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Households' censored mobile phone spending and its determinants in Turkey: an inverse-hyperbolic sine double-hurdle model

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Abstract

The roles of socio-demographic and economic characteristics in the probability and levels of household mobile phone spending were determined by estimating the inverse hyperbolic sine double-hurdle model (IHS-DH). Data were obtained from the Household Budget Surveys conducted by the Turkish Statistical Institute during 2019. The IHS-DH model has a statistical advantage over all other competing models. In addition, statistical test results have provided support for the heteroscedastic error specification and use of instruments in parameter identification. Findings suggest that most of the socio-demographic and economic characteristics of the household and the head of household have significant effects on the probability to spend and levels of spending on mobile phones. In particular, the creation of different policy and intervention structures suitable for the statistically significant characteristics of the family will both ensure the efficiency of resource allocation and facilitate the adoption of appropriate marketing strategies in the country. The Global System for Mobile Communications operators is thought to be one of the biggest beneficiaries of the returns to be received from all kinds of subventions or investment incentives made in areas where the telecommunication infrastructure is insufficient.

Keywords Demographic factors · Double hurdle model · Household · Spending · Mobile phone · Turkey

1 Introduction

Economies can work more effectively and efficiently and maintain their competitiveness on the world stage only with a smooth flow of information. Regardless of the purpose of their use, computers, the internet, and telephony, as constantly developing, have become the tools needed for accessing, using, and storing information in many fields. Today, the internet and mobile communication are considered among the most important elements of daily life. People try to meet even their most basic needs through the internet. Bank transactions, marketing, shopping, education, health, and social interactions, as well as access to government programs and medical test results, are increasingly done by virtual means [1]. Information and Communication Technologies, which is spreading worldwide well above the population growth, is one of the most important developments in the telecommunication sector. While the world population increased by approximately 1.1% in 2018, mobile phone use increased by 2%, and internet and social media use by 9% [2]. According to a survey conducted in the USA by the [3], the smartphone market doubled between 2011 and 2016, with a penetration rate increasing from 35 to 77%.

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It has been argued that digitalization increases capital and labor productivity and becomes a driving force of economic growth by reducing transaction costs and facilitating access to global markets [4–8]. Studies have found that improvements in telecommunication infrastructure lead to economic growth [9–11]. Information and communication infrastructures, like other infrastructure services, are linked to the health, education, agriculture, trade, and defense sectors of the economy. The production of goods and services related to information and communication contributes to economic growth both directly and indirectly through increased productivity and positive externalities it induces in other sectors [12]. In [12] Argue that digitalization contributes to economic growth regardless of the development level of a country. Mobile technology not only increases the Gross Domestic Product (GDP) but also changes people's lives [13]. The use of mobile phones has increased the frequency and volume of financial transactions and savings at the household level [14, 15]. Technological progress has contributed to the industrialization process in many developed countries, especially concerning the share of the manufacturing sector in employment [16]. The global telecommunication sector, which has undergone a great change and transformation in parallel to technological developments, has also brought about radical changes in the way consumers work, communicate, and behave [12]. In [17] Argues that positive developments in internet and mobile services in South Korea significantly affect the structure of household expenditures.

Telecommunication has become an indispensable part of modern life. In line with global trends, the use of mobile phones has become increasingly common among people belonging to all classes of income, ages, and occupations. At a time when curfews were imposed all over the world due to the global Covid-19 pandemic, people tended to meet even their most basic needs through mobile services and the internet. The outbreak of Covid-19 has accelerated the expansion of e-commerce based on company, customer, and product [18]. Studies conducted in the last two decades have already proven the benefits of mobile phone use in terms of both the communication between individuals and the organization of daily life activities [19]. As such, it is very important to develop appropriate policies to further spread the use of mobile and internet services throughout the country, which make significant contributions to the economy and social welfare, as well as to enable the use of mobile services by people from all walks of life. This, however, requires analysis at the micro-level. The reach of information that shapes mobile phone expenditures at the family scale, in general, and the determination of family profiles, in particular, can provide insights into re-forming government policies that are of key importance in ensuring more effective marketing and rational resource allocation for the Global System for Mobile Communications (GSM) operators, the national stakeholders; as well as providing a more effective and dynamic determination of telecommunication services.

As a case in point, Indonesia is the leading country with the most mobile users in the world, with users spending an average of 5.5 h a day in mobile applications (hereafter, apps). Among average Android phone users, 3.9 to 4.2 h were spent per day in the second quarter of 2021 in the United States (U.S.), and 4.0 h per day in the UK, up from 3.8 in the second quarter of 2021. An average user in South Korea spends 5 h a day on mobile apps compared to 4.8 in the second quarter of 2021 while, in the same region, Japanese users increased by 10% from the previous quarter, from 4.4 to 4.8 h, in the third quarter of 2021. Mobile phone users in Turkey spent 4.2 h in the same period [20]. In the U.S., in 2014, those living in the highest income percentile or households with five or more people spent an average of $1,500 per year on cell phone services, while a single person spent an average of $500 per year [21]. In Turkey, in 2021, the average annual communication expense of a family of four, each of whom has a fixed telephone and broadband internet subscription, was 4,238 Turkish Lira (₤), taxes included [22].

In a highly competitive telecommunications market, it is crucial to identify the key stimulants of family cell phone spending. Better serviceability has become imperative for network providers to meet the demands of mobile users. By uncovering the demographic, economic, and behavioral factors that shape mobile phone spending, policymakers, development practitioners, and industry suppliers or operators can more effectively identify appropriate ways of providing affordable information services to households. It is important to understand such broader patterns to better design and target household cost-reducing interventions and related policies by government and local agencies. As the family's spending behavior is likely an effective unit within which intervention can occur, information derived from family segmentations is much more crucial in determining where policies should be targeted. In addition, by identifying such stimuli, mobile network operators will be able to outreach higher quality and qualified audiences by exerting an appropriate marketing divide. This study, therefore, aims at a comprehensive quantitative analysis that elicits the effects of socio-demographic, economic, and behavioral factors of households and heads of households on mobile phone spending in Turkey.

Our use of a statistical model is dictated by one of the important data features—the observed zero observations in the dependent variable. To address such zero observations in mobile phone spending we use a censored regression model known as the double-hurdle (DH) model [23, 24], extended by the Inverse Hyperbolic Sine (IHS) transformation in the dependent variable to accommodate potential nonnormality in the variable, and by a heteroscedastic specification in the error term, to obtain consistent (unbiased) estimates of the model parameters.

As in a conventional DH model, the advantage of the IHS-DH model is to collapse the household decision into two basic stages, such as spending decision and spending level, and improve the tendency of household characteristics to moderate their spending behavior for goods and services by creating appropriate marketing segmentations. The main reason for this is to exert the existence of the inherent spending impulses belonging to the family and to elicit the distinctive segregation in determining the spending decision and the spending levels. As mobile phone expenditures in some households are, however, reported as zero because some households are still deprived of mobile phone services for a variety of reasons, a censored model was preferred in the study. The reason for preferring the IHS transformation was that it is among the most ideal censored models that make the spending observations close to the normal distribution. Examining the literature, there is a dearth of studies, in terms of both number and scope, on this topic. In this regard, this study, in particular reference to Turkey, will both contribute to the limited international literature and provide access to reliable information by expanding the scope of such studies. Also, to fully understand the mobile phone spending and level decisions in different households with their potential, we need to understand how household spending decisions and spending levels change with family characteristics. To that end, marginal effects were measured together with their standard errors. Marketing professionals can better understand the spending and level and level decisions based on such segregated quantitative units, along with their effects, and can gain an advantage in resource allocation (e.g., better service offerings) by developing effective and dynamic strategies. Thus, the extensive household-level findings obtained in this study, by bringing on operational appropriate marketing strategies and tactics, are capable of providing important and useful information that can assist GSM operators. Findings in this study may also provide insight into mobile phone use in other countries with similar family characteristics to those in Turkey.

2 Material and method

2.1 Econometric model

Our statistical framework is dictated by one unique feature in the dependent variable—the observed zero observations in mobile phone spending level. Econometric approaches to such "censored" dependent variable include the Tobit model [25], which governs zero-positive outcomes with one censoring mechanism; and the sample selection model [26] and single-hurdle model [23], Eqs. (7), both featuring a binary selection rule that dictates the zero–one outcome, and a continuous stochastic process governing the level. There is also a double-hurdle (DH) model [23], Eqs. (5, 6); [24], which includes both a binary choice rule to determine a zero result and an additional censoring mechanism that admits zero values in itself. We used the last model, the DH, extended with an inverse hyperbolic sine (IHS) transformation in the dependent variable to accommodate non-normal and extreme values in the variable; and with a heteroscedastic error specification. Failure to accommodate nonnormality or heteroscedasticity results in inconsistent (biased) parameter estimates because the wrong probability density function is used in estimation.

In the same principle as the conventional DH model [24], the IHS-DH model features one stochastic process $z_i' + u_i$ governing the selection and an additional process $x_i'\beta + v_i$ governing level (which can be censored) such that, for observation i,

$$
\begin{aligned}
I(y_i, \theta) &= x_i'\beta + v_i \text{ if } z_i'\alpha + u_i > 0 \text{ and } x_i'\beta + v_i > 0 \\
&= 0 \qquad \text{otherwise}
\end{aligned} \tag{1}
$$

where z_i and x_i are vectors of explanatory variables that explain the binary spending decision and spending level decision, respectively, and β are corresponding conformable parameter vectors and the error terms (u_i, v_i), specific to each equation and occur outside the control of the researcher, are assumed to be distributed as bivariate normal with means (0, 0), standard deviations (1, σ), correlation ρ, and covariance æœ. The value of $x_i'\beta + v_i$ is equivalent to the latent variable y_i^*, where if the mobile spending amount is less than the reservation amount predetermined by their household members or the household, they can opt to receive a bill for mobile phone usage at the end of a term or to purchase the service by topping up minutes to the sim card in exchange for a pre-payment. It is worth noting that households will, unfortunately, face income constraints from the pre-determined reservation amount for mobile telecommunications service, as it is expected that relatively low-income but large-scale households are a more disadvantaged group from such income restrictions. In this case, two decision mechanisms need to be processed concurrently. In the first decision stage, it should be decided whether to pay a fee for receiving a mobile service, whereas the second decision stage includes the payment of the total cost of the decided service, including zero cost. Of course, while income may seem to be the biggest reason for reporting zero spending, there are other factors, such as the availability of a landline at home or lack of network like fiber-optic service in the vicinity. A family consisting of elderly members is more likely to be content with a landline at home. Sometimes payments for this type of service can be made by a relative of the household, resulting in a report of zero expense. For the elderly living alone, mobile service expenses may not be reported since the purchase of the service is covered by their children or other close relatives. While this is a good example of zero reported spending in the second stage, it is unknown to what extent such households are present in our sample.

The IHS transformation is performed on the dependent variable y_i with a scale parameter θ such that [27]

$$I(y_i, \theta) = \log\left[\theta y_i + (\theta^2 y_i^2)^{1/2}\right]/\theta = \sinh^{-1}(\theta y_i)/\theta \quad (2)$$

where, operationally, θ is restricted to positive because the transformation is symmetric about 0. The literature suggests heteroscedasticity is often unavoidable in unit-level data [28]. By ignoring this feature in the estimation of nonlinear models (with maximum likelihood techniques), an incorrect probability density function is maximized, resulting in biased and inconsistent parameter estimators [29]. We parameterize the error standard deviation (σ) as an exponential function of a vector of w_i variables (without a constant), mapping the standard deviation of the error term to a conformable parameter γ such that

$$\sigma_i = \sigma \exp(w_i'\gamma) \quad (3)$$

This exponential transformation ensures that the standard deviation is both identified and positive with $\gamma \neq 0$ [29].

In general, when modeling mobile phone spending, it is more appropriate to start with two decision steps. While the mobile phone spending decision has a causal relationship with social and behavioral stimuli in the first decision, the spending amount decision has a causal relationship with economic factors such as budget constraints in the second stage. For maximum likelihood estimation, the sample likelihood function for the heteroscedastic IHS-DH model is

$$\begin{aligned} L = &\prod_{y_i=0}\left\{1 - \Phi_2\left(z_i'\alpha, \frac{x_i'\beta}{\sigma_i}, \rho\right)\right\} \\ &\times \prod_{y_i>0}\left\{(1+\theta^2 y_i^2)^{-1/2}\sigma_i^{-1}\phi\left[\frac{I(y_i, \theta) - x_i'\beta}{\sigma_i}\right]\right. \\ &\left.\Phi\left[\frac{z_i'\alpha + \rho\left[I(y_i, \theta) - x_i'\beta\right]/\sigma_i}{(1-\rho^2)^{1/2}}\right]\right\} \end{aligned} \quad (4)$$

where ϕ is the probability density function and Φ the cumulative distribution function of the standard normal distribution, Φ_2 is the standard bivariate cumulative distribution function, and $(1+\theta^2 y_i^2)^{-1/2}$ is the Jacobian of the transformation which maps $I(y_i, \theta)$ to y_i. The transformation becomes linear when the scaling parameter (θ) approaches zero and approaches the logarithmic transformation form for large values of y_i, as is the case for mobile phone spending. Another feature of the transformation is that it dampens the negative effects of outliers by avoiding data loss from dropping such outliers, and makes the error terms of the original non-normal random variable robust against the transformed normal random variable [29].

Applying the parametric constraint $\rho = 0$ to the model results in an independent, heteroscedastic IHS-DH [30], the additional constraint $\theta = 0$ further reduces the model to the independent DH model [23], Eqs. (5), (6). Testing only the $\theta = 0$ condition elicits whether the normality assumption is violated. Finally, the homoscedastic specification is acquired by imposing the restriction $\gamma = 0$. All restricted models are nested, and testing is performed using conventional methods for nested specifications, i.e., likelihood ratio, Lagrange multiplier, or Wald test [31].

To exert the direction and effects of explanatory variables on spending and level decisions, the positive observation probability and the unconditional mean of spending level are, respectively,

$$\Pr(y_i > 0) = \Phi_2\left(z_i', x_i'\beta/\sigma_i, \rho\right) \quad (5)$$

$$\begin{aligned} E(y_i) &= \int_0^\infty y_i(1+\theta^2 y_i^2)^{-1/2} \\ &\times \sigma_i^{-1}\phi\left[\frac{I(y_i, \theta) - x_i'\beta}{\sigma_i}\right]\Phi\left[\frac{z_i' + \rho\left[I(y_i, \theta) - x_i'\beta\right]/\sigma_i}{(1-\rho^2)^{1/2}}\right]dy_i \end{aligned} \quad (6)$$

and the conditional mean is obtained by

$$\mathrm{E}(y_i|y_i > 0) = \mathrm{E}(y_i)/\Pr(y_i > 0) \quad (7)$$

using (5) and (6). Marginal effects of continuous (binary) explanatory variables can be obtained by differentiating (differentiating) Eqs. (5) to (7). All marginal effects were calculated for each observation and then averaged over the sample. For statistical inference, standard errors of (average) marginal effects are derived by a mathematical approximation procedure known as the delta method.

An important issue in the use of an endogenous selection model relates to the use of exclusion restrictions to achieve parameter identification. This was accomplished by including unique variables in the selection equation (e.g., household factors such as stove and property category) that are excluded from the level equation as demand theory dictated, drawing on the random utility theory [32]. Although not essential for identification, household income group variables were only included in the level equation.

2.2 Data

Data used in this analysis were obtained from household budget surveys (HBS) conducted between 1 January and 31 December 2019 by the Turkish Statistical Institute (TSI).

The 2020 data could not be collected due to the COVID-19 pandemic. Therefore, the 2019 data set remains up-to-date. A stratified two-stage cluster sampling method was used in the 2019 HBS. The basic sampling frame used in the selection of blocks, which is the first stage sampling unit, was supplied from the National Address Database. In the second stage, blocks were created based on information from the first stage, which was determined from urban, rural, and village areas with a municipal organization with probability proportional to the size of the settlement; households in each block were then systematically selected. The exemplary structure of 2019 HBS was created to make inferences across "Turkey". The non-response rate was 25.9% across Turkey.

TSI aimed to limit seasonality effects on spending by replacing nearly a thousand households with similar characteristics each month. The study sample included 10,962 households after removing observations with outliers and missing data on important variables. Socio-demographic and economic characteristics of the household and household head, along with the expenditure variable, are presented in Table 1. Households spend an average of 91.50 Turkish Lira (£) per month on their mobile services. A proportion (5.9%) of the sample did not spend on mobile services for various reasons, calling for the use of a statistical model which addresses such censoring. Among the mobile phone users, the average spending was 97.25£. The proportion of households headed by baby boomers, generation X-cohorts, and millennials (Y-cohorts) is 43%, 34%, and 23%, respectively. The monthly conditional telecommunication expenditures of the households whose heads are Baby Boomers, X, and Y cohorts are 87.82£, 109.33£, and 95.80£, respectively. Figures 1 and 2 show the correlations and distributions of conditional telecommunications spending and households with Baby Boomers, X, and Y generation heads. Family conditional telecommunication spending was negatively correlated with baby boomer-headed families, positively correlated with X-headed families, and negatively correlated with Y-headed families (Fig. 1). The highest level of correlation (0.16), with a statistically significant, is found in conditional telecommunication expenditures and families with X-cohort heads. The distribution of monthly telecommunication expenditures of families by cohort structure is given in Fig. 2. Families with X-cohort heads both spend more on telecommunication than families with other generations, and the monthly cost is more volatile. Monthly conditional average telecommunications expenditure differs statistically between family types by generation (cross-comparative p-values are presented in the figure). As can be deducted from the figure, families with X-cohort heads spend more on average than families with other generations. Probably the underlying rationale behind such a result is that these families have, on average, a higher number of adults and family size than the other two family types. Our data support such a notion. Among telecommunications spenders, while the average number of adults in X-cohort-headed households is 2.90 and family size is 4.00, the corresponding values are relatively lower in families with other generations (2.66 and 2.94 for families with baby boomers and 2.06 and 3.50 for Y-generation families, respectively). It is also probable that the number of workers increasing with the increasing number of adults in X-generation-headed households is likely, in which the results support such a concept. While the number of employees in X-generation-headed households was 1.48, it was 0.99 and 1.24 in baby boomers and Y-generation-headed households, respectively.

While 77.4% of the households were headed by a male, the proportions of never-married-headed, divorced-headed, and widowed-headed households are 4.9%, 5.1%, and 10.2%, respectively. Approximately 40% of households have a head with a primary school diploma, and 13.7%, 16.7%, and 17.8% are comprised of households whose heads have completed secondary school, high school, or at least two years of vocational colleges, respectively.

Nearly half (49.4%) of the households had wage-earner household heads, the ratio of employer households remained at approximately 21%. While the ratio of retiree-headed households is 21.4%, the ratio of those earning their living from agriculture is quite high (18.2%). While more than half of the households live in apartments (56%), the ratio of tenant households is around 25%. While the ratio of households with savings remains about 40%, the ratio of households with at least one passenger car is quite high in country conditions. Interestingly, more than half (53%) of households were credit card users and half dined out. Approximately 45% of the households heated the dwelling with a traditional heating system other than natural gas, and 5% of households live in residences with an area of 160 square meters and above. About 47% of households own at least one real estate, and nearly every household has one child and two adults. Finally, households in the first quartile of income earn at most 2477 TL per month, and those in the fourth quartile at least 5595 TL per month. In addition, the distribution relationship between family income, cohorts, and telecommunication bills is given in Fig. 3. As the income level of families increases, monthly telecommunication expenditures increase, which is especially higher in X-cohort-headed households. It is noteworthy that families in the last two income groups both spend more and have a higher distribution compared to other income groups. It shows that income loses its effect on shaping mobile phone bills, especially in higher-income families with X-generation heads, and instead, the bills can be shaped by the tastes and preferences of those who use the phone in the family.

Table 1 Variable definitions and sample statistics

Variable	Definition	Mean (SD)
Dependent variable		
Expenditure	Mobil phone expenditure in Turkish Lira (₺) per month	91.502
		(59.204)
	Among the consuming (94.1% of the sample)	97.251
		(56.169)
Household head characteristics: binary variables (yes = 1, no = 0)		
Baby boomers	Born in 1965 and before	0.430
X-Cohorts	Born between 1966 and 1986	0.340
Millenniums	Born after 1986	0.230
Male	Gender is male	0.774
Married	Married (reference)	0.798
Unmarried	Never married	0.049
Divorced	Divorced	0.051
Widow	Widow	0.102
No school	Not holding a diploma (reference)	0.120
Elementary	Has elementary school education	0.398
Secondary	Has secondary school education	0.137
High school	Has high school education	0.167
College	Has college and higher (master or PhD) education	0.178
Salaried	Salaried, paid or full time or part-time employees	0.420
Employer	Employer or full and part-time self-employed	0.209
Retired	Retired	0.214
Other job status	Other job status (e.g., disabled and/or unable to work due to permanent health problems, housework, compulsory military service, and other conditions) (reference)	0.125
Agricultural job	Working in agriculture	0.182
Household characteristics: binary variables (yes = 1, no = 0)		
Compulsory insurance	Has compulsory health insurance	0.835
Greene card	Health expenses covered by the state	0.111
State aids	Receives cash or in-kind aid from government	0.261
Private aids	Receives cash or in-kind aids from private person and or intuitions	0.172
Apartments	Resides in an apartment	0.559
Tenant	Resides in a rental house	0.246
Stove heating	House with traditional stove heating	0.454
Spouses only	Family consisting of only spouses	0.196
Spouses with kids	Family consisting of spouses and kids	0.484
Other family types	At least one nuclear family and other members or more than one member without a nuclear family (reference)	0.319
Savings	Makes monthly savings	0.394
First quartile income	Family income less than 2477.17 ₺ per month (reference)	0.253
Second quartile income	Family income between 2477.17 and 3712.50 ₺ per month	0.253
Third quartile income	Family income between 3712.50 and 5595.47 ₺ per month	0.251
Fourth quartile income	Family income greater than 5595.47 ₺ per month	0.243
No real estate	No real estate like a detached house, apartment, summer house, shop, or hotel (reference)	0.322

Table 1 (continued)

Variable	Definition	Mean (SD)
One real estate	Owning only one of the properties described above	0.466
Two real estate	Owning only two of the properties described above	0.134
Three and more real estate	Owning three and more of the properties described above real estate	0.078
Credit card(s) habit	Families with the habit of using credit cards	0.525
Smoking habit	Families with the habit of using tobacco products	0.522
Alcohol habit	Families with the habit of using alcohol products	0.069
Eating out habit	Families with the habit of having food away from home	0.502
Cinema habit	Families with the habit of going to the cinema	0.089
Newspaper habit	Families with the habit of occasional reading of newspapers	0.050
Game habit	Families with the habit of playing game	0.042
Coffee house habit	Families with the habit of frequently going to coffee house	0.281
Bazaar habit	Families with the habit of going to Bazaar frequently	0.612
Internet habit	Families with an Internet connection at home	0.141
Working persons	Families with than two working individuals at home	0.070
Residence area	House with a living area of more than 160 square meters	0.050
Cars	Families with at least one passenger car at home	0.476
Household characteristics: continuous variables		
Kids	Number of children	0.981
		(1.280)
Adults	Number of adults	2.395
		(1.022)
Working persons	Number of working members in the family	1.171
		(0.932)
Sample size		10,962

Standard deviations, in parentheses, are reported for continuous variables only

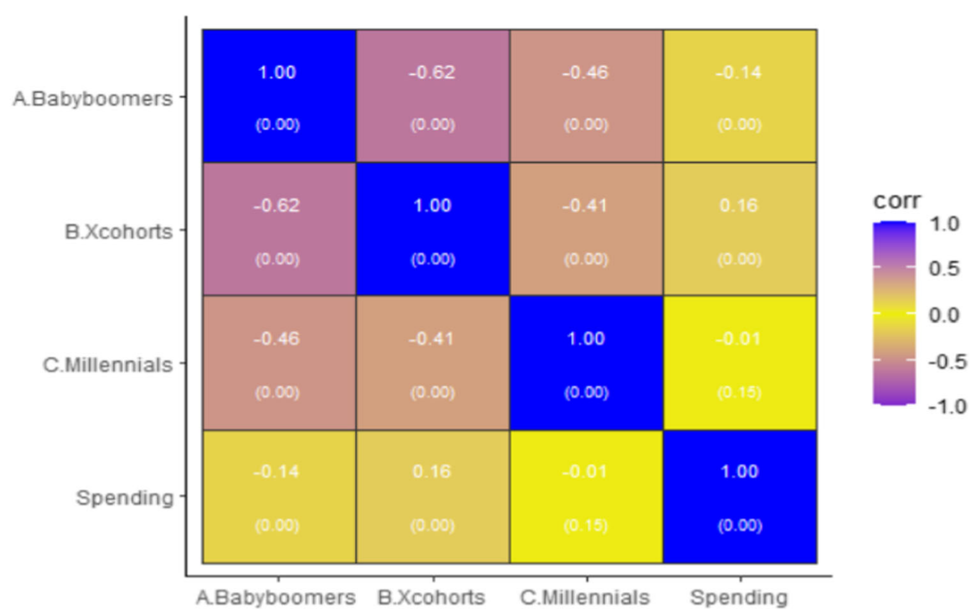

Fig. 1 Correlation between households' monthly mobile phone bills and families with different cohort heads

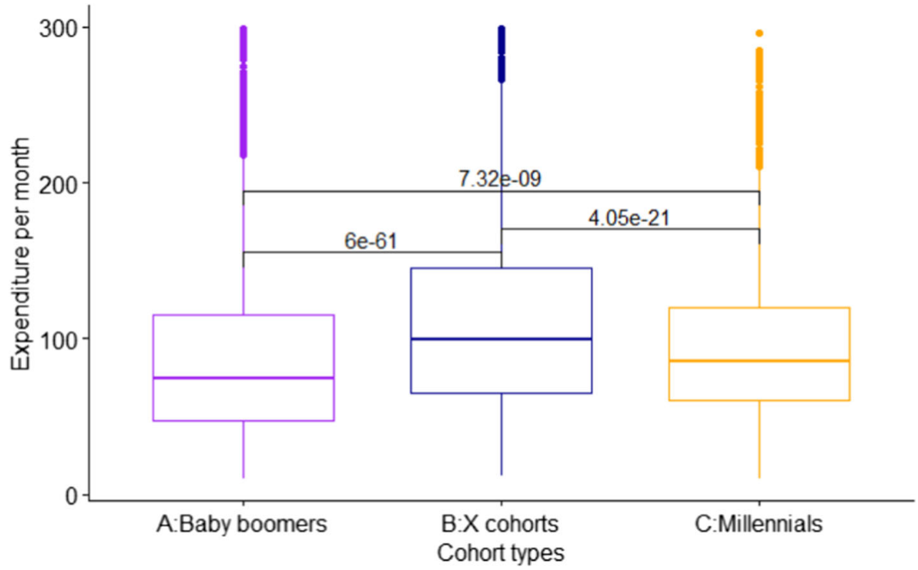

Fig. 2 Distribution of monthly telecommunication bills of households by household with different cohort heads

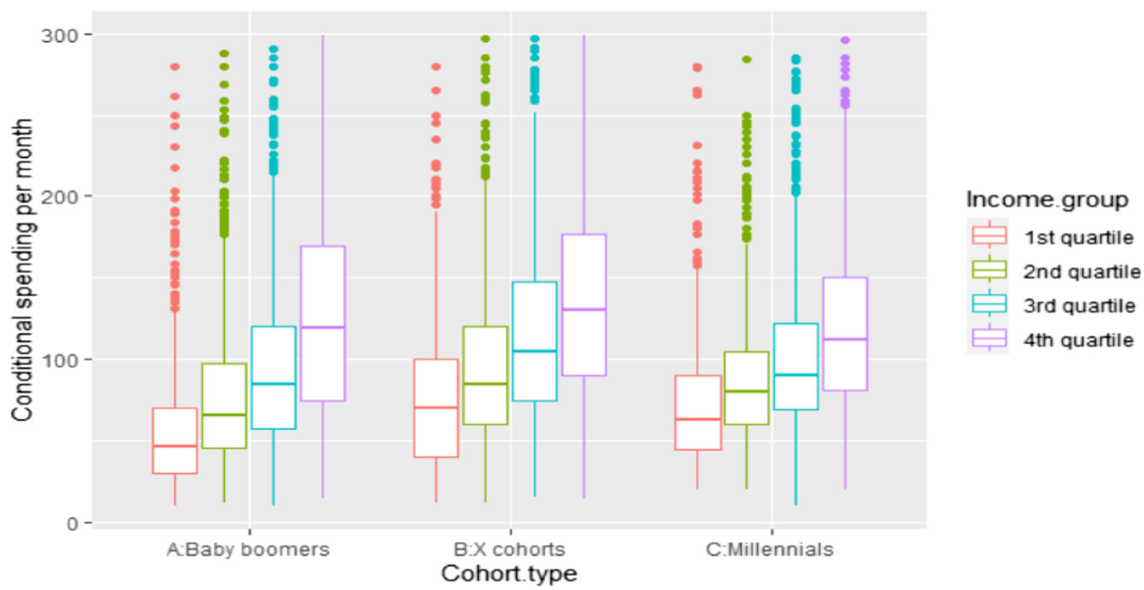

Fig. 3 Distribution of monthly telecommunication bills of households by household income and families with different cohort heads

3 Results

3.1 Specification tests

All variance-inflation factors (VIFs) are well below the rule-of-thumb threshold of 10.0 indicating no multicollinearity problem in the selection or level equations. Against the IHS-DH model, there are some competing models with the same distribution (i.e., normal) but different structures (truncation), such as the IHS-single-hurdle (IHS-SH) and the IHS-sample selection (IHS-SS) models,[1] all with inverse IHS transformation and heteroscedastic errors. As these three models are not nested, they are distinguished with [33] nonnested specification test. In cross-testing between IHS-DH and IHS-SS (Vuong's standard normal statistic $z = -0.94$) and between IHS-SH and IHS-SS (Vuong's standard normal statistic $z = -0.96$), the results were insufficient to favor a model. Between IHS-DH and IHS-SH, the statistical superiority is also inconclusive ($z = -0.87$). The IHS-DH has slightly lower Akaike Information Criteria (AIC) (log-likelihood value = − 54,571.14 and AIC = 108,986.29) than IHS-SH (log-likelihood value = − 54,571.32 and AIC = 108,986.63) and HIS-SS (log-likelihood value = − 54,571.76 and AIC = 108,987.53), suggesting marginal preferability of the former, which is more consistent with the

[1] Results of these models including the VIF results are available upon request.

two-stage process following consumer choice theory [32, 34, 35]. The IHS-DH is retained for further analysis.

Also, based on IHS-DH, Wald test results suggest rejection of $\theta = 0$ ($\chi^2 = 38.06$, df = 1), $\rho = 0$ ($\chi^2 = 79.76$, df = 1), and ($\rho = 0$, $\theta = 0$) ($\chi^2 = 95.08$, df = 2), all with a p-value < 0.0001, favoring the fully parameterized dependent and heteroscedastic IHS-DH over the dependent heteroscedastic DH, independent heteroscedastic IHS-DH, and independent heteroscedastic DH models, respectively. Meanwhile, the first test with $\theta = 0$ provides evidence that the normality assumption of the error terms is violated. Wald tests also reject homoscedasticity (vector $\gamma = 0$) in the full model ($\chi^2 = 11.27$) and all nested models above, each with df = 4 and a p-value < 0.05. In sum, the results of the above tests support the dependent errors, the IHS transformation, and the heterogeneity of the error term of the level equation features, and support the use of the fully parametrized IHS-DH model.

The instruments used in the selection equation (i.e., all household factors, residential area, heating system (stove), and property variables) showed significance with the Wald test ($\chi^2 = 93.14$, df = 14, p-value < 0.05), which rejects the weak instruments hypothesis and implies adequate instrumentation for parameter identification. Both the number of children, the number of adults, and the three distinct income variables in the level equation were jointly significant ($\chi^2 = 42.21$, df = 5, p-value < 0.0001), confirming their inclusion. Finally, Wald test results show that the explanatory variables are jointly significant in both the decision ($\chi^2 = 834.63$ and df = 39), and level ($\chi^2 = 43.31$ and df = 30) equations, all with a p-value < 0.0001 (Table 2).

The error correlation coefficient is significant and negative, suggesting that unobserved factors affect the binary and level decisions in opposite directions. Also, while the signs of parameter estimates are generally conformant with economic theory, the signs of parameters, especially in variables reflecting the marital status of the head of the household, are different between the equations of the decision to spend and spending level, highlighting an advantage of double-hurdle parameterization over the Tobit model. The Tobit model is known to be restrictive in this context because all variables are forced to affect probability and level in the same direction.

3.2 Marginal effects

Since the probability, conditional, and unconditional mean expectations derived from the model are not linear, marginal effects with their standard errors were obtained by differentiating (differencing) Eqs. (5) to (7) and averaged over the sample. Subsequent discussions will be on the (average) marginal effects (Table 3).

When referencing baby boomer (born before 1965) households, families with X-cohort heads are 1.1 percent more likely to spend on mobile phones. While the monthly conditional (7.98£) and unconditional (8.84£) monthly expenses of the X-cohort-headed households are higher, respectively, and the Y-cohort-headed households have also higher monthly conditional (7.01£) and unconditional (7.46£) telecommunication expenses, respectively, though such expenses are lower than the X-cohort-headed households. As we discussed in the descriptive statistics section, the relatively higher number of adults and employees in generation X-headed households may be among the reasons why families could spend more on telecommunications. Although [36] measured the probability of individuals' mobile phones and services have-nots, their results can be compared with the probability results we obtained in this study. For example, they found that age, one of the socioeconomic factors, was significantly associated with the probability of a mobile phone and its services have-nots [36]. Also, baby boomers-headed households with lower spending decisions and spending levels compared to other cohorts-headed households are consistent with the findings of [1]. This is because individuals give up their habits as they get older, due to an increase in age-related health impairments, the decrease in the number of individuals in the family over time (with children growing up and leaving home), or the fact that households with children transfer a significant amount of their income to their children when the children reach the age of marriage. It can be explained by the fact that they want to buy (saving) housing or that these individuals spend less on mobile phones with the increase in the opportunity cost of time (especially when considering the most productive periods in their business life in the period up to retirement age). In addition, considering that there are more adult individuals and more workers in X-cohort-headed households, it is clear that the probability and amount of spending on telecommunications will increase with the relatively high incomes of such families. Older people are less likely to adopt Information and Communication Technologies (ICT) than adolescents [37, 38]. Taking into account the current behavior of such family segmentation, GSM operators can develop a relatively inexpensive add-on campaign offer for these families. For example, family packages, internet-based packages, or mobile or internet applications that make it easier for the individuals in the said group to carry out transactions in the digital environment can be developed for individuals with a high opportunity cost of time. For older age groups, more home service applications can be offered, and such applications can be aimed at meeting even the most basic needs of these individuals. At the same time, such campaigns should especially target families with generation X heads, as these families are more active in business and mobile phone services are

Table 2 Maximum-likelihood estimates of the inverse hyperbolic sine double-hurdle censored regression

	Selection		Level		Heteroscedasticity	
Variable	Estimate	S.E.	Estimate	S.E	Estimate	S.E.
Constant	0.379 ***	0.157	25.182 ***	15.347	–	–
X-Cohorts	0.218 ***	0.071	1.450 ***	0.352	–	–
Millenniums	0.125	0.087	1.304 ***	0.386	–	–
Male	0.113	0.070	− 0.571 *	0.316	–	–
Unmarried	− 0.521 ***	0.116	1.445 ***	0.576	–	–
Divorced	− 0.190 *	0.111	1.619 ***	0.572	–	–
Widow	− 0.366 ***	0.096	0.819	0.500	–	–
Elementary	0.137 **	0.062	1.471 ***	0.406	–	–
Secondary	0.162 *	0.089	2.532 ***	0.559	–	–
High school	0.203 **	0.095	2.935 ***	0.606	–	–
College	0.380 ***	0.120	2.152 ***	0.544	–	–
Compulsory insurance	0.434 ***	0.085	− 0.112	0.416	–	–
Greene card	0.335 ***	0.097	− 1.865 ***	0.567	–	–
Salaried	− 0.110	0.083	− 0.995 ***	0.389	–	–
Employer	− 0.193 **	0.094	0.041	0.400	–	–
Retired	− 0.032	0.072	− 0.534	0.371	–	–
Agricultural job	− 0.092	0.082	− 2.138 ***	0.449	–	–
State aids	0.033	0.059	− 1.309 ***	0.327	–	–
Private aids	− 0.452 ***	0.053	0.318	0.258	–	–
Apartments	0.202 ***	0.066	0.853 ***	0.263	–	–
Tenant	0.060	0.074	1.230 ***	0.293	–	–
Spouses only	− 0.182 **	0.089	0.407	0.395	–	–
Spouses with kids	0.082	0.083	2.429 ***	0.472	–	–
Savings	− 0.043	0.054	− 1.284 ***	0.280	–	–
Cars	0.472 ***	0.062	0.681 ***	0.224	–	–
Working persons	0.249 ***	0.042	0.757 ***	0.195	–	–
Credit card(s) habit	0.246 ***	0.057	–	–	–	–
Eating out habit	0.268 ***	0.057	–	–	–	–
Cinema habit	0.135	0.117	–	–	–	–
Game habit	0.158	0.139	–	–	–	–
Coffee house habit	− 0.051	0.055	–	–	–	–
Bazaar habit	0.050	0.047	–	–	–	–
Smoking habit	0.184 ***	0.049	–	–	–	–
Alcohol habit	0.060	0.108	–	–	–	–
Newspaper habit	0.115	0.139	–	–	–	–
Stove heating	− 0.098	0.063	–	–	–	–
Residence area	0.052	0.131	–	–	–	–
One real estate	0.134 **	0.063	–	–	–	–
Two real estates	0.319 ***	0.093	–	–	–	–
Three and more real estates	0.218 ***	0.112	–	–	–	–
Kids	–	–	0.423 ***	0.108	–	–
Adults	–	–	3.431 ***	0.540	0.019 ***	0.007

Table 2 (continued)

	Selection		Level		Heteroscedasticity	
Variable	Estimate	S.E.	Estimate	S.E	Estimate	S.E.
Second quartile income	–	–	2.231 ***	0.421	– 0.011	0.021
Third quartile income	–	–	4.600 ***	0.742	– 0.041 *	0.022
Fourth quartile income	–	–	7.549 ***	1.194	– 0.028	0.024
Error std. dev. (σ)	–	–	–	–	2.158 ***	0.140
Error correlation (ρ)	– 0.520***	0.058	–	–	–	–
Scaling (θ)	–	–	0.054***	0.008	–	–
Log-likelihood						
Wald (df)[*p*-value]	834.63 (39)[< 0.001]	43.31 (30)[< 0.001]	–	–		

***$p < 0.01$, **$p < 0.05$, *$p < 0.10$. Wald tests are for joint significance of all variables in equation

an indispensable part of their daily lives. Meanwhile, similar to the finding by [36] of no causal relationship between the probability of mobile phone have-nots and the services and gender, we also found the probability of mobile phone spending unrelated to male-headed households.

Never-married-headed households were found to be less likely to spend on mobile phones bill (by 4.5% points) but with a higher conditional expenditure level (5.07£) compared to married-headed households. These results are in line with expectations and economic theory, as the increasing number of adults in married-headed households alludes to higher demand and spending on mobile phones. The promotion of services including social sharing, mobile communication, and internet packages aimed at eliminating the loneliness of the individuals in question for single-headed or never-married-headed households may increase their mobile phone expenditures. On the other hand, divorced-headed households spend 7.68£ more conditionally and 6.31£ more overall for mobile phones compared to married-headed households. Such families may be on a constant quest to either share family problems with relatives or otherwise communicate with others.

The probability of spending on mobile phones bill and the unconditional spending levels of households whose heads hold primary, secondary, high school, and university degrees are in respective order: 0.7% points and 8.31£ more for primary school, 0.8% points and 14.25£ more for secondary school, 1.0% points and 16.67£ more for high school, and 1.6% points and 13.52£ more for university graduation cases. Among all education classes, the high school graduates-headed households were determined to be the group that spends the most on mobile phones. The results show that there is a non-linear inverse U-direction relationship between the education level of the household head and the mobile phone expenditure of the household. The household mobile phone expenditure first increases with the education level of the household head, but then decreases when the education level reaches a university degree or higher. Heads of households with a university or higher education level spend less on mobile phones bill compared to other groups. This can be attributed to the fact that the heads of the households give up their habits or their opportunity cost of the time is higher. The human capital that individuals grow through higher education creates an economic scale on household size, reducing the household's mobile phone expenditure. In [36] Found that individuals with low education levels (who did not complete high school) are less likely to have cell phones and services, with an increasing trend over time, while [39] found education level contributes to individuals' decision to adopt mobile phones. A higher education level provides digital competencies for the use of ICT [40, 41]. Age and education level, among the sociodemographic factors, are important shaping factors in internet use, and the importance of both variables has been confirmed in the literature [37, 41–43]. It is expected that GSM operators will be among the institutions that will gain the most in the long run if investments in education and human development are supported in areas with low education levels, especially in rural areas, or if individuals, private and public institutions, and organizations are encouraged to make investments in these areas. The policy proposal raised in this study regarding education is also in this direction.

The probability and unconditional expenditure level of the household mobile phone with compulsory health insurance-headed are, respectively, 3.2% points and 3.94£ more compared to the households with heads without health insurance. While the likelihood of mobile phone spending of the households whose head has a green card is 1.4% points higher than those whose head does not have any health insurance, their conditional and unconditional spending levels are 8.17£ and 6.78£ less. As green card ownership is an indicator of poverty, households in this group are

Table 3 Marginal effects of explanatory variables on the probability of spending and levels of spending

Variable	Probability		Conditional level		Unconditional level	
	Estimate	S.E.	Estimate	S.E.	Estimate	S.E.
Constant	0.030*	0.017	90.721***	0.568	88.637***	0.584
X-Cohorts	0.011***	0.003	7.983***	1.377	8.835	1.380
Millenniums	0.006	0.004	7.014***	1.720	7.455***	1.724
Male	0.007	0.004	− 2.502	1.513	− 1.844	1.516
Unmarried	− 0.045***	0.014	5.071*	2.746	0.649	2.995
Divorced	− 0.012	0.008	7.679***	2.735	6.307**	2.755
Widow	− 0.027***	0.009	2.714	2.418	0.167	2.460
Elementary	0.007**	0.003	7.819***	1.658	8.309***	1.617
Secondary	0.008**	0.004	13.775***	2.185	14.249***	2.152
High school	0.010**	0.004	16.058***	2.213	16.667***	2.188
College	0.016***	0.004	12.194***	2.303	13.522***	2.293
Compulsory insurance	0.032***	0.008	1.102	1.998	3.936**	2.034
Greene card	0.014***	0.003	− 8.171***	2.273	− 6.784***	2.227
Salaried	− 0.006	0.005	− 5.286***	1.746	− 5.714***	1.740
Employer	− 0.012*	0.006	− 0.445	1.955	− 1.502	1.977
Retired	0.002	0.004	− 2.740	1.742	− 2.833	1.709
Agricultural job	− 0.005	0.005	− 10.576***	1.415	− 10.778***	1.439
State aids	0.002	0.003	− 6.331***	1.235	− 6.032***	1.226
Private aids	− 0.033***	0.005	− 0.157	1.219	− 3.177***	1.254
Apartments	0.011***	0.004	4.878***	1.104	5.782***	1.142
Tenant	0.003	0.004	6.428***	1.169	6.580***	1.215
Spouses only	− 0.011**	0.006	1.426	1.945	0.379	1.968
Spouses with kids	0.004	0.004	12.408***	1.516	12.528***	1.537
Savings	− 0.002	0.003	− 6.497***	0.982	− 6.560***	0.998
Cars	0.025***	0.003	4.828***	0.968	6.992***	0.997
Working persons	0.019***	0.004	4.599***	0.703	6.083***	0.795
Credit card(s) habit	0.015***	0.003	0.768***	0.226	1.984***	0.502
Eating out habit	0.007	0.003	1.168***	0.293	2.465***	0.507
Cinema habit	0.007	0.005	0.196	0.470	0.791	0.835
Game habit	0.007	0.006	− 0.267	0.487	0.412	0.902
Coffee house habit	− 0.003	0.003	− 0.642	0.454	− 0.884	0.602
Bazaar habit	0.003	0.003	0.155	0.147	0.400	0.377
Smoking habit	0.010***	0.003	0.571***	0.191	1.475***	0.430
Alcohol habit	0.003	0.005	0.179	0.310	0.457	0.783
Newspaper habit	0.006	0.006	0.328	0.371	0.834	0.921
Stove heating	− 0.005	0.003	− 0.306	0.202	− 0.788	0.510
Residence area	0.003	0.007	0.156	0.381	0.398	0.963
One real estate	0.007**	0.003	0.412**	0.206	1.059**	0.504
Two real estates	0.014***	0.003	0.829***	0.243	2.073***	0.517
Three and more real estates	0.010**	0.004	0.589**	0.28	1.479**	0.654

Table 3 (continued)

Variable	Probability		Conditional level		Unconditional level	
	Estimate	S.E.	Estimate	S.E.	Estimate	S.E.
Kids	–	–	2.087***	0.428	2.039***	0.418
Adults	–	–	12.246***	0.313	11.968***	0.308
Second quartile income	–	–	11.464***	1.425	11.200***	1.392
Third quartile income	–	–	24.436***	1.675	23.875***	1.638
Fourth quartile income	–	–	41.975***	2.194	41.011***	2.145

***$p < 0.01$, **$p < 0.05$, *$p < 0.10$

likely to have lower mobile phone spending. Although many socio-demographic factors such as cohort (or age), gender, education, and occupation are effective in accessing ICT, income differences of households are one of the most important features [44–47]. Considering the income levels of such a disadvantaged group, providing mobile phone services with promotions or at low tax rates in agreement with public institutions may enhance the revenues of GSM operators.

Full-time and part-time employed-headed households were found to have lower mobile phone expenditure levels than the households with another job status. Similarly, households whose heads work in the agricultural sector spend 10.58£ (conditionally) and 10.78£ (unconditionally) less on mobile phones. Mobile phone expenditures of these households are expected to be low due to apparent stimuli such as network insufficiency, being small communities with a homogenous job type, and insufficient income. In this respect, rural areas in developing countries are disadvantaged compared to urban areas due to their low population density, highly heterogeneous geographical and orographic characteristics, and socioeconomic inequalities [48, 49]. In [36] Also found that the number of unemployed without mobile phones and services is extremely small with an insignificant level of relationship. On the other hand, the mobile phone expenditure levels of the households receiving cash or in-kind assistance from the state were 6.33£ and 6.03£ lower in the conditional and unconditional spending levels. Households receiving cash or in-kind assistance from individuals or private institutions, on the other hand, were found to be less likely to spend on mobile phones (3.3% points), and they have less mobile phone spending level (3.18£ overall). As expected, the households receiving aid have a very low income, having to devote a significant portion of their budget to meet basic needs such as food [50]. Also, considering that the households in these groups do not have a regular job or that they have a low income, they can be said to spend less on mobile phone bills, which is in line with expectations. Discount campaigns such as suitable invoice tariffs that can be made especially for households in these groups can promote mobile phone expenditures. In [51] Noted that a drop in the price of a subscription causes internet subscribers to spend more time online.

For households residing in an apartment, the probability of mobile phone spending, and conditional and unconditional spending levels were found to be 1.1% points, 4.88£, and 5.78£ higher, respectively, compared to non-apartment residents. Similarly, the conditional and unconditional mobile phone spending levels of the tenant households were 6.43£ and 6.58£ higher compared to non-tenant households. Considering the likelihood of households living in apartments or tenants residing in city centers rather than rural areas, we can deduce that the results are in line with expectations as they are likely to use telecommunication services more in many areas such as education, health, communication, marketing, and financial transactions. As stated in [40], income level, education level, and geographical location of households are stimuli factors in determining household internet access. In terms of geographic location, rural communities have fallen behind urban communities due to their low population densities and lack of telecommunication infrastructure given their distance from city centers, whereby private companies regard investment in such areas as unprofitable [52, 53]. In [36] Also found that individuals who rent a house with fixed infrastructure are not more likely to not have mobile phones and services than those who own a house. As in every development in the telecommunication infrastructures in which GSM operators operate, GSM operators can increase revenues by increasing their subscriber numbers if telecommunication and development services to rural households are supported or encouraged together with private, local, and public institutions. In this regard, GSM operators are thought to be one of the biggest beneficiaries of all kinds of support or incentive investments they can make in rural areas or in areas where telecommunication infrastructure is insufficient. Therefore, they should develop important projects to encourage individuals, institutions, and organizations, while also supporting all kinds of investments in such areas [41, 49].

Compared to the other household types (the reference group), conditional and unconditional mobile phone spending levels of households with children are 12.41£ and 12.53£ higher, respectively. As the number of children in the household increases, families are expected to spend more on mobile phone bills, as the frequency of making expenses on education (especially during online education across the world during the global COVID-19 pandemic), health, communication, marketing, and financial transactions will increase. In addition, longer time on social platforms by children is the main trigger of household mobile phone spending (or bills). On the other hand, for working couples with children, monitoring the interior and surroundings of the house with 24/7 security systems for the safety of their children is one of the factors that may trigger the mobile service expenditures of the households. Further, households with children can be expected to spend more on mobile phone bills as their children will have to use mobile phone services to perform other productive online activities such as homework, courses, and blogging. By making agreements with educational institutions, GSM operators can reach more subscribers by offering advantageous packages for familial, social platform, and internet use to households with children, reducing mobile billing expenditures of households while also increasing their revenues significantly.

Households with savings have lower cell phone bill spending levels than households without savings. In line with economic theory, households who save tend to spend less on cell phone bills. GSM operators, by developing policies in cooperation with financial institutions, aiming to direct the savings of the saving-households to more secure digital investment instruments, through either advertisement or by SMSs, will attract such households to the mobile environment, resulting in revenues of both GSM operators and financial institutions. Adoption of the internet and related technologies often leads to increased revenues. The use of the internet will also pave the way for banks to access funds from the previously unbanked population by hosting deposits of mobile money services provided by telecommunications companies. Considering these policy recommendations is expected to have a positive impact in all segments.

Households with at least one passenger car are 2.5% points more likely to spend on mobile phones than households without a car, while their conditional and unconditional spending levels are 4.83£ and 6.99£ more, respectively. As expected, car ownership, as an indicator of wealth, increases the probability and level of spending on mobile phones due to the presence of the equipment and technology such as blue-tooth, navigation, internet, TV, 5G, android car tape, Wi-Fi, USB port, in-car camera, etc. inside the cars. These results are also consistent with the result of other studies in the literature [54]. GSM operators, collaborating with automobile industry representatives to support or encourage the adaptation of smartphone applications and mobile services integrated into automobiles, will have created quite a large incentive for themselves and further boost the number of areas where GSM operators have a say in the future. On the other hand, the households' probability of mobile phone bill spending and conditional and unconditional spending levels increase by 1.9% points, 4.60£, and 6.08£, respectively, with each additional working person in the household. Such a conclusion is consistent with both expectations and the economic theory since consumption expenditures also increase as the household's incomes increase. In addition, households are obliged to spend on mobile phones and services to meet some necessities of employed individuals required by business life. As a way of increasing the number of subscribers, GSM operators can make a cooperation with the workplaces of the individuals, and offer campaign options to the individuals in question, thereby reducing the mobile phone expenditures of the households as well as increasing their revenues, by a win–win policy for both parties.

The probability of mobile phone bills, conditional and unconditional spending levels of households using credit cards, in comparison to non-users, were 1.5% points, 0.77£, and 1.98£ more, respectively. In the case credit cards are used for mobile phone spending, we can expect that households will spend more as credit card payments offer some advantages to consumers. In mobile banking, there are attractive cases, such as automatic payment of monthly mobile service bills, and banks offer promotions to their customers for using such payment methods. GSM operators can reach more subscribers by offering advantageous package campaigns to households that pay their mobile service and internet bills with a credit card or an automatic payment order. On the other hand, a similar causal relationship was observed between household eating out and the probability of household spending on mobile phones, conditional and unconditional spending levels (0.7% points, 1.17£, and 2.47£, respectively). The fact that families with a habit of eating out tend to spend more can be explained by the fact that these families are generally socialized, high-income families. Similarly, smoking habits of households also increase the households' probability to spend on mobile phones, and conditional and unconditional spending levels by 1.0% points, 0.57£, and 1.48£, respectively. As the tendency of talking to other people on the phone while smoking is likely, we expect that the mobile phone bills of smokers will increase as the number of individuals increases in the family.

A positive non-linear relationship was obtained between the number of real estate, such as detached houses, apartments, summer houses, shops, and hotels, owned by the household and their spending probability and spending levels. The mobile phone bills of the household were found to increase at first as the number of real estate owned by the household increased. However, it decreases when the number reaches three or more. For example, the household's probability of spending on mobile phones and their conditional and unconditional spending levels is 0.7% points, 0.41£ and 1.06£, respectively, when the number of real estate owned by the household is one, 1.4% points, 0.83£, and 2.07£ at two, 1% point, 0.59£, and 1.48£ at three or more. The conclusion that real estate is an indicator of wealth is in line with both expectations and economic theory. In this regard, an increased number of real estate creates an economic scale in the household and provides an advantage to the household in terms of mobile telecommunication expenditures. Additionally, as the number of real estate owned by the household increases, the management and follow-up tasks related to these assets, such as the rental, sale, or other business-related to these real estates, can positively affect the mobile phone expenditures made by the households. The increase in the number of children in the household, on the other hand, was found to increase the conditional and unconditional mobile phone bills by 2.09£ and 2.04£, respectively. The result also confirms the result of the variable of households with children. Similarly, a positive relationship was obtained between the number of adults in the households and the probability of households spending on mobile phones and their spending levels. Considering each individual's expenditures, the cell phone bills probability and invoice levels increase with the number of adult individuals in the household, which is in line with expectations.

A positive linear relationship was obtained between family income and mobile phone bills. For example, compared to households in the first quartile income group, households in the second, third, and fourth quartiles have higher conditional and unconditional mobile phone spending levels by 11.46£ and 11.20£, 24.44£ and 23.88£, and 41.98£ and 41.01£, respectively. In particular, households in the upper-income group spend three times more than the households in the second-quartile income group and more than twice as much as the households in the second-quartile group. In [54] Argue that there is an asymmetry in access to mobile communication in Mexico to the detriment of low-income people and that there is a positive relationship between access to mobile communication and income. Households' current income increases the likelihood of purchasing goods and digital services [55, 56]. In [36] Also stated that household income is very important as a predictor of mobile phone and service usage. Since high-income households have a wide variety of jobs, having to contact thousands of people is likely to result in high mobile expenses. GSM operators can have the advantage of having these households as customers by organizing and presenting different campaigns for such households with a wide business range. In addition, the families with the heads of the X and Y cohorts include more adults and working individuals, so mobile phone bills will inevitably increase with the increase in their income levels. GSM operators can increase their profits in the number of customers by creating suitable and attractive package tariffs for such families.

4 Conclusion and recommendations

On the methodological front, we showed how reasonable it is to correct for both heteroscedasticity and non-normality of the error terms in an example with outliers dominating mobile phone bills. The IHS transformation is applied to the mobile telephone spending decision and levels and the heterogeneous variance of the error terms, both supported by statistical tests. With only one additional (scale) parameter, the IHS transformation offers a powerful alternative to traditional transformation methods such as the logarithmic transformation in regression analysis. The transformation has the advantage of addressing extremity in the dependent variable—especially high phone bills due to employer households communicating too much as a matter of their distinct business requirements. Therefore, we use the IHS transformation to account for excesses and skewness in monthly mobile phone expenditures. The negative error correlation estimate suggests that uncontrolled household characteristics adversely affect the household's mobile phone spending decision and billing level. In addition, the fact that the effects of some factors, such as marital status (e.g., widow) and spouses only, are opposite in probability and expenditure levels, constitutes strong justification for the use of the IHS-DH model vis-à-vis the Tobit model.

The socio-demographic and economic factors of the household head and the household have very important effects on the determination of the household mobile phone expenditure probability and billing levels. This information is of great importance in terms of innovations to be made by GSM operators and market segmentation appropriate to the socio-demographic and economic factors of the households, and the development of marketing strategies. In this context, a positive relationship was obtained between households' mobile phone spending probability and spending levels, and X and Y-cohort-headed households, the education level of the household head, having compulsory health insurance, living in an apartment, and being a tenant, having at least two children, the number of automobiles owned by the household, the number of employed individuals, credit card ownership, eating/drinking habits, smoking habits, number of real estates owned, number of children, number of adults and income levels. On the other hand, green card ownership, being a wage-earner, part-time and full-time employee, working in agricultural jobs, and receiving cash and in-kind assistance, were found to be negatively related to the households' probability of spending on mobile phones and their spending levels. It is of great importance to effectively implement socio-economic policies that can increase the education level and income of the households, and to group households according to these profiles, taking into account the socioeconomic and demographic factors of the households, and to develop and monitor separate (selective) strategies instead of general marketing strategies for these groups. Based on all the findings, GSM operators that desire to appeal to a wider audience and increase their revenues may focus on the socio-demographic and economic factors of the household head and the household that reduces mobile phone bills, and accordingly offer them more favorable tariffs, facility of payments or promotion packages to increase the mobile phone expenditures of these groups.

One of the most important results obtained from the study is that the probability and spending levels of mobile phone bills in rural households are very low mainly due to the inadequacy of the telecommunication infrastructures. On that account, GSM operators are thought to be one of the biggest beneficiaries of the return of any support or investment incentives they can make in the areas where telecommunication infrastructure is insufficient. It is therefore recommended that GSM operators support all kinds of investments in such areas as well as make significant efforts to encourage individuals, institutions, and organizations. Another important finding of the study is that socioeconomic factors such as green card ownership and not having a regular job, which plays an important role in determining the income level of households and which are considered an important indicator of low income, significantly reduced the probability and expenditure levels of households to spend on mobile phones. Cooperating with public institutions and organizations, through promotional mobile services offered by GSM operators or lower tax rates applied by the government, GSM operators will not only be able to provide services to such households but will also significantly increase the number of their subscribers. In addition, considering the likelihood of more adults and employees in families with X-generation heads, the fact that GSM operators create more attractive tariffs for these family types may cause a significant change in their profits. Meanwhile, the preparation of more functional tariff package programs that will attract the attention of families with X-generation heads and high incomes will surely boost the profits of GSM operators. Policymakers are advised to develop policies to increase the incomes of households alongside education and training to improve the use and access of mobile telephony services. In addition, policymakers need to intensify their efforts toward the adoption and use of ICT by supporting GSM operators and service providers through subsidies or by providing the necessary infrastructure for the growth of the ICT sector. All parties, the respective country, in particular, the producers and consumers, are all believed to win if the broad policy recommendations proposed in this study were implemented.

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Declarations

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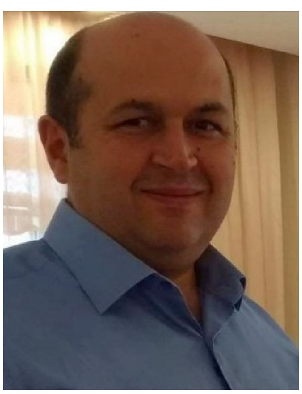

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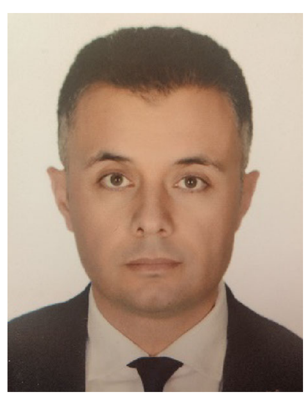

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