https://dergipark.org.tr/tr/pub/ijhmt Doi Number: 10.31201/ijhmt.811239

Int Journal Of Health Manag. And Tourism 2021

JHMT Editorial

International Journal Of Health Management And Tourism

MODELING OF ACCESS TO HEALTH SERVICES IN TURKEY: THE COUNT DATA MODELS WITH A POISSON DISTRIBUTION

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Received: 13.10.2020
Accepted: 4.02.2021
Research Article

Abstract: In simple terms, access refers to people's ability to obtain and use quality health care technologies when they need. In this study, data collected by TurksStat, Turkish Statistical Institute, through Turkey Health Survey which was applied across the country was analyzed. This survey was carried out every two years, for the first time in 2008 and the last time in 2016. The aim of this study is to examine the level of access to health services in terms of some socio-demographic variables such as gender, age, education, health status and income in Turkey between the years 2008-2016. The results obtained with the analysis show that all variables differ according to years and they are statistically significant. According to the analysis conducted as part of the study, it was concluded that, in Turkey, the status of income and health insurance do not constitute a risk factor on the access to health services. It is thought that the presence of a social security system involving the whole country has an effect on this result. Considering from this point

of view, in countries that do not have a strong social security system, out-of-pocket health spending and private health insurance increase the inequalities among the social segments. Therefore, private health insurances and income systems to reduce dependence on out-of-pocket health spending should be developed, and access to health services should not be an indicator of income. In this respect, more research is needed in which access to health services is evaluated from all aspects.

Keywords: *access, health, the count data models, healthcare management*

Introduction

Patients' recognition of their needs for services and their decisions to seek medical care generally form the first step in the process of accessing services. The probability of utilizing services depends on the balance between individuals' perceptions of their needs and their attitudes, beliefs and previous experiences with health services (Mechanic, 1978). Access to health services implies that individuals recognize and accept their need for services, consent to a role as service user, and acknowledge socially generated resources that they are willing to utilize. The U.S. Institute of Medicine defined access as 'timely use of personal health care to achieve the best possible outcome' (Millman, 1993). On the other hand, access as a concept is an "uncertain and complicated" process for policy makers and practitioners as well as the public (Racher and Vollman, 2002). Access to a health technology depends on providing the "right" product in the "right" place, with the "right" protocol at the "right" time (Frost and Reich, 2008: 8). In this respect, the proof of access is not only the existence of a facility, but the use of the service (Donabedian, 1972). Penchansky and Thomas developed this idea by Donabedian, suggesting that access describes the 'degree of compliance' between patients and the health system (Penchansky and Thomas, 1981). This 'degree of compliance' may be affected by the acceptability, affordability and provision of services. Penchansky and Thomas's approach has taken the concept of access beyond service usability, considering the personal, financial and organizational barriers to service use (Gulliford et al., 2002: 187).

In order to measure access, service use and the results obtained from the use are brought together. This structure is used to define five basic components: health policy, features of delivery system, population at risk, consumer satisfaction. (Ricketts and Goldsmith, 2005: 274). Having access to health care requires an adequate supply of health services available. According to this dimension, access to health care is concerned with the opportunity to obtain health care when it is desired or needed. The availability of services is measured traditionally using indicators such as the numbers of doctors or hospital beds per capita (Gulliford et al., 2002).

One of the main issues in access assessment is the assessment of access equity. The difficulty in the assessment of equity is that health problems of different groups are diverse, health care needs for similar health problems vary and different groups have their own priorities and values. Groups with different needs require access to services that are appropriately differentiated in terms of volume and quality. This vertical dimension to equity (the unequal treatment of nonequals) is acknowledged to be more difficult to measure than the horizontal, not least because there is little consensus on how vertical equity could be judged to exist. In this respect, it is necessary to distinguish between horizontal and vertical equity. With horizontal equity, while the health care system needs to deliver essentially the same health care services (or a distribution of services that equate results) for people in approximately the same economic conditions, vertical equity requires government participation in the financing of care. Achieving horizontal equity requires this to be at the level of government (Fein, 2005: 4-5). Health-related facilities and services can be available within a country, but they can also be inaccessible to all those who need them. For example, access to essential medicines is an indispensable part of the right to health care in many aspects. First, medicines must be accessible in remote rural areas as well as in urban centers, which has major implications for the design of medicine supply systems. Inequality in access to medicines is part of inequality in health care. Since equal access is not always guaranteed by equal treatment, the state should sometimes take measures in favor of disadvantaged people (Hunt and Khosla, 2008: 99; Hogerzeil and Mirza, 2011: 8).

One of the main reasons why access is difficult is that there are other failures under most insufficient access situations. Access problems occur as a result of a combination of market failures, government failures and nonprofit failures. In order to eliminate more than one error, several steps should be taken for actors at the global, national and local level, and this requires a variety of expertise. Solutions often include economic, political and perceptual strategies. Problems related to access can rarely be solved by providing more money. Similarly, intellectual property rights can be a challenging barrier to access new products but removing patent barriers does not necessarily and immediately provide access (Frost and Reich, 2008: 10).

1. Research Methodology

Analysis carried out in this study were based on data collected by TurksStat through Turkey Health Survey which was applied across the country. This survey was carried out every two years, for the first time in 2008 and the last time in 2016. With Turkey Health Survey, it is aimed to close the information gap by retrieving the data related to the health indicator which has an important share in development indicators showing the development level of countries. In addition to reflecting the country in general, the study is considered to be important in terms of both providing international comparisons and shedding light on national needs. It aims to examine the level of access to health services in terms of some socio-demographic variables such as gender, age, education, health status and income in Turkey between the years 2008-2016.

1.1 Statistical Analysis Methods

In order to examine the distribution of variables as well as their changes by years, chi-square analysis was applied for categorical variables and one-way analysis of variance (ANOVA) was used for continuous variables. Detailed information is given in Table 1.

In the continuation of the study, assumptions were tested. It is tested to find which of the discrete distributions of access to health services are suitable. According to this, it shows Poisson distribution (χ^2= 8.354; p = .138), not Negative Binomial (χ^2= 12.072; p =.016). The null hypothesis, on the other hand, is based on the distribution of interest appropriate. In addition, Poisson regression is used in non-negative variables with the mean and variance being equal or close, and Negative Binomial regression is used when variance exceeds the mean ($\bar{x}_{\text{Access to Health Services}}$=.327, $s_{\text{Access to Health Services}}$=.683). However, the assumption of variance equals to the mean resulting in being very difficult for the zero excess count data to follow a Poisson model (Xu et.al., 2017). Since the distribution of access to health services is Poisson distribution, the models and theoretical knowledge are emphasized on Poisson distribution. The results of the modeling of access to health services were given in Table 2-4.

1.2 Modeling

The main control mechanism for continuous variables is based on normal distribution. However, the situation is different for discrete variables. The types of discrete variables also differ. Binary, ordinal, categorical and count type variables can be listed as examples. For this type of variables, model selection is the most important thing. In particular, count variables are often used in modeling in epidemiology. In this study, the variable that we want to estimate is of the count type and is a variable with many zero observations.

As is known from many studies, count variables rarely meet the distributional assumptions of ordinary least squares linear regression (Hofstetter et al., 2016). However, zero excess is not an issue to be dealt with, such as the assumption of distribution. When the outcome variable is of the count type, already known methods (such as multiple regression) will no longer be sufficient. While the known methods have nothing to do for exceeds of zeros, count regression approaches, as the name suggests, will be a much more convenient technique. The most commonly used models for modeling outcome variables of count type are Poisson Regression, Negative-Binomial Regression, Zero-Inflated Poisson Regression, Zero-Inflated Negative-Binomial Regression and Hurdle (Poisson, Negative-Binomial) Regression. These methods have their own assumptions as in linear regression. In model selection, commonly used criteria can be used such as AIC, Akaike information criterion and BIC, Bayesian information criterion. Since the distribution of the outcome (dependent) variable is important among the assumptions, the suitability of the outcome (dependent) variable in our study was tested. In addition, Poisson regression is used in non-negative variables with the mean and variance being equal or close. Negative Binomial regression is used when variance exceeds the mean (Hu et al., 2011).

Poisson Regression Model

Poisson regression is quite similar to multiple linear regression except that the dependent Y (outcome) variable is a non-negative count with the Poisson distribution. Thus, the non-negative counts 0, 1, 2, 3,… and mostly, large counts are uncommon.

Let Y be the number of events occurring in a fixed period of time t and $y_i, i = 1,2, \dots n$ is the value of the dependent variable. Besides, Y is a Poisson distribution with parameter μ. The parameter μ, represents the expected number of occurrences in a fixed period of time $E[Y] = \mu$ (Cameron and Trivedi, 1998).

In Poisson regression, suppose that the Poisson mean (incidence rate) $\mu_i, i = 1,2, \dots n$ is determined by a function of covariates $\boldsymbol{x} = [x_{i1}, x_{i2}, \dots, x_{ik}]^T, i = 1,2, \dots, n$. This is also defined as $\mu_i = exp(\boldsymbol{x_i^T\beta})$. The regression coefficients $\boldsymbol{\beta} = [\beta_1, \beta_2, \ldots, \beta_k]$ are unknown parameters related to k covariates.

Then the Poisson regression model is as follows:

$$P_{Poisson}(Y_i = y_i) = \frac{e^{-\mu_i}(\mu_i)^{y_i}}{y_i!} \tag{1}$$

Zero Inflated Poisson Model

The Zero-inflated Poisson (ZIP) model is used for count data that exhibit overdispersion and excess zeros. So that the model assumes a mixture of a zero component distribution and a count distribution. In other words, a zero count can be estimated in either the excess zero part (2)(a) or in the count distribution (2)(b). Most of the notation is common with the Poisson model. $\mu_i, i = 1,2, \ldots n$ is determined by a function of covariates $\boldsymbol{x} = \left[x_{i1}, x_{i2}, \ldots, x_{ik_1}\right]^T, i = 1,2, \ldots, n$. It is defined as $\mu_i = exp(\boldsymbol{x_i^T\beta})$. The regression coefficients $\boldsymbol{\beta} = \left[\beta_1, \beta_2, \ldots, \beta_{k_1}\right]$ are unknown parameters related to k_1 covariates in the count part (2)(b). k_1 denotes the number of independent variables in the count part. The estimated probability of occurrences of excess zero part is π_i and it is known as the logistic link function. It is shown as $\pi_i = e^{z_i\gamma}/1 + e^{z_i\gamma}$ where $\boldsymbol{z} = \left[z_{i1}, z_{i2}, \ldots, z_{ik_2}\right]^T, i = 1,2, \ldots, n$ is a vector of independent variables in the excess zero part and $\boldsymbol{\gamma} = \left[\gamma_1, \gamma_2, \ldots, \gamma_{k_2}\right]$ is a vector of coefficients.

$$P_{ZIP}(Y_i = y_i) = \begin{cases} \dfrac{e^{z_i\gamma}}{1 + e^{z_i\gamma}} + \left(1 - \dfrac{e^{z_i\gamma}}{1 + e^{z_i\gamma}}\right) e^{-\mu_i} & if\ y_i = 0\ (a) \\ \left[1 - \dfrac{e^{z_i\gamma}}{1 + e^{z_i\gamma}}\right] \dfrac{e^{-\mu_i}(\mu_i)^{y_i}}{y_i!} & if\ y_i > 0\ (b) \end{cases} \tag{2}$$

The excess zero part (2)(a) represents the subpopulation of individuals who have no problems with access to health services, whereas the count part (2)(b) represents those individuals who have problems with access to health services.

Hurdle-Poisson Model

The hurdle model (H-P) is also a count model with two parts, which was introduced by Mullahy (1986). In particular, the hurdle model combines a dichotomous outcomes part (3)(a) and a truncated count part (3)(b). The truncated count part is also known as the hurdle part (3)(b). The dichotomous outcomes part (3)(a) models the probability that the threshold is crossed. In general, the threshold is usually at zero but can be any value. The notations are the same as the zero-inflated Poisson model (ZIP). $\mu_i, i = 1,2,\ldots n$ is determined by a function of covariates $\boldsymbol{x} = \left[x_{i1}, x_{i2}, \ldots, x_{ik_1}\right]^T, i = 1,2,\ldots,n$ and defined as $\mu_i = exp\left(\boldsymbol{x}_i^T\boldsymbol{\beta}\right)$. The regression coefficients $\boldsymbol{\beta} = \left[\beta_1, \beta_2, \ldots, \beta_{k_1}\right]$ is a vector of coefficients belonging to $\boldsymbol{x}$ in the zero hurdle part (3)(b). k_1 denotes the number of independent variables in the zero hurdle part. $\boldsymbol{z} = \left[z_{i1}, z_{i2}, \ldots, z_{ik_2}\right]^T, i = 1,2,\ldots,n$ is a vector of independent variables in the excess zero part and $\boldsymbol{\gamma} = \left[\gamma_1, \gamma_2, \ldots, \gamma_{k_2}\right]$ is a vector of coefficients belonging to $\boldsymbol{z}$ (Zeileis et al., 2008).

$$P_{H-P}(Y_i = y_i) = \begin{cases} (1 + e^{z_i\gamma})^{-1} & if\ y_i = 0\ (a) \\ [1 - (1 + e^{z_i\gamma})^{-1}]\dfrac{e^{-\mu_i}(\mu_i)^{y_i}}{(1 - e^{-\mu_i})y_i!} & if\ y_i > 0\ (b) \end{cases} \tag{3}$$

The dichotomous outcomes part shows the subpopulation of individuals ($Y = 0$) who have difficulties in accessing the health care services and the truncated count part is a modeling that shows individuals (for those with $Y > 0$) who have problem with accessing the health care services.

From eq. (2) and (3), the difference between the zero-inflated and hurdle models is the way they model zero values. The zero-inflated model allows a large number of zeros in the model while the hurdle model does not.

For the model selection, classical methods such as Akaike information criterion (Akaike, 1973) and Bayesian information criterion (Schwarz, 1978) can be used. Other methods can be also considered such as the Vuong statistic (Vuong, 198). It can be also used to decide which model has a better fit (Sheu et. al., 2004). The purpose is to test the validity of the hurdle model against the zero-inflated model, the hurdle model against the Poisson model and the zero-inflated model against the Poisson model. Significant Vuong statistics show that one model is closer to the true model.

2. Analysis

Table 1. Descriptive Statistics Test Statistics Results according to Years

Year	2008	2010	2012	2014	2016	p-value
	(n=20624)	(n=20200)	(n=37979)	(n=26075)	(n=23606)	
Gender						**<0.001[b]**
- Male	9703 (47.05%)	9122 (45.16%)	18015 (47.43%)	12276 (47.08%)	10973 (46.48%)	
- Female	10921 (52.95%)	11078 (54.84%)	19964 (52.57%)	13799 (52.92%)	12633 (53.52%)	
Age	31.00 ± 20.85	32.12 ± 21.53	33.04 ± 21.40	33.27 ± 21.78	33.92 ± 22.35	**<0.001[a]**
Education						**<0.001[b]**
- No answer	2062 (10.00%)	2021 (10.00%)	3468 (9.13%)	2566 (9.84%)	2376 (10.07%)	
- Illiterate	6710 (32.53%)	6411 (31.74%)	10831 (28.52%)	5319 (20.40%)	4515 (19.13%)	
- Primary school	6962 (33.76%)	6925 (34.28%)	13690 (36.05%)	10260 (39.35%)	8875 (37.60%)	
- Middle school	1154 (5.60%)	1076 (5.33%)	1682 (4.43%)	1967 (7.54%)	2170 (9.19%)	
- High school	2457 (11.91%)	2280 (11.29%)	4937 (13.00%)	3362 (12.89%)	3106 (13.16%)	
- 2-Year/ University	1185 (5.75%)	1387 (6.87%)	3132 (8.25%)	2359 (9.05%)	2335 (9.89%)	
-Masters/ Doctorate	94 (0.46%)	100 (0.50%)	239 (0.63%)	242 (0.93%)	229 (0.97%)	
Social Security Status						**<0.001[b]**
- Social Security Institution (SSI)	17683 (85.74%)	17720 (87.72%)	35077 (92.36%)	23952 (91.86%)	21872 (92.65%)	
- Private	22 (0.11%)	105 (0.52%)	220 (0.58%)	479 (1.84%)	126 (0.53%)	
- SSI + Private	53 (0.26%)	118 (0.58%)	255 (0.67%)	1543 (5.92%)	493 (2.09%)	
- No insurance	2866 (13.90%)	2257 (11.17%)	2427 (6.39%)	101 (0.39%)	1115 (4.72%)	
Marital Status						**<0.001[b]**
- No answer	5969 (28.94%)	5753 (28.48%)	9924 (26.13%)	6946 (26.64%)	6364 (26.96%)	
- Single	4378 (21.23%)	4417 (21.87%)	8835 (23.26%)	5968 (22.89%)	5330 (22.58%)	
- Married	10277 (49.83%)	10030 (49.65%)	19220 (50.61%)	13161 (50.47%)	11912 (50.46%)	
Working Status						**<0.001[b]**
- No answer	11443 (55.48%)	5753 (28.48%)	9924 (26.13%)	6946 (26.64%)	6364 (26.96%)	
- Working	3147 (15.26%)	5243 (25.96%)	10445 (27.50%)	7415 (28.44%)	6457 (27.35%)	

- Not Working	6034 (29.26%)	9204 (45.56%)	17610 (46.37%)	11714 (44.92%)	10785 (45.69%)	
Income						**<0.001[b]**
- 0 - 1100 TL	18912 (91.70%)	17425 (86.26%)	30676 (80.77%)	8470 (32.48%)	5183 (21.96%)	
- 1101- 1700 TL	1085 (5.26%)	1435 (7.10%)	3683 (9.70%)	5288 (20.28%)	6629 (28.08%)	
- 1701 - 2300 TL	257 (1.25%)	534 (2.64%)	1580 (4.16%)	4184 (16.05%)	4326 (18.33%)	
- 2301 + TL	370 (1.79%)	806 (3.99%)	2040 (5.37%)	8133 (31.19%)	7468 (31.64%)	
Health Status						**<0.001[b]**
- No answer	5973 (28.96%)	5766 (28.54%)	9928 (26.14%)	6946 (26.64%)	6364 (26.96%)	
- Very good	1465 (7.10%)	1395 (6.91%)	3584 (9.44%)	2169 (8.32%)	1554 (6.58%)	
- Good	7564 (36.68%)	7504 (37.15%)	15543 (40.93%)	8988 (34.47%)	8720 (36.94%)	
- Moderate	4018 (19.48%)	3911 (19.36%)	6700 (17.64%)	5646 (21.65%)	4901 (20.76%)	
- Bad	1396 (6.77%)	1392 (6.89%)	1960 (5.16%)	1982 (7.60%)	1852 (7.85%)	
- Very bad	208 (1.01%)	232 (1.15%)	264 (0.70%)	344 (1.32%)	215 (0.91%)	
Chronic Disease						**<0.001[b]**
- No answer	5969 (28.94%)	5753 (28.48%)	9923 (26.13%)	6946 (26.64%)	6364 (26.96%)	
- Have chronic disease	5744 (27.85%)	2165 (10.72%)	3694 (9.73%)	7161 (27.46%)	6027 (25.53%)	
- No chronic disease	8911 (43.21%)	12282 (60.80%)	24362 (64.15%)	11968 (45.90%)	11215 (47.51%)	
Disorders						**<0.001[b]**
- No answer	5994 (29.06%)	5792 (28.67%)	9951 (26.20%)	6946 (26.64%)	6364 (26.96%)	
- No disorders	7896 (38.29%)	7848 (38.85%)	16233 (42.74%)	8640 (33.14%)	7922 (33.56%)	
- Have disorders	6734 (32.65%)	6560 (32.48%)	11795 (31.06%)	10489 (40.23%)	9320 (39.48%)	
Difficulty in payment						**<0.001[b]**
- No answer	19877 (96.38%)	19602 (97.04%)	37253 (98.09%)	13881 (53.23%)	14277 (60.48%)	
- Yes	332 (1.61%)	270 (1.34%)	228 (0.60%)	2382 (9.14%)	1474 (6.24%)	
- No	415 (2.01%)	328 (1.62%)	498 (1.31%)	9812 (37.63%)	7855 (33.28%)	
Late appointment						**<0.001[b]**
- No answer	19877 (96.38%)	19602 (97.04%)	37253 (98.09%)	12804 (49.10%)	13877 (58.79%)	
- Yes	12 (0.06%)	3 (0.01%)	12 (0.03%)	3338 (12.80%)	2524 (10.69%)	

- No	735 (3.56%)	595 (2.95%)	714 (1.88%)	9933 (38.09%)	7205 (30.52%)	
Transportation problems						**<0.001[b]**
- No answer	19877 (96.38%)	19602 (97.04%)	37253 (98.09%)	14473 (55.51%)	14933 (63.26%)	
- Yes	27 (0.13%)	20 (0.10%)	48 (0.13%)	2221 (8.52%)	1576 (6.68%)	
- No	720 (3.49%)	578 (2.86%)	678 (1.79%)	9381 (35.98%)	7097 (30.06%)	
Access to Health Services						**<0.001[b]**
- No	19867 (96.33%)	19597 (97.01%)	37249 (98.08%)	12079 (46.32%)	12988 (55.02%)	
- Major	416 (2.02%)	321 (1.59%)	338 (0.89%)	6639 (25.46%)	4163 (17.64%)	
- Moderate	331 (1.60%)	277 (1.37%)	388 (1.02%)	6946 (26.64%)	6364 (26.96%)	
- Minor	10 (0.05%)	5 (0.02%)	4 (0.01%)	411 (1.58%)	91 (0.39%)	

a. One-way ANOVA test, b. Chi-Square test

The results shown in Table 1 indicate that all variables differ according to years and they are statistically significant.

Table 2. Summary of Possion Regression Models For Access to Health Services

Count Data Model	***Poisson section***	
(Possion)	$\boldsymbol{\beta}$ $(\boldsymbol{s.e})$	***p-value***
Intercept	-4.437 (0.038)	**<0.001**
Year	0.311 (0.006)	**<0.001**
Age	-0.004 (0.0005)	**<0.001**
Gender	0.045 (0.010)	**<0.001**
Education	0.010 (0.004)	**0.018**
Social Security Status	-0.008 (0.007)	0.303
Marital Status	0.066 (0.016)	**<0.001**
Working Status	-0.023 (0.015)	0.114
Income	0.028 (0.004)	**<0.001**
Health Status	0.163 (0.0109)	**<0.001**
Chronic Disease	-0.254 (0.014)	**<0.001**
Disorders	0.243 (0.017)	**<0.001**
Difficulty in payment	0.668 (0.015)	**<0.001**
Late appointment	1.205 (0.017)	**<0.001**
Transportation problems	-0.0787 (0.016)	**<0.001**
n	128484	
df	15	

$-2\log L$	-45592.2
p-value	**<0.001**
AIC	91214.39
BIC	91360.85

Poisson model shows that social security status and working status do not affect access to health care. The model is statistically significant ($-2\log L$ =-45592.2; p<0.001).

Table 3. Summary of Zero-Inflated Poisson Regression Models For Access to Health Services

Count Data Model	***Possion section***		***Logit section***	
(ZIP)	$\beta\ (s.e)$	*p-value*	$\beta\ (s.e)$	*p-value*
Intercept	0.556 (0.054)	**<0.001**	31.122 (39211.78)	0.999
Year	-0.072 (0.010)	**<0.001**	-0.172 (7444.01)	0.999
Age	0.001 (0.0005)	**0.015**	.0003 (375.6288)	0.999
Gender	0.007 (0.010)	0.466	.054 (11330.2)	0.999
Education	-0.006 (0.004)	0.192	.013 (4375.61)	0.999
Social Security Status	-0.008 (0.008)	0.293	.013 (7318.973)	0.999
Marital Status	-0.065 (0.016)	**<0.001**	-.192 (10869.07)	0.999
Working Status	-0.067 (0.015)	**<0.001**	-.276 (10923.49)	0.999
Income	-0.003 (0.004)	0.376	-.078 (4996.197)	0.999
Health Status	-0.058 (0.011)	**<0.001**	-.033 (7130.434)	0.999
Chronic Disease	-0.051 (0.014)	**<0.001**	-.003 (9936.682)	0.999
Disorders	-0.072 (0.018)	**<0.001**	-.182 (10983.14)	0.999
Difficulty in payment	0.079 (0.011)	**<0.001**	-54.808 (18039.01)	0.998
Late appointment	0.072 (0.014)	**<0.001**	-54.766 (16831.25)	0.997
Transportation problems	0.078 (0.014)	**<0.001**	-57.360 (48779.02)	0.999
n	128484			
df	30			
$-2\text{Log}\,L$	-34579.86			
p-value	**<0.001**			
AIC	69219.72			
BIC	69512.63			

The Zero-inflated Poisson model in the logit section shows that none of the variables were risk factors which affect access to health care. On the other hand, this section tries to model those who do not have problems in accessing health services. The Poisson section shows that gender, education, social security status, and income did not have a significant effect on access to health care. Other variables have an effect on access to health care. The model is also statistically significant ($-2\log L$ =-34579.86; p<0.001).

Table 4. Summary of Hurdle - Poisson Regression Models For Access to Health Services

Count Data Model	***Poisson section***		***Logit section***	
(H-P)	$\boldsymbol{\beta}\ (\boldsymbol{s.e})$	***p-value***	$\boldsymbol{\beta}\ (\boldsymbol{s.e})$	***p-value***
Intercept	-1.426 (0.121)	**<0.001**	-8.371 (0.143)	**<0.001**
Year	-0.102 (0.012)	**<0.001**	0.899 (0.023)	**<0.001**
Age	0.0005(0.001)	0.675	-0.001 (0.001)	0.225
Gender	0.025 (0.015)	0.087	-0.053 (0.039)	0.173
Education	-0.0005 (0.008)	0.945	0.021 (0.015)	0.160
Social Security Status	-0.061 (0.014)	**<0.001**	0.076 (0.026)	**0.003**
Marital Status	-0.139 (0.040)	**<0.001**	0.175 (0.039)	**<0.001**
Working Status	-0.185 (0.033)	**<0.001**	0.142 (0.039)	**0.034**
Income	-0.006 (0.006)	0.285	0.098 (0.017)	**<0.001**
Health Status	-0.140 (0.027)	**<0.001**	0.132 (0.025)	**<0.001**
Chronic Disease	-0.264 (0.035)	**<0.001**	-0.057 (0.035)	0.101
Disorders	0.091 (0.044)	**0.041**	0.168 (0.039)	**<0.001**
Difficulty in payment	-0.230 (0.032)	**<0.001**	2.592 (0.035)	**<0.001**
Late appointment	-0.186 (0.042)	**<0.001**	3.064 (0.037)	**<0.001**
Transportation problems	1.612 (0.056)	**<0.001**	0.357 (0.045)	**<0.001**
n	128484			
df	30			
$\boldsymbol{-2\log L}$	-32164.51			
p-value	**<0.001**			
AIC	64389.02			
BIC	64681.93			

In the Hurdle Poisson model, the Poisson section shows that results are close to those in ZIP's Poisson section. In the Poisson section, age, gender, education, and income do not affect access to health care for those who have problems in accessing health services. The logit section indicates that, as mentioned in the previous section, the way of modeling the excess zeros parts shows differences. The logit section shows that age, gender, education and having a chronic disease do not contribute to having any problems accessing to health care. Age, gender and education are not significant in modeling those who have problems accessing to health care as well. The model is also statistically significant ($-2\log L =$-32164.51; p<0.001).

Table 5. The Results of the Vuong Statistics

Count Data Model	Vuong z-statistic	p-value
Zero-Inflated Poisson vs Poisson	101.60	**<0.001**
Hurdle – Poisson vs Poisson	78.249	**<0.001**
Hurdle – Poisson vs Zero-Inflated Poisson	16.970	**<0.001**

According to the results of table 2-5, in terms of AIC and BIC for model selection, the H-P model's AIC= 64389.02 and BIC=64681.93 values are the lowest when compared to others. Vuong statistics show that comparing the zero-inflated Poisson model with the Poisson model, the Vuong statistic is significant (Vuong = 101.60, p < 0.001). It indicated that the zero-inflated Poisson model showed a better fit. Comparing the hurdle Poisson model with the Poisson model, the Vuong statistic is significant (Vuong = 78.249, p < 0.001). It indicated that the hurdle model showed a better fit. Comparing the hurdle Poisson model with the zero-inflated Poisson model, the Vuong statistic is significant (Vuong = 16.970, p < 0.001). It indicated that the hurdle model showed a better fit.

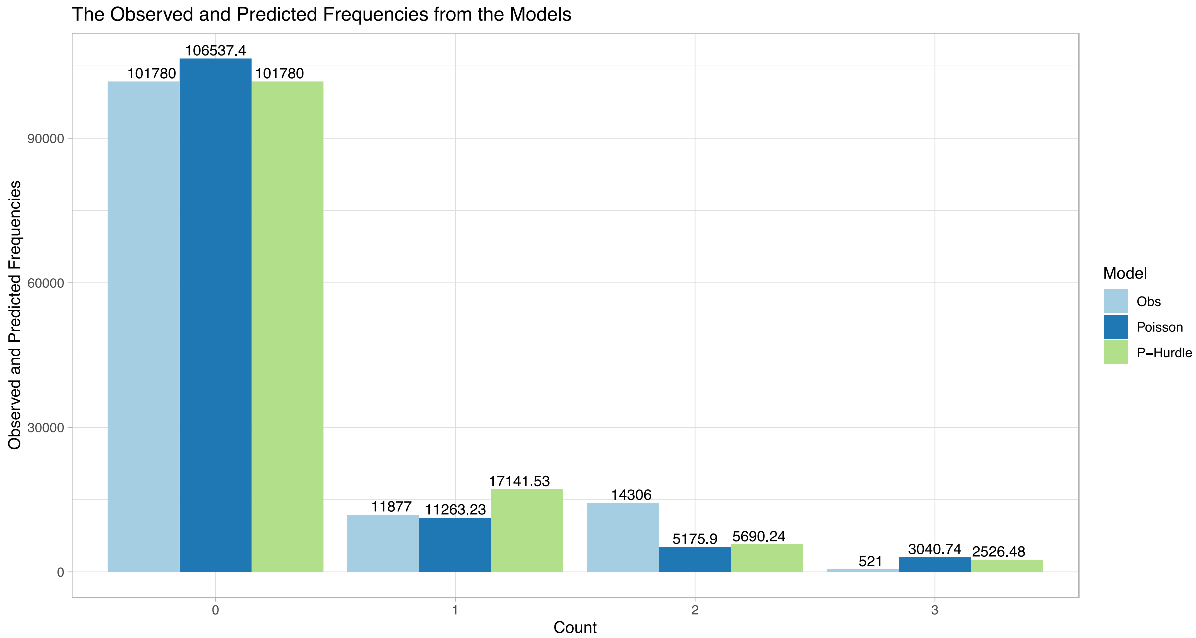

Figure 1. The Observed and Predicted Frequencies from the Models

According to table 5, frequencies were not calculated for the zero-inflated Poisson model. In figure 1 The Poisson model does not adequately fit the count data. However, The Hurdle Poisson model does not fit the bigger count data. It may result from some reasons: (a) outcome variable has extreme over-dispersion, (b) correlated data which cannnot be explained with covariates and (c) unobserved heterogeneity.

3. Discussion and Recommendations

Access, in general terms, refers to the ability of people to obtain and use quality health technologies when they need. It is not only a technical issue involving the logistics of moving a technology from the supplier to the end user, but it also includes social values, economic interests and political processes, and it requires a product as well as services and is linked to how health systems perform in practice (Frost and Reich, 2008: 8). Research on the utilization of health services suggests important manipulable (policy) dependent variables and nonmanipulable (control) independent variables that might be incorporated into a framework for the study of access to health care (Candidate and Anderson, 1974: 216). (Candidate and Anderson, 1974: 216). The right to have the highest achievable health standard covers medical care, access to safe drinking water, adequate health care, education, health information, and other key determinants of health; it includes rights such as the right to exemption from discrimination and involuntary medical treatment, and rights such as basic primary care right (Committee on Economic, Social and Cultural Rights, 2000).

In the study, data obtained from the Turkey Health Survey, which was conducted throughout Turkey every two years by TurkStat were analyzed. The results obtained with the analysis show that all variables differ according to years and they are statistically significant.

It is stated that user costs and other costs arising from access to care affect different socio-economic groups in different ways. While access may not be compromised for some groups, costs may be an important deterrent to others (Lundberg et al., 1998). The impact depends on the magnitude of the costs and on the user's willingness and ability to pay. In other words, equal costs do not necessarily give equal access. Financial incentives for service providers can also affect the availability of services and the types of services available (Gulliford et al., 2002).

The level of access to health services vary in the same country in terms of socio-demographic variables as well as countries. For example, in the USA, access often refers only to whether the individual is insured, and while differences such as the level of insurance or the size of payments are of secondary importance, in Europe, where almost all citizens are insured, access can be a very sensitive concept (Goddard and Smith, 2001). In Turkey, social security institutions were entegrated and Social Security Institute was established in 2008 providing that all citizens pay a certain premium under the guarantee of the social security system.

In countries at all levels of income, health and illness follow a social gradient: the lower the socioeconomic position, the worse the health. According to the analysis conducted as part of the study, it was concluded that the status of income and health insurance do not constitute a risk factor on the access to health services. It is thought that the presence of a social security system involving the whole country has an effect on this result.

In researches about access, it is stated that the scope of health insurance is a very important predictor of the use of services (Berk and Schur, 1998). According to the analysis conducted as part of the study, it was concluded that the status of income and health insurance do not constitute a risk factor on the access to health services.

Health services can have an important impact on health inequalities both in a positive and negative way. There is, however, much that can be done to increase the probability that the effect will be beneficial. This requires a better understanding of the reciprocal relationship between poverty and ill health, ensuring that the organization of care is such that it collects resources fairly, enhances access to care, and takes advantage of the opportunities actively to promote health. Action is also required to address the specific needs of disadvantaged populations, in a way that is contextually appropriate. Countries should develop income systems to reduce dependency on these systems, as out-of-pocket health spending and private health insurance increase inequalities among the community. In this respect, more research is needed in which access to health services is evaluated from all aspects.

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