2017. Under the new legislation, first-level PHC is provided by local health units (ToMYs) and by physicians who have private practices and contracts with the EOPYY. Second-level PHC is provided by health centers [52].



Of course, individuals may alternatively use purely private health professionals, who are paid privately [53]. Both public and private PHC services, provide a number of services, including those related to diagnostic, curative, and preventive health [54].

Regarding preventive care, it should be mentioned that several services, such as vaccinations, Pap smears, and mammograms, are made available at no cost by the public health care services [55, 56].

Based on the information mentioned above, since the categorization of zeros is not evident, the objective of this study is to investigate whether the dual-state-process assumption holds in the case of preventive services use.

## **METHODS**

### ***Study participants and sampling***

For the purpose of this study, data from a Panhellenic cross-sectional survey were used [57]. The survey was conducted in 2017 and used stratified random sampling. The sample selection strata were based on the 2011 Census of the Hellenic Statistical Authority, and they were defined by age, gender, urbanity status of permanent residence and prefecture based on the Nomenclature of Territorial Units for Statistics II (NUTS II). The sample size was 2003 individuals aged 18 years or older ( $n = 2003$ ). A computer-assisted telephone interviewing (CATI) method was used for the data collection.

### ***Study instruments and measures***

The questionnaire has been previously validated [58]. The questions about preventive services use were based on the structure of the Greek health care system. In 2016 (the reference period of the survey), PHC was provided by: a) the outpatient departments of public hospitals, b) ESY

health centers and their health surgeries, c) PEDY units, d) the outpatient departments of private hospitals, e) private diagnostic centers, f) private practice physicians contracted with health insurance funds, g) private practice physicians not contracted with health insurance funds, and h) social clinics. As a result, the respondents were asked to report their monthly preventive services use (counts taking values greater than or equal to zero) for each of the aforementioned modes of delivery services. The total monthly preventive health services use (response variable) was derived as the sum of the abovementioned variables.

In addition, the Time Interval (TI) since the individual's last general preventive check-up was reported as being: a) within the last year, b) last year < TI ≤ last two years; c) last two years < TI ≤ last five years, d) TI > last five years, or e) never.

Since the outcome variable was the number of times that preventive health services were used, the analysis was based on a zero-inflated negative binomial model that included the following independent variables as potential predictors: a) gender (0 = male, 1 = female); b) age; c) marital status (1 = married or unmarried partnership, 2 = single living alone, 3 = single living with parents, 4 = widowed, 5 = divorced); d) self-reported health status (1 = very bad, 2 = bad, 3 = moderate, 4 = good, 5 = very good); e) existence of a diagnosed chronic health condition (0 = no, 1 = yes); f) monthly income (1 = 0€, 2 = 1€-500 €, 3 = 501€-1000€, 4 = 1001€-1500€, 5 = 1501€-2000€, 6 = 2001€-3000€, 7 ≥ 3001€); g) occupation (1 = employed, 2 = unemployed, 3 = pensioner, 4 = housewife, 5 = student, and 6 = other occupation); h) education (1 = basic, 2 = primary, 3 = secondary, 4 = tertiary); j) household economic difficulties (1 = very great to 6 = very little); i) frequency of economic difficulties (1 = most of the time, 2 = sometimes, 3 = never); k) proportion of household monthly income spent on bills and debt payments (1 = up to 25%, 2 =

up to 50%, 3 = up to 75%, 4 = up to 100%, 5 = more than 100%); l) public insurance coverage (0 = no, 1 = yes); m) private insurance coverage (0 = no, 1 = yes); and n) urbanity status of permanent residence (0 = rural, 1 = urban).

From the variables mentioned above, age and the ordinal variables (e.g., self-reported health status, monthly income, education, household economic difficulties, frequency of economic difficulties and proportion of household monthly income spent on bills and debt payments) were treated as continuous variables. From each nominal variable with  $k$  categories (e.g., marital status, occupation),  $k-1$  dummy variables (0, 1) were obtained and used as binary variables in the analysis. The following variables were treated as binary variables: gender, existence of a diagnosed chronic health condition, public insurance coverage, private insurance coverage, urbanity status of permanent residence.

### ***Ethical aspects***

The ethical approval from the Bioethics Committee of the Greek National School of Public Health was obtained for this study.

### ***Data analysis***

The dual-state-process assumption was tested using the Vuong test [59, 60], specifically, the corrected Vuong test. The Vuong test evaluates whether the zero-inflated count model or the standard count model is closer to the true model. The specific metric of model fit is the Kullback-Leibler divergence (KLD) from the true model that generated the data. A random variable  $\omega$  is defined as the vector of  $\log L_z - \log L_s$ , where  $L_z$  is the likelihood of the zero-inflated count model, and  $L_s$  is the likelihood of the standard count model. The vector of differences over the  $n$  observations is then used to define the statistic:

$$V = \frac{\bar{\omega} \sqrt{n}}{\sqrt{\frac{\sum (\omega - \bar{\omega})^2}{(n-1)}}}$$

The test statistic is normally distributed  $N(0, 1)$ , with significant positive values favoring the zero-inflated count model, and significant negative values favoring the standard count model. Non-significant Vuong statistics indicate no preference for either model. However, since the estimated log likelihood is a biased estimator of the KLD, the Vuong statistic is biased. The bias arises from the fact that the same data are used to estimate both the parameters of the model and the average value of the log likelihood. Nevertheless, the bias is corrected if computing the Vuong statistic using corrections based on the Akaike and Bayesian (Schwarz) information criteria [61, 62].

Regarding health care use, the Vuong statistic evaluates whether there is a mechanism that splits individuals between non-users, and potential users [3].

The models' goodness of fit was investigated with the  $\chi^2$  goodness of fit test for count data models [63]. In addition, the existence of specification error was investigated with a link test [64]. The STATA 14 statistical software package was used for the analysis.

## **RESULTS**

Approximately fifty-two percent (52.22%) of the respondents were females. The average age in the sample was  $49.97 \pm 16.18$  years. The mean reported monthly preventive services use was  $0.09 \pm 0.42$  ( $1.45 \pm 0.91$ , when nonusers were excluded).

Approximately ninety-four percent of the respondents (93.81%) declared zero preventive health services use within the last month (Table 1).

**Table 1.** Monthly preventive health services use.

<b>Monthly Preventive Health Services</b>	
<b>Use</b>	<b>% (n)</b>
Yes	6.19 (124)
No	93.81 (1879)
<b>Total</b>	<b>2003</b>

Among those who reported zero monthly preventive health services use within the last month, approximately twenty-one percent (21.46%) declared an unmet health care need within the last year. Approximately six percent (6.04%) of those who did not suffer from a chronic health condition made use of preventive health services within the last month, while a similar percentage (6.36%) of those who rated their health as being good or very good made use of preventive health services within the last month.

Approximately seventy-five percent of the respondents (74.91%) reported having a general preventive check-up within the last year (Table 2).

**Table 2.** Time Interval (T) since the last general preventive Check-Up.

<b>Time Interval (TI)</b>	<b>% (n)</b>
$TI \leq$ Last Year	74.91 (1493)
Last Year < $TI \leq$ Last Two Years	12.69 (253)
Last Two Years < $TI \leq$ Last Five Years	6.47 (129)
$TI >$ Last Five Years	4.01 (80)
Never	1.91 (38)
<b>Total</b>	<b>1993</b>

In addition, approximately sixty-nine percent (68.52%) of those who did not suffer from a

chronic health condition reported having a general preventive check-up within the last year, while approximately seventy-three percent (73.05%) of those who rated their health as ‘good’ or ‘very good’ reported having a general preventive check-up within the last year. The descriptive measures mentioned above indicate that a substantial percentage of healthy individuals reported having a general preventive check-up within the last year. To test the dual-state-process assumption, a zero-inflated negative binomial model was fitted. According to the results (Table 3), no statistically significant variables were found for the zero-inflation process. Furthermore, preventive services use depends on gender and the proportion of household monthly income spent on bills and debt payments. Women use preventive services more frequently than men. Similarly, individuals whose households spend more on bills and debt payments use preventive services more frequently than individuals whose households spend less on bills and debt payments.

**Table 3.** Zero-Inflated Negative Binomial Model.

Process	Coefficient	<i>P</i>	95% Confidence Interval	
<b>Count Process</b>				
Gender	0.70	0.001	0.28	1.12
Proportion of Monthly Income Spent on Bills and Debt Payments	0.28	0.005	0.09	0.48
Constant	-4.30	<0.001	-5.19	-3.41

<b>Inflation</b>				
<b>Process</b>				
Constant	-12.85	0.995	-4187.71	4162.01
ln(alpha)	2.14	<0.001	1.76	2.52
alpha	8.50		5.82	12.41

The  $\chi^2$  goodness of fit test ( $P < 0.001$ ) indicates that the zero-inflated negative binomial model does not fit the data well. The AIC-corrected Vuong statistic (-744.63) indicates a significant ( $P < 0.001$ ) selection of the negative binomial model, and the BIC-corrected Vuong statistic (-2811.62) also indicates a significant ( $P < 0.001$ ) selection of the negative binomial model (Table 4). Based on the Vuong test, the dual-state-process assumption is not valid.

**Table 4.** Negative Binomial Model.

<b>Variable</b>	<b>Coefficient</b>	<b>P</b>	<b>95% Confidence Interval</b>	
Gender	0.70	0.001	0.28	1.12
Proportion of Monthly Income Spent on Bills and Debt Payments	0.28	0.005	0.09	0.48
Constant	-4.30	<0.001	-5.19	-3.41
ln(alpha)	2.14		1.76	2.52
alpha	8.49		5.82	12.41

The Pearson's dispersion statistic of the negative binomial model was found to be almost equal to 1 (1.07), indicating that there is no overdispersion (for the Poisson model, the Pearson

dispersion statistic was found to be equal to 1.84, indicating that overdispersion exists). The  $\chi^2$  goodness of fit test ( $P = 0.93$ ) indicates that the negative binomial model fits the data well. According to the link test, the negative binomial model is correctly specified (Table 5).

**Table 5.** Link Test.

Variable	Coefficient	<i>P</i>	95% Confidence Interval	
h	-0.35	0.872	-4.62	3.92
h <sup>2</sup>	-0.28	0.534	-1.17	0.60
Constant	-1.57	0.543	-6.61	3.48
ln(alpha)	2.14		1.77	2.52
alpha	8.53		5.84	12.45

## DISCUSSION

According to the results of this study, preventive services use depends on gender and the proportion of monthly income spent on bills and debt payments. More specifically, women use preventive services more frequently than men, which is consistent with the international literature [65]. In addition, individuals whose households spend more on bills and debt payments use preventive services more frequently. Since preventive medical care is less costly than other types of medical care [66] and does not concern only individuals in need [67], planned debts (such as those in this study) may not weigh as heavily on individuals when they are considering the expenses that they can afford, such as a visit to the doctor when they decide to seek preventive care [68]. Furthermore, as mentioned in the introduction, several preventive services are made available at no cost by public health care services. Additionally, a large part of the private sector enters into contracts with the EOPYY.



Based on the results of this study, the dual-state-process assumption is not valid for preventive services use.

Regarding zeros that represent corner solutions, it should be mentioned that some preventive services such as Pap smears, mammograms, or colonoscopies are characterized as being cost prohibitive [69], indicating an economic or structural factor influence on preventive services use [70]. It is useful to mention that in Greece, the impact of austerity measures on family budget has led to a lower frequency of preventive medical care [71]. Thus, despite the results of this study, further investigation is needed to assess the degree to which the zeros represent corner solutions. Regarding zeros due to infrequency, it should be mentioned that preventive services differ with regard to intervals for repeat testing [72]. For example, some preventive services, such as pneumococcal vaccinations, are administered once, and others, such as colonoscopies, are infrequent (every 10 years) [73]. In addition, neither risk factors nor the frequency of receiving preventive care are stable over time [74–76].

Furthermore, since a high percentage of the individuals who did not report using preventive care services within the last month, did report having a general preventive check-up within the last year, we may argue that the majority of the zeros in this study is resulting from infrequency. This argument is justified from the fact that the use of several preventive services is positively associated with a general health check [77, 78] i.e., one of the most common reasons that adults seek medical attention [79]. Additionally, the recall period of this study (one month) is relatively short [80].

Regarding zeros due to abstention, it should be mentioned that there are several reasons for never using health services. Indeed, reasons for health care service avoidance include unfavorable

evaluations as a result of seeking medical care, such as a fear of bad news or an absence of trust in doctors [81], among others. However, since there is evidence that, in some cases, screening investigations are initiated after symptoms have already occurred [82], questions can be posed about the degree of abstention's influence on preventive care-seeking behavior during an individual's lifespan. However, based on the results, only 1.91% of the respondents had never had a general preventive check-up. Thus, most of the zeros are probably not caused by abstention.

According to the information mentioned above, the non-applicability of the dual-state process assumption is mainly due to the infrequency of preventive services use, i.e., the nonuse of preventive services during the survey period, meaning that most of the zeros are sampling zeros [83].

At this point, the question of whether the dual-state process assumption holds in health care systems different from the Greek system should be discussed. The answer is partially given by taking into account the retesting intervals. For example, regarding cancer prevention, the recommendations of the European Union to its member states include that: a) Pap smear intervals should be between three to five years (screening must not start before the age of 20 or later than the age of 30); b) mammography intervals should be between two to three years (for women aged from 50 to 69); and c) fecal occult blood test intervals should be between one to two years (for men and women aged between 50 to 74 years) [84].

Furthermore, according to the 2016 European guidelines on cardiovascular (CV) disease prevention, the interval of CV risk assessment should be five years (for men older than 40 years and women older than 50 years) [85].

On the other hand, although the utilization of preventive services requires interaction with the health care system, e.g. it is influenced by access [86], in many developed countries where a high health coverage is achieved, underuse of preventive care is common even when services are free [87]. In Italy, for example, despite the fact that preventive care is free and health insurance is universal, preventive care is underutilized [88]. A similar result is evident also in the United States [89], where the majority of the population receives health insurance coverage from private voluntary health insurance [90]. Indeed, only eight percent (8%) of Americans aged 35 and older reported having received all of the appropriate, high-priority clinical preventive services recommended for them [91].

Based on the previous points, preventive care use is infrequent. This means that the dual-state process assumption also may not hold in health care systems different from the Greek system.

At this point, it should be mentioned that although this study is focused on preventive care, the dual-state process assumption also may not hold for diagnostic and curative care. A possible reason is that in the health production process, the transition probabilities in a sequence of health states are governed by chance [92]. In addition, since individuals cannot accurately assess their level of health, the demand for health care is affected by the uncertainty about health and by the uncertainty surrounding the effectiveness of health care [93].

The main limitation of this study is the non-availability of information about the type of preventive care. Such information would provide a better understanding of corner solutions, infrequency and abstention. However, this shortcoming is partly overcome by the availability of information about the time interval since the last general preventive check-up, given that general health checks may include several major health screenings, such as mammography or fecal

occult blood testing [94, 95]. Therefore, this study should be considered as a starting point for further research in the field.

## **CONCLUSION**

Strategic policy formation in all health care systems should be based on information relating to health services use [96], among others. Since the results of statistical analyses often have significant policy implications [97], it is extremely important to understand the quantitative aspect of the studies and the statistical methods used to analyze the data. Therefore, testing the assumptions behind the models is necessary.

How data are analyzed is important to understanding how to ensure an unbiased, valid result. Because each statistical method requires that certain assumptions hold, understanding the assumptions and the effects of their violation offers a critical skill to researchers and meta-analysts for correctly interpreting the published literature.

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