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INFORMAL HEALTH CARE PAYMENTS IN GREECE: A FLEXIBLE MIMIC MODEL ADAPTATION

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ABSTRACT:

The healthcare system in Greece faces challenges based on underfunding, lack of staff, and the SARS–CoV–2 pandemic, have severe consequences like informal payments because of preventive and tackling measures absence. Even though the MIMIC model, normally employed in shadow economy size estimation, is for the first time used to estimate informal health payments, which determine our paper's originality. Based on primary survey data, an estimation approach combines the calculation of an unofficial health payment index with a flexible MIMIC model, considering causes and indicators' transformations of patients' black payments. We apply these transformations to correct variables' consequences on informal health payments indicators (IPs*). Results showed to use estimated model parameters and derived informal payments indexes because of further research and especially for the collection of irregular health payments indicators and related variables, including information on IPs*.

Keywords: *informal payments, Greek healthcare system, flexible MIMIC model.*

1. INTRODUCTION.

Debt crisis caused eroded Greek economy (Economou et al., 2017; Pelagides, 2020). Health resources restrictions (Souliotis, Koufopoulou, 2020) preserve private health payments' dynamics (Economou, 2020). Recent data, reveal that Greek total health expenses are under OECD countries (8.8%) average up to 7.8% of GDP (OECD, 2021). Specifically, total health expenditure comes to an average of €15,239.3 million, when public, private and other health expenditures are 61.4%, 37.85% and 0.75% of them (ELSTAT, 2015, 2016, 2017, 2018, 2020a, 2020b, 2021).

Public health expenditure occupied 37.85% of total health expenditures. Private health expenditures were from 2008 to 2015 (ELSTAT, 2019). Out of pocket payments they are used by low-paid workers (Balabanova, McKee, 2002; Buligescu, Espinoza - Pena, 2020; Giannouchos et al., 2020; Meda et al., 2020; Precupetu, Pop, 2020; Zarei et al., 2021; Park., 2021) and mainly detected in services provision (ELSTAT, 2017, 2018). Informal payments are most OOPs known type reflecting public health resources, misallocation, and unnecessary healthcare services (Stepurko et al., 2015). Consist illegal transactions between doctors and patients (Meskarpour – Amiri et al., 2019) lack equal services or avoid their treatment (Burak, Vian, 2007; Tambor et al., 2014).

Pavlopoulos (1987), Niakas et al. (1990), Kyriopoulos (1992), and Kyriopoulos and Karalis (1997) study informal health payments. Are more frequent in cesarean sections than in normal deliveries (Mossialos et al., 2005). Liaropoulos et al. (2008) found that 36% of people treated in public hospitals reported at least one informal payment to a doctor. Moreover, 42% of them gave those payments fearing that they will not receive appropriate care, with 1/5 of them forced by the doctor. Pay illegal amounts to bypass the waiting queue and having earlier surgery. Kaitelidou et al. (2013) found that 74.4% of women resorted to informal payments and 56.3% under obstetrician's requests. Souliotis et al. (2016) proved that 33% of patients gave informal amounts ranging from €200 for childbirth or a simple eye surgery up to €5.000 for complex operations, eliminating household budget by 27%. At the same time, it gave no receipt for 55.2% of the money to a public unit reaching €1.5billion, depriving public revenues of up to €500 million. Horodnic et al. (2017) found that informal health payments for public services users in Greece reached up to 11%. Also, in Cyprus, Italy, Malta, Portugal, Spain and Greece are attributed to Institutional Asymmetry Index (Horodnic, Williams, 2018).

The aim of our study is to examine patients' attitude towards informal health payments (Zhang, 2021; Zarei et al., 2021; Souliotis et al., 2016; Gaal et al., 2021; Habibov et al., 2021). Even though many studies attached informal health payments phenomenon, our paper contributes to existing theory cause combines two different methods in order to calculate the related index, structured questionnaire (direct method) and multi-indicators - multiple causes model with informal payments as a latent variable (indirect method).

ESTIMATION MODEL.

We considered informal health payments as a latent variable (Rabe - Hesketh, Skrondal, 2008; Bishop, 1999; Aigner et al., 1984). An individual correlation stands, such as for *HD* health care (health services use for a health problem or other reason, health problem existence, daily activities absence, health problem identification, formal health service use and justification for this option, explanation for treatment interruption) and individual behaviors regarding informal *IPsA* payments like health services to which money was given, the equivalent in euros of benefit in kind, health care service provision, patient's costs for medicines, total payment amount as total charge. Healthcare services demand and informal payments dimensions expressed with indicators (demographic characteristics, willingness to pay) of *IPs** latent variable.

Informal payments index *IPs** are estimated with variables that interpret latent variable *IPs** and comprise its major causes. Applied in shadow economy studies with multi-indicator and multiple causes model (Afonso, Goncalves, 2011; Boitano, Abanto, 2019; Buehn, Schneider, 2008; Cassar, 2001; Davidescu, Schneider, 2019; Remeikiene et al., 2019; Chen et al., 2020). We used extensively it in health research (Iliceto et al., 2013; Normand et al., 2020; Lin, Wu, 2018) but not in informal health payments modeling. We took advantage of directions surveys of Anderson (2018), Fonta et al. (2010), Belli et al. (2002), Stepurko et al. (2013), Cohen and Filc (2007), Doshmangir et al. (2020), Habibov and Cheung (2017), Horodnic and Williams (2018), Horodnic et al. (2017), Giannouchos et al. (2020) and Giannouchos et al. (2021).

We adapt Van Vliet and Van Praag's (1987) model to our survey data regarding informal healthcare payments as a latent variable of the flexible MIMIC Model, calculating an index. Has major components regulating informal health payments' existence and evolution, like variables of health services demand, behaviors showing illegal amounts, their willingness to pay informally, and demographics.

We separate an $IPs^*(X)$ function from flexible MIMIC models where X captures informal payments causes. Construction of alternative informal health payments measurements based on lack of information, having variables for determinants and indicators. Our knowledge of age, gender, occupation, household size, education, and income is precise but not for patients' attitudes towards informal payments and their belief in their legitimacy likelihood. So, we have information on health services use during the study period and/or the different conditions of occurrence.

2.2. Model description.

First, we describe the variables (Table 1). Two types of indicators for behaviors related to *IPsA* and demand for *HD* health services will be defined. Next, we report three categories of explanatory variables *X1*, *X2*, *X3*. Finally, we have *IPs** as the unobserved latent variable.

The original form of our model has the following structure:

$$HDi = \delta 1iIPs^* + \alpha' 1iX1 + \alpha' 2iX2 + \varepsilon 1i, \qquad i = 1,\ldots\ldots I, \qquad (1)$$

$$IPsAj = \delta 2jIPs^* + \beta' 2jX2 + \varepsilon 2j, \qquad j = 1,\ldots\ldots I, \qquad (2)$$

$$IPs^* = \gamma' 2X2 + \gamma' 3X3 + \varepsilon 3, \qquad (3)$$

where $\delta 1i$, $\alpha 1i$, $\alpha 2i$, $\delta 2j$, $\beta 2j$, and $\gamma 2$ are vectors ($\delta 1i$, and $\delta 2j$ one - dimensional) of the unknown parameters and $\varepsilon 1i$, $\varepsilon 2j$, *and* $\varepsilon 3$, are vectors ($\varepsilon 3$, one - dimensional) of the perturbations (Table 1).

Model structure defines vectors X1, X2, and X3. Vector *X1* includes variables of informal payments behaviors, such as services to which patients paid informally for each health service use, equivalent in euros in kind, level of health care provision, drugs' cost, and total amount as a total charge from informal payments. Vector *X2* includes variables related to patients' willingness to pay as their attitude towards informal payments, expenditure on medicines, and health services besides drugs. Vector *X3* contains age, gender, household size, Region of residence, family income, education, and employment status where $\delta 1i$, $\alpha 1i$, $\alpha 2i$, $\delta 2j$, $\beta 2j$, and $\gamma 2$ are vectors ($\delta 1i$, and $\delta 2j$ one-dimensional) of unknown parameters (to be estimated) and $\varepsilon 1i$, $\varepsilon 2j$, and $\varepsilon 3$, are vectors ($\varepsilon 3$, one-dimensional) of the perturbations.

Table 1. *Description of variables*

Variable	Description
IPs	Informal health care payments index
Healthcare Services Demand (*HD) X*	
USE	Healthcare services utilization, for one or more household members, adults or children, patients or children during the last 4 months, percentage.
USE_PREV	Healthcare services utilization for one or more household members,

	for any purpose other than illness, during the last 4 months, percentage.
HCPE	Health problem existence likelihood, 2 levels, 0= yes, 1= no.
DAYS	Exercise's obstruction from normal activities continuation, number of days, 5 levels, 1= 1 to 7 days, 5= over 3 months.
HCP	Specific health problem, based on description/report of the disease, otherwise the symptoms/ICD – 10.
FOSE	Formal healthcare service to treat the mentioned health problem, 6 levels, 1= Primary Health Care, 6 = other services (physiotherapy, rehabilitation etc).
FOREA	Specific healthcare service choice justification, 8 levels, 1=closest, 8=other.
UNSE	Justification for non-completion of health care provision, 7 levels, 1 = I didn't buy/get all the prescribed medicines by my doctor, 7 = other.
Informal healthcare payments behaviors (*IPsA*) X_1	
PROV	The services to which patients paid an informal amount in euros (€) for each specific incident of healthcare services use.
SEIF	Specification of the equivalent in euros (€) of the benefit in kind, provided care level, and the service to which they paid it.
AMDRUG	Informal patients' expenditures for drugs, in euros (€).
TOTAL	Total paid amount, in euros (€).
INFOB	Total cost from informal payment for healthcare services provision.
Payment preparedness X_2	
ATT	Patients' attitude/perception towards informal payments, 5 levels, 1= very negative, 5= very supportive.
LEGAL	Legalizing informal payments possibility in public healthcare services, 4 levels, 1= no because most of the population doesn't pay anything and couldn't pay, 4= I don't know/I don't answer. The possibility of legalizing informal payments to public health services
DRUG	The maximum monthly amount patients will defray/or pay, for supply/taking drugs, in euros (€).
NONDRUG	The maximum monthly amount patients will defray/or pay, for free healthcare services receiving (besides drugs), in euros (€).
Demographic variables X_3	
AGE	Age in years
SEX	Dummy variable, 1= woman, 0= man
HOUSE	Household size
PERF	Region of residence
INC	Family income
EDU	Educational status, 4 levels, 1= he didn't go to school at all, 7= Master–Doctoral level
EMPL	Employment regime, 6 levels, 1= yes, full employment, 6= child/preschool education.

In this paper, we focus on the description and application of a method for the production of informal health payment indicators from a model of multiple indicators - multiple causes (Figure 1).

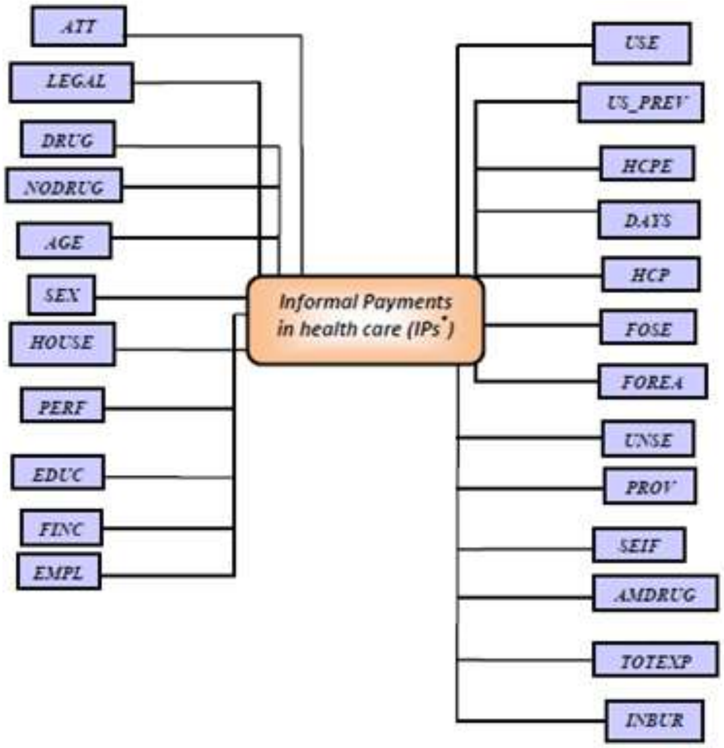

Figure 1: An initial flexible model of multiple indicators - multiple causes for informal healthcare payments in Greece (11-1-13)

Equation (3) has a mixed demand-production function: some of the independent variables can affect health services demand (income) while others affect health services productions (household size, age) (Van de Ven, Van der Gaag, 1982). Three issues are crucial for our model. We should clarify the health insurance type. Liberal health systems focus on private insurance (Amelung, 2013) while is restricted in European health insurance systems. Public health insurance dominates with insurance companies' minimal contribution. The Unified Social Security Institution (EFKA) covers most of the population as the Unified Organization for Health Services Provision (EOPYY). Another issue is income's limited contribution, in our model. It depends on their behaviors related to informal health payments. Since the economic crisis manifestation, income has become insufficient and containing low benefits and pensions. We know household income in total (when there is over one person with a fixed salary) but not at an individual level (unless the only one who has money is the head of the household). A majority of the sample are pensioners and employees, contributing totally to household expenses, supporting many family members.

Educational status has a significant contribution to informal payments (Meskarpour-Amiri et al., 2019). Focuses on patients' and society's knowledge and attitude, consisting of culture in countries with shadow economy size and corruption. Medical staff salaries are lower, requiring them to ask for envelope payments, which is not justified.

Regarding random disorders, we assume they are normal with zero mean and unrelated. We scaled the latent IPs variable defining all variables for deviations from their medians, and setting $\delta 11 = -1$. We assume that many of the coefficients are zero and estimate the flexible structural equation models such as this with the LISREL computer program (Joreskog, Sorbom, 1978). However, we used SPSS Version 24 for our analysis.

2.3. Flexible Mimic Model with Informal Healthcare Payments Evaluation.

With equation (3) we found it possible to evaluate informal payments in individuals' health incident *n*, imprinted as *IPsn* knowing vectors *X2n* and *X3n* (having estimates for the parameters). Information on *X3* vector variables is unavailable to individuals not included in our population sample. Vector's *X1* variables had intermediate difficulty, while *X2* and X3-vectors variables are immediately observable. Information on one or more health indicators is available through primary survey data, as variables of behaviors for informal payments are difficult to get. That is why we express our idea in the following. Given equation (2) for a particular *j*. Then we can write, assuming $\delta 2j \neq 0$,

$$IP_s^* = \frac{1}{\delta_{2j}}\left[IP_{sj} - \beta'_{2j}X_2 - \varepsilon_{2j}\right]$$

Ignoring the $\varepsilon 2j$ we have for every *j* an alternative estimate for informal health payments, it could be this:

$$ip^*_{s_j} = \frac{1}{\delta_{2j}}\left[IP_sA_j - \beta'_{2j}X_2\right] \qquad (4)$$

The difference between the structural variable *IPs* and the proxy variable *ips*, is proved in equation (5):

$$ip^*_{s_j} - IP_s^* = \varepsilon_{2j}/\delta_{2j} \qquad (5)$$

We know if β2j and δ2j estimates, *ipsj* is easily computable as *IPsAj* and *X2* are easily workable. The proxy variable *ipsj* is an unbiased estimate of *IPs* and the error variance is $\beta^2(\varepsilon_{2j})/\delta^2_{2j}$.

Also, this applies its estimator replaces if δ2j. Proxy variable *ipsj* can be interpreted as a function of the dimension of informal payments in *IPsj* health where a correction applied to the *X2* variables that affect *IPsAj* health behaviors with latent variable *IPs* but also directly. This method can apply to all situations of informal *IPsAj* payments (*j = 1,… ..J*) also available on-demand for *HDi* health services (*i = 1,… ..1*), if the *X1* vector variables are available. In the latter case, equation (31) changes:

$$ip^*_{s_j} = \frac{1}{\delta_{1i}}\left[\mathrm{HD}_i - \alpha'_{1i}X_1 - \alpha'_{2i}X_2\right] \qquad (4')$$

Thus, proxy variable ipsj is a function of the demand for HDi health services where a correction was accomplished out for the effect of vector X2- like X1- vector variables. The latter affects health services demand HDi and informal payments. Thus, providing medical care may affect the number of outpatient visits, but we assume it does not affect informal payment behaviors.

We will generalize over one proxy variable from the estimated model. So it is important to use a weighted set:

$$\widehat{IP_s}^* = \sum_{k\in K} p_k ip^*_{s_k} \qquad (6)$$

where,

K shows the set of values of the *j* indicators for our data, and where the *pk* weights are included in one. Thus, *pk* weights' ideal choice is minimizing its variety:

$$\widehat{IP}_s^{\ *} - IP_s^* = \sum_{k \in K} p_k \left(ip_{s_k}^{\ *} - IP_s^* \right) = \sum_{k \in K} p_k \left(\varepsilon_k / \delta_k \right) \quad (7)$$

where εk and δk underline the error terms and the δ - coefficients from equations (6) and (2) used in the construction of the weighted set in equation (6). Since we assumed that ε's are unrelated, we have:

$$var\left(\widehat{IP}s^* - IPs^*\right) = \sum_{k \in K} p_k^2 \frac{\sigma^2(\varepsilon_k)}{\delta_k^2} \quad (8)$$

Minimize equation (8) concerning pk, below the constraint

$$\sum\nolimits_k p_k = 1$$

returns:

$$p_k^m = \frac{\delta_k^2 / \sigma^2(\varepsilon_k)}{\sum_{i \in K} \delta_i^2 / \sigma^2(\varepsilon_i)} \ \forall \ k \varepsilon K \quad (9)$$

We found the largest weight in proxy variable ipsj for which σ2 (εk) is small, eg the equation is a fairly accurate description, and for which δ_k^2 is large, eg the effect of informal IPs payments on the associated health index is possible. Its minimum price, $var\left(\widehat{IP}_s^{\ *} - IP_s^*\right)$, reached in pm, is $1/\left[\sum_{k \varepsilon K} \delta_k^2 / \sigma^2(\varepsilon_k)\right]$. Including an added proxy variable $\widehat{IP}_s^{\ *}$ leads to a better approximation of IPs [given values for δk and $\sigma^2(\varepsilon_k)$ for each k].

Equations (4) and (8) show that measurement changes indicators' units neither of the two *pm* nor $\widehat{IP}_s^{\ *} = p^{m^{-1}} ip_s^*$. Thus, $\widehat{IP}_s^{\ *}$ is independent of the scaling of informal payment indexes. Weighted vector *pm* means relevant information value for each informal payment ratio. Informal payments specific indicators measurement resolves its obstacles.

2.4. Estimated Model.

Our model's cross–sectional data are based on a survey conducted in two consecutive periods, December 2015 to January 2016, and from December 2016 to January 2017 to Greek citizens of the 13 Regions. We use convenience sample method and we select a sample concerning those who used public and private health services, over 18 years old, and complete structured questionnaires in 4,218 households covering 4,393 health incidents.

Even though that Part B of the questionnaire describes healthcare services is linked to similar to Van de Ven and Van der Gaag's findings (1982). Data set includes information on informal payments behaviors, the amount paid for drugs, total amount, and total burden. Contains variables for health services demand regarding their utilization, a health problem, its identification and the days that prevent patients from continuing their activities, services type, and the reasons for treatment interruption. Contains variables about patients' willingness to pay informally and their attitude towards this act, their opinion about legitimacy likelihood, their readiness to pay informally for drugs, and free public services (excluding drugs). Demographic variables such as age, gender, household size with a common budget, region of residence, income, educational level, and employment status are crucial.

2.4.1. Principal Component Analysis.

Principal Component Analysis (PCA) for control indicators' construction of Likert scale variables is one of the techniques of Multivariate Statistical Analysis. Focus on a creation a small and manageable number of unrelated linear combinations of the initial variables, containing original variables information. Initial multiple data are represented graphically through the main components, providing a simple and clear representation of the original information. For main components' construction is necessary to find samples table's of variations-covariances eigenvalues and eigenvectors or original data's correlation table. The highest eigenvalue and the corresponding eigenvector correspond to the first major component, second largest eigenvalue to the second major component etc. Main components use implies full coverage of original data the variation, while some main components are omitted some of the original information will be lost. PCA implementation allows faster and economical management and storage of original data, due to the significant reduction of their volume (Wold et al., 1987; Abdi, Williams, 2010; Schreiber, 2021; Ganan–Cardenas, Correa–Morales, 2021). Based on PCA analysis, first important quality control measure is whether is statistically significant and then the statistical fitness index of the sample for Kaiser- Meyer-Olkin factor analysis (this index gets values greater than 0 and less than 1) is greater than or equal to 0.5. Closer the index is unit stronger is our analysis (Beavers et al., 2013; Kaiser, Rice, 1974).

2.4.2. Regression Analysis.

Regression analysis for the construction of a model where we will identify the relationship between indicators and specifically Experience Index and other indicators, we examined the relationship between two or more variables in order to predict the values of one, through the values of the other (or others). In each regression problem we distinguish two types of variables, the independent or controlled or explanatory (independent, predictor, casual, input, explanatory variables) and the dependent or response (dependent, response variables). The selection criteria a good or satisfactory model is the R2 index which takes values greater than zero and less than one (Helland, 1987; Emerson, 2020; Kim et al., 2020). The closer the R2 values are to the unit (>= 0.5) the better our model explains our data (Groebner et al., 2018). Equally important in addition to R2 is the result of the ANOVA Analysis Table 6 which shows us the statistically significance of the regression.

2.4.3. Modeling Strategy.

2.4.3.1. General.

Our analysis requires application of PCA aiming the construction of indicators from multiple questions into an indicator or sub - indicators for easier management and possible results modeling. We innovate by building an indicator for informal payments (IPs). Based on

literature (Van Vliet, Van Praag, 1987; Van de Wen, Van der Gaag, 1982) this indicator consists of the following questions:
• The services to which an amount was paid in € by the patients informally (ie without receiving an official receipt or other necessary tax document) for each specific incident of health services use.
• Determination of the equivalent in € of the benefit in kind, the level of health care service provision.
• Patient costs for medicines, in euros.
• Total payment amount, in euros.
• Total cost/charge from informal' s own payment for health services provision.
The following tables present the results of this analysis.

Table 2. Kaiser – Meyer – Olkin control

Kaiser-Meyer-Olkin Measure of Sampling Adequacy		0,317
Bartlett's Test of Sphericity	Approx. Chi-Square	529,099
	df	6
	Sig.	0,000

Based on the above, this analysis appears statistically significant since it gives us p-value (sig.) = 0.000 so in a confidence interval α = 5% the p-value is less than 0.05 (α = 5 %). Also, based on the value of the Kaiser - Meyer - Olkin criterion = 0.736 the analysis is acceptable. Therefore, the table below shows the percentage of responses covered by the constructed index.

Table 3. Total variation of interpretation of answers by the factor/s - indicator(s)

Extraction Sums of Squared Loadings		
Component	% of Variance	Cumulative %
1	63.87%	63.87%

Based on the results of the table above, the factor interprets 63.9% of the answers. Table 4 presents the coefficients of the following index - factor.

Table 4. Factor's Coefficients

	Component
	1
How much did you pay for drugs?	0,316
What was the total cost/burden from informal payment healthcare services provision/treatment?	0,384
The services to which an amount was paid in euros (€) informally by patients informally (ie without receiving an official receipt or other necessary tax document) for each specific incident of healthcare services use.	0,362
Determination of the equivalent in euros (€) of benefit in kind, the level of provided care and the service to which it was given.	0,114

Informal Health Payments Index (IPs), based on Table 4 results, is represented by the structural equation (10):

$$IP_s = \ 0{,}316 * AMDRUG_{i,t} + \ 0{,}384 * INFOB_{i,t} + 0{,}362 * PROV_{i,t} + \ 0{,}114 * SEIF_{i,t} \quad (10)$$

when,
IPs = the index of unobtrusive informal health payments, with base year in 2015.
$AMDRUG_{i,t}$ = the amount paid (€) by the users of health services for medicines.

$INFOB_{i,t}$ = the total users' cost/burden (€) from informal payment for health services provision.
$PROV_{i,t}$= the services to which an amount (€) was paid informally by patients (ie without receiving an official receipt or other necessary tax document) for each specific health incident.
$SEIF_{i,t}$ = determination by patients of the equivalent in € of the benefit in kind, the level of care provided and the service provided.

3.4.3.2. Modeling Process Of Informal Health Care Payments Index.

We went one step further trying to model our index with the rest of our variables, in order to estimate results from whatever value that index will receive.

To achieve this goal we apply regression analysis which will have the form Y = a1 + a2*X1 + a3*X2 +… + an*Xn where Y is defined as our dependent variable which will be the Index non observed informal health payments (IPs) and X1, X2,…, Xn, our other variables that will play the role of our independent variables. Tables 5 and 6 present the results of the analysis.

Table 5. Model synopsis

Target	Informal non – observable healthcare payments index (IPs)
Automatic Data Preparation	On
Model Selection Method	Forward Stepwise
Information Criterion	-47,119

According to Table 5 , our model used the forward stepwise regression method (Sutter, Kalivas, 1993), which helps to identify the optimal statistical relationship between the questions included in our model, exporting this of variable questions which destroy the model's dynamics but also its statistical significance. The information criterion is used to compare to models. So, models with smaller information criterion values fit better. Thus our model presents an acceptable adjustment or efficiency with R2 = 0.417 or 41.7%, which shows us that our model shows a significant recommendation. However, is necessary to show our model's importance degree and for this reason we proceeded to analysis of variance (ANOVA) (Table 6).

Table 6. Variance analysis (ANOVA)

Source	Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	50,316	9	5,591	9,595	0,000
Residual	57,684	99	0,583		
Corrected Total	108,000	108			

According to Table 6 results, our model is presented as statistically significant since the value received by p-value (sig.) = 0.000 for a confidence interval α = 5% (0.05) the p-value is lower.

3.4.3.3. Partial Information As A Tool For Informal Healthcare Payments Estimation.

Our justification was based on a diagonal table of error terms. But, there are no non-zero fluctuations contained in $\Sigma_{\hat{\varepsilon}\hat{\varepsilon}}$. He argues that equations (7), (8) and (9) need to be modified accordingly. We write according to equation (7):

$$\widehat{IPs^*} - IPs^* = \sum_{k \in K} p_k \cdot \varepsilon_k / \delta_k \qquad (11)$$

with variance,

$$var\left(\widehat{IP}_s^* - IP_s^*\right) = p'\left[diag(\delta)^{-1} \sum\nolimits_{\hat{\varepsilon}\hat{\varepsilon}} diag(\delta)^{-1}\right] p$$

$$= p'\left[diag\,(\delta)^{-1}(1-B)^{-1} \sum\nolimits_{\varepsilon\varepsilon} (1-B')^{-1}\, diag\,(\delta)^{-1}\right] p$$

$$= p'Ap \qquad (12)$$

where the vector p includes the unknown weights pk, diag (d) underlines a diagonal frame including the δ-correlations, $\Sigma_{\hat{\varepsilon}\hat{\varepsilon}}$ is the diagonal matrix with positive fluctuations of the residuals of the structural model and where A is implicitly defined. Minimization of the square form in equation (12) object of the constraint p't = 1 [t = (1,1,…, 1) '] can be achieved by minimizing the Lagrange equation with respect to p,

$$L = p'Ap + 2\lambda\,(p't - 1) \qquad (13)$$

We take first class conditions

$$\begin{cases} \dfrac{\partial L}{\partial p} = 2Ap - 2\lambda_t = 0 \\ \dfrac{\partial L}{\partial p} = 2\,(p't - 1) = 0 \end{cases} \qquad (14)$$

where we used A '= A. We can separate from equation (14)

$$p^m = A^{-1} l * \frac{1}{t' A^{-1} l} \qquad (15)$$

$$\min_{p}\left[var\left(\widehat{IP}_s^* - IP_s^*\right)\right] = p^{m\prime} A p^m$$

$$= \frac{1}{t' A^{-1} t} \qquad (16)$$

with

$$A^{-1} = diag(\delta)(1 - B') \sum\nolimits_{\varepsilon\varepsilon}^{-1} (1 - B)\, diag(\delta) \qquad (17)$$

We have found that equations (14) and (15) are in fact generalizations, for B ≠ 0, of equations (8) and (9) mentioned earlier. Furthermore, the earlier hypothesis that structural types of errors are unrelated (and that they $\Sigma_{\hat{\varepsilon}\hat{\varepsilon}}$ is diagonal) can be easily disproven since they are not necessary for the production of equations (16) and (17).

The non-zero non-diagonal elements of the A-1 can be considered as corrections of the correlations between those parts of informal payment indices that provide information about these IPs*. If any of the weights are not positive, the signal of the corresponding indicators of informal payments should be revised, proving that it is a low index of informal payments in health.

We can derive matrix A (6x6) from the six proxy variables ipsj, which are based on the informal payment ratios used in our model. If we then want to make informal IPs payments in the selection of proxy variables we need to calculate pm from equation (15) by omitting the appropriate rows and columns of A-1. Thus, for each of the proxies of informal payments we receive a different set of stations. Overall, we can construct $\sum_{i}^{6} = t\binom{6}{i} = 2^{6} - 1 = 63$ different choices.

Of all our variables, based on the Forward Stepwise method of regression analysis, there are six questions - variables that are emphasized. We focused on the possibility of a health problem that prevents the patient from continuing his normal activities (HCPE) but also the days when this problem prevents him from continuing his normal activities (DAYS). In addition, we considered it very important to report (specify) the health problem (HCP) based on the official diagnoses of doctors. Also, as we have proven, the catalyst is the recording of any kind of formal/formal health service that the patient received related to the specific health problem (or other reasons, for example pregnancy) during the last 4 months (FOSE). Undoubtedly we could not omit the variable concerning the reason why the provision of health care (UNSE) was not completed. Education level has been shown to have a catalytic effect on the formation of informal health payments (EDU).

3.4.4. Coefficients Of Informal Payments In Health Care Model.

Our model has an acceptable fit of R2 = 0.417 and it is statistically important that we calculate the coefficients a1, a2, a3, ..., a7 of our model, as shown in Table 7.

Table 7. Model's coefficients

Model	Standardized Coefficients Beta	Sig.	Importance
(Constant)	0,818	0,037	
What is/was the exact health problem you faced?	1,519	0,000	0,350
How many days prevented you from continuing your normal activities?	0,603	0,002	0,254
Why was health care not completed?	-0,902	0,013	0,124
Record any use of a formal health service related to your particular health problem (or other reasons, such as pregnancy) in the last 4 months - Health Service Level	-0,457	0,052	0,124
Does a specific health problem prevent/prevent you from continuing your normal activities?	-0,298	0,051	0,075
Education	0,566	0,054	0,073

As we found out of all the variables only six of them are statistically significant for our model and will be the variables of our final model. According to the results of the table above in the Beta column are displayed the values that will receive the coefficients a1, a2, a3, a4 of our model.

3.4.5. Final Model Of Informal Payments In Health Care.

$$\boldsymbol{IP_s} = 0{,}818 + 1{,}519 * \boldsymbol{HCP_{i,t}} + 0{,}603 * \boldsymbol{DAYS_{i,t}} - 0{,}902 * \boldsymbol{UNSE_{i,t}} - 0{,}457 * \boldsymbol{FOSE_{i,t}} - 0{,}298 * \boldsymbol{HCPE_{i,t}} + 0{,}566 * \boldsymbol{EDU_{i,t}}$$

IPs = informal payments in health, with base year in 2015.

HCP = specific patient's health problem ($p = 0.000 < 0.05$).
DAYS = number of days that the existing health problem prevented the patient from continuing his normal activities ($p = 0.002 < 0.05$).
UNSE = the reason (s) for which the patient did not complete the specific health care provided to him ($p = 0.013 < 0.05$).
FOSE = any use of formal - standard health service, related to the specific health problem (or other reasons, for example pregnancy) during the last 4 months - health service level ($p = 0.052 > 0.05$).
HCPE = possibility of a patient health problem ($p = 0.051 > 0.05$).
EDU = patient's educational level ($p = 0.054 > 0.05$).

In our ultimate model, informal payments are latent variable. Three of the six independent variables, *HCP*, *DAYS*, and *EDU* have a positive effect on informal payments level. Most health services users did not state having a health problem, so they proceed for precautionary reasons. But those who suffer from an illness come to health services to improve their condition or to be treated. Patients' majority were absent from daily activities from 1 day to 7 days and many less than 1 to 3 months. Subsequently, the respondents' majority were of higher educational level by 43% and 1/5 of the sample were Primary Education graduates. These variables affect informal health payments by 1.519, 0.603, and 0.566 times, only if other variables remain constant. In case the other three variables are unstable, *FOSE*, *HCPE* as well as the *UNSE*, we also draw the following conclusions. Most of the patients paid for public health and less to private units, meaning that patients use their insurance coverage and less inclination towards private insurance, justified of their salaries reduction. Most of them have respiratory problems, exogenous causes, injuries, and poisonings. However, a smaller proportion has neoplasms, neurological diseases, and chromosomal abnormalities, marking the untimely diagnosis of genomes that increase the likelihood of specific illnesses. Unfortunately, sometimes the patient may not complete his treatment.

The most profound impact on informal payments has the type and severity of the health problem faced by health services users. Doctors demand different amounts from patients with severe illnesses, creating a dependent atmosphere. Is not totally related to user's income level, as cases of bribery exist in higher-income scales as well. A private health unit without participation is chosen by the patient, mostly closest to his place of residence. Illegal money of €404.64 (± 761.44) is paid in all services and less for medicine. Most patients are against these payments, while there are still some of them who are fond of them. Patients are more willing to pay for non-medicated health services than for medicines.

Our primary concern is illegal payments' total burden on health services. A high correlation is observable, with illegal payment in euros reaching 0.680. Compared to the equivalent in euros, a similar situation is noticeable up to 0.496 as in pharmaceutical expenses by 0.488 but still in the total amount paid.

Our model's variables, that regulate the number of informal payments show a probability of a health problem, its specification, patient's absence days from regular activities, reasons for treatment miscarriage, as official services use, and patients' educational level.

4. CONCLUSION.

We focus on the description and application of a new method for deriving healthcare indexes from a MIMIC informal payments health care model. This differs from the traditional approach, where indexes for health care payments arise from causes and indicators. Indicators contain measures of health care demand (the days that patient is absent from continuing normal activities and the reason health care is incomplete) and informal payments' behavior (health services characterized by shadow payments and users' burden from these payments). Causes include measures related to preparedness of payments (patients' perception and their opinion about informal payments legalization) and demographic variables (age, sex, household size and income, region of residence, education, and employment). We essentially derived informal healthcare indexes by applying a weighing procedure to transformations of related indicators. Variables are better with changes influencing informal health indexes but not related behaviors (*IPs**) itself. Information on *IPs** might be a part of two or more informal payments indicators.

Based on the model's parameters, we derive weights, which are used to calculate indexes. These weights reflect the relative information value of each health indicator for the latent variable IPs*. They offer a decision criterion for including or excluding informal payments indicators that appear to contain no or hardly any information on behaviors related to them. We use health indicators for IPs construction for variables' effects which influence health indicators but not informal payments. We circumvent classical problems that healthcare use as an indicator of health leads to conclusions such as: 'increasing healthcare services use for one or more household members, during the last 4 months leads to more use and thus in the highest amount of informal payments'.

Application of this method based on primary survey data can collect only those indicators and variables which appear to contain health information and to combine them for a reliable informal healthcare payment index. The basic MIMIC model contains structural relations between the endogenous indicators. These relations lead to modifications or our weighing procedure which can be corrections because of information on IPs*, in two indicators at least. The derived health indexes are independent of a linear transformation of the indicators.

Is difficult to approximate IPs* using variables that affect informal payments than to do it by indicators related to specific behaviors. Our method of a MIMIC healthcare model revealed that five variables combined with education, whereas expressed the informal health payments index (IPs*) in a model of 11 determining factors.

Available data show consistently that IPs bulk in the Greek healthcare system is informal fees for service, so we should shift policy focus from the public sector's corruption to reform those characteristics which induce and maintain fee–type IPs. Reforms that focus on efficiency improvements and reallocate savings to shortage areas and short–term measures should combat the informal payments. Among quick–fix policies, the only viable option is IPs formalization: removing physician's choice from the publicly financed patient pathway and introducing user charges for those who want to keep it. It aims to eliminate the access barrier that IPs create. Political risks of quick-fix policy should be against the detrimental impact of letting IPs persist, but such risks might be eliminated by the application of change management and large–scale system transformation techniques and skills which appear to be critical success factors in an NHS driving change.

Health systems' reflections on accountability, transparency, and complaints' control to informal payments are inadequate. We detect a gap to cause shadow payments' misregistration in all cases because doctors created a climate of dependence culture with patients. If that transaction isn't taking place patient is receiving hardly health services as common sense. We have redefined health policy with falling public spending and a slight increase in private health spending, specifically informal payments. The pandemic shook the health system and corruption, highlighting its preparedness, by strengthening lost pandemic phenomena like informal payments.

There are some limitations in our study that needs to be considered. First, respondents in our study were adults from over the age of 18 years old. Second, total sample of our survey were Greeks, so we exclude some foreigners from our sample. Finally, in case of children's illness and health care services use, only parents gave detailed information about their situation. All the mentioned issues should be considered for future research.

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