NATIONAL RESEARCH UNIVERSITY
HIGHER SCHOOL OF ECONOMICS

Aleksey L. Chadov, Eygeniya A. Shenkman,
Maria R. Temirkaeva

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Aleksey L. Chadov[1], Eygeniya A. Shenkman[2], Maria R. Temirkaeva[3]

THE INFLUENCE OF INDIVIDUAL MOBILITY ON CONSUMER CHOICE: A MODEL OF TARIFF CHANGE

This paper investigates the influence of individual mobility on consumer choice in the mobile phone market. The aim is to understand whether consumer mobility influences the switching of an individual to another tariff within one mobile operator. Data were obtained from 1,154 mobile phone users of one of the largest mobile operators in Russia for the period from November 2011 to November 2012. Customers had limited choices in fast and low-cost switching from one operator to another. Hence, we use data of users switching between tariffs within one operator. The data were analyzed by a mixed logit model which is applied to a discrete choice from a variety of disordered alternatives. This solves the restriction of the standard logit model by allowing for random taste variation. We developed three mobility metrics limiting the drawbacks of established metrics. The results show that mobility does influence consumer choices. Tariff plans differ from each other according to the categories of people that use them. Subscriber mobility is one of the features that separate these categories. There are tariffs preferred by highly mobile people, and those that are preferred by people with low mobility. When the individual's mobility changes, it is highly likely that she will switch to another tariff plan. Mobile operators should take consumer mobility into account when analyzing consumer behavior to increase retention rates.

JEL Classification: D12, C23.

Keywords: cellular communication, mobility, tariff plan, switching.

[1] National Research University Higher School of Economics (Perm, Russia). Senior Lecturer, Department of Economics and Finance. E-mail: alchadov20@gmail.com

[2] National Research University Higher School of Economics (Perm, Russia). Senior Lecturer, Department of Economics and Finance. E-mail: shenkmanea@gmail.com

[3] National Research University Higher School of Economics (Perm, Russia). Young Research Fellow, Group for Applied Markets and Enterprises Studies. E-mail: mariatemirkaeva@gmail.com

Introduction

The mobile operator market is characterized by a high penetration rate and high competition. Under these circumstances, firms attempt to maintain their market share by focusing on the needs of current consumers instead of trying to recruit new clients. Customer retention is regarded as the simplest and most reliable source of high performance (Gengeswari et al., 2013; Reichfeld and Sasser, 1990). In a competitive market, companies that understand which factors impact consumer switching are more likely to retain customers.

Many studies of the mobile phone market focus on factors that encourage people to change mobile operator, including demographic characteristics (Kim et al., 2010), the parameters of the tariff plan (Iyengar, 2004), the structure of consumption (Train et al. 1987) and switching costs (Ida and Kuroda, 2006; Kim, 2006). The market is closely linked to the network effect (Birke and Swann, 2005; Birke and Swann, 2006; Grajek, 2007; Kim and Kwon, 2003). In this paper, we focus on the consumer switching issue without reference to the network effect (Kim et al., 2010; Iyengar, 2004; Train et al. 1987; Ida and Kuroda, 2006; Kim, 2006). Particularly, we consider the influence of consumer mobility on switching between the tariff plans. We use term "mobility" to refer to "spatial or physical mobility", or in other words, to the intensity of an individual's movements. These movements are mainly affected by cycles of urban lifestyles and people's everyday routine. Given that, mobility is just “a special social practice” (Jensen, 2009) which affects people behavior. Therefore, the inclusion of mobility in traditional models of consumer behavior in the mobile phone market may improve their explanatory power.

The impact of consumer mobility on their choice of tariff plan has not yet been studied. This paper fills that gap and shows to what extent individual mobility affects tariff switching.

There are different mobility metrics, the most commonly used metric is radius gyration (Gonzalez et al., 2008; Hawelka et al., 2014). The mathematical expectation of the distribution of human movements (Brockmann et al., 2006; Jurdak et al., 2015) is sensitive to outliers and is based on Euclidean distance, which gives errors in distance calculation. It is critical to choose the correct distribution function when using mathematical expectation, therefore, given the data of base station location, we propose other three mobility metrics. The first is the number of unique base stations included in the range where an individual makes calls during the month. The greater the number of base stations, the more mobile a consumer. We also propose to use a second mobility metric that has not been previously considered in the literature. This metric is based on the Herfindahl-Hirschman index. According to this metric, base stations perform separately, and each station is assigned a unique weight depending on its importance and utility to an individual. By assigning a unique weight to each base station, it is possible to calculate the depth and intensity of a person's monopolization of their space. In other words, how strong individual consumption is concentrated in space.

The third mobility metric is akin to radius gyration and is calculated as the geometrically-weighted average distance from the base station to the individual center of mass. We use the haversine formula instead of Euclidean distance to calculate distance between base stations and the center of mass because the haversine formula gives a more accurate calculation of distances between two objects on Earth. The use of the geometric mean compared to the arithmetic mean gives greater resistance to outliers (Schlink et al., 2010). The use of the weighted mean reduces the importance of distances to rarely used base stations.

We hypothesize that different human mobility is associated with different consumption of mobile phone services. If this is true, then observing an increase in the level of mobility, we can conclude that the volume of consumption will increase or decrease in the future. This increase or decrease of consumption directly affects the person's costs. Because of the change in costs, the person may decide to switch to another tariff plan. Thus, we assume that mobility reflects a person's value attitude, changes behavior, and therefore changes the costs on which the choice depends.

To test this assumption, we use a mixed logit model which is applied in terms of discrete choice from a variety of disordered alternatives (Grzybowski and Pereira, 2011; Grzybowski and Liang, 2015). This model solves the restriction of the standard logit model by allowing for random taste variation. Data were collected from a Russian mobile operator for the period from January to November 2012. During the period under review, customers of Russian mobile operators did not have the opportunity to keep their previous phone numbers when changing the service provider, therefore we only consider switching between tariff plans of the same service provider.

The results confirm the influence of mobility on consumer choice. Highly mobile people prefer tariffs which are suitable for a high level of consumption, i.e. pre-paid tariffs and rates with price differentiation. People who are less mobile choose mainly linear rates. That is why the mobility increase of linear-rate clients may point to their eventual switching to another tariff. Knowing this helps mobile operators to effectively react to consumer switching by offering suitable and flexible tariffs.

The paper proceeds as follows. The first section briefly describes the methods and data for calculating mobility. Sections 2 and 3 present the data and methodology. Section 4 discusses and interprets the empirical results. Section 5 concludes with recommendations.

Mobility measurement

Most researchers define mobility as the patterns of human movement in space. These patterns are fundamental to solving problems in different spheres of human life (Jurdak et al., 2015) including transport management (Calabrese, 2010), planning urban infrastructure (Makse et al., 1995; Roth et al., 2011), crime control (Bernasco, 2018), information dissemination (Onnela et al., 2007), the spread of diseases and epidemics (Balcan et al., 2009) and geo-marketing (Quercia et al., 2010).

There are two ways to measure human movement: direct or indirect. Direct measurement is not possible due to high costs. In practice, therefore, an indirect method of measurement is used more often. This method is based on human activity data from which information about displacement can be extracted. Such proxy data for movement include information on social networks with geolocation (twitter in the work of Jordan et al., 2015), observation of banknotes circulation (Brockmann et al., 2006; Thiemann et al., 2010) and GPS data of vehicles (Tang et al., 2015; Wang et al., 2015; Barbosa, 2018).

This paper, as in González et al., (2008), Kang et al. (2012), Calabrese et al. (2013), uses mobile phone location data, i.e. an indirect measurement of an individual's movements. Typically, such data contain the date, time, and coordinates of the base station routing calls between people at a particular time. Using these data, we restore not the real trajectory of consumer movement, but the trajectory of movement based on the base stations. First, the trajectories are calculated up to the radius of action of the base stations (about 3 kilometers). Secondly, people do not use mobile phone services all the time. Therefore, not all movements can be traced through these trajectories. However, despite the shortcomings, this method measurement is actively used in the research (Palchycov etc. 2014; 2014 Hawelka, etc.). Due to the widespread use of mobile phones, this method can be used to assess the impact of mobility on consumer behavior.

There are several approaches to calculate the mobility index in the literature using data on individual movement. All approaches are based on the following: for each consumer, an individual trajectory of movement, i.e. the graph of movement, is built. Each graph is characterized by vertices that are the points in space at which a consumer made the call, and the edges of the graph are the distance between the points from which the calls were made. All approaches may be divided into two groups: approaches based on the vertices of the graph and approaches based on the edges of the graph.

Using the vertices-based approach, we assume that each vertex of the consumer movement graph is a realization of a random individual-specific variable with a distribution density $\Phi(x,y)$, measuring the probability that a person will move to a place with x and y coordinates (Gonzalez et al., 2008; Barbosa et al., 2018). The distribution density is unique for each consumer and determines her mobility. To study the impact of mobility patterns, different statistics are calculated based on this distribution density. The most commonly used metric is radius gyration (Gonzalez et al., 2008; Hawelka et al., 2014), which is calculated as the average spread of consumer movement relative to the center, or "the orbit of customer movements" (Jurdak et al., 2015). The consumer's place of residence or the calculated center of mass can be used as the center. Small values of the radius gyration mainly characterize movements around the center of mass, while large values reflect the consumer's tendency to move over longer distances. In addition to the radius gyration, Gonzalez et al. (2008) calculated the index of the isotropy of vertices of the graph. This is calculated as the ratio of the standard deviation of the coordinates along the x-axis and the standard deviation along the y-axis. The greater this metric, the less stable and more chaotic a person's movement.

The edges-based approach assumes that the edge length d of the client movement graph ("jump length" by Brockmann et al., 2006; "displacement" by Jurdak et al., 2015) is a random value with the distribution density $P(d)$. Similar to the vertices-based approach, the distribution density is unique for each consumer and determines her level of mobility. The mathematical expectation of the found type distribution can be used as a mobility metric. However, the edges-based approach is used much less often than the vertices-based approach, because it is critical to choose the correct distribution function and different studies suggest different types: from distribution functions with thick tails to exponential and binomial forms (Szell, 2012).

Therefore, in this paper, the vertices-based approach is used to calculate mobility. Before proceeding to the description of the metrics of mobility we use in our study, it is necessary to mention several basic issues related to mobility evaluation. First, base stations located only in Perm Krai are used, because according to the data the coordinates of base stations outside Perm Krai are unknown. Secondly, we are dealing only with base stations that were used to provide a connection between clients in terms of calls and SMS messages inside and outside the network and calls to fixed-line telephones. These services are the most popular among customers in terms of total customer costs as described in the next section.

The first metric of mobility (CountBS) is the number of unique base stations that a person used during the one-month period. It is assumed that a greater number of base stations indicates higher mobility. However, this method has two drawbacks. Firstly, this metric is very sensitive to outliers. The frequency of the base station use is not taken into account. Secondly, individuals can make calls from a small number of base stations that are located at a great distance from each other, which leads to an underestimation of the individual mobility index. The reverse situation is also possible: calls are made from a larger number of base stations with a short distance between them, which leads to an overestimation of individual mobility.

To overcome the drawback of sensitivity to outliers, the mobility metric (HHI) based on the Herfindahl-Hirschman index (Rhoades, 1993) is used. Weights are assigned to base stations according to their significance for a consumer. The more frequently a consumer uses a base station, the more significant it becomes, and a greater weight is assigned to it. The weight of base station *s* for person *i* in month *t* is defined by costs of person *i* in month *t*.

We calculated weights based on money and time costs. As the name implies, the monetary cost weight (*W*) is calculated as the share of costs that person *i* spent on base station *s* in month *t*.

$$W_{ist} = \frac{Costs_{ist}}{Costs_{it}}, \quad (1)$$

where $Costs_{ist}$ are the monetary costs of person *i* spent on base station *s* in month *t* and $Costs_{it}$ are the overall *t*-month costs of person *i*.

For example, person *i* used three base stations in month *t* and paid 100 rubles for the cellular services. Person *i* spent 80 rubles in month *t* on base station s_1, and spent 10 rubles on base stations s_2 and s_3. The weight of base station s_1 for person *i* in month *t* is calculate as 0.8, the weights of the others are each 0.1.

Calculating weights based on monetary costs makes is insensitive to incoming calls which are free. The share of incoming calls in total consumption varies by subscriber, but we assume that the individual costs at each base station are proportional to the volume of service consumption at that base station. In other words, we assume that for each subscriber the share of incoming calls in the total consumption in the zone of this base station is close to its average for all base stations.

In order to take into account incoming services, we also used time costs to calculate base station weights. Using time costs allows us to consider outgoing and incoming services. Time costs are how much time a person spent on voice and SMS messages. Because SMS messages have no time-measurement, we assume that they last 60 seconds[4]. The weight (*W*) of base station *s* for person *i* in month *t* is calculated as follows:

$$W_{ist} = \frac{Costs_{ist}}{Costs_{it}}, \quad (2)$$

where $Costs_{ist}$ are the time costs of person *i* for base station *s* in month *t*, and $Costs_{it}$ are the overall *t*-month time costs of person *i*.

By assigning the weight of each base station, it is possible to calculate the HHI of person *i* in month *t*, i.e. how much his consumption is concentrated in space:

[4] The price list of tariffs contains a fee for 1 minute of call and 1 SMS message. Based on the price list, it is may be assumed that the mobile operator in some sense equates 60 seconds of voice message to one text message. Therefore, we suppose that one text message is equal to 60 seconds.

$$HHI_{it} = \sum_{s=1}^{n} W_{ist}^2, \tag{3}$$

where n is number of base stations used by person i in month t, W_{ist} is the weight of base station s used by person i in month t and is calculated on the basis of monetary or time costs.

The second metric is the inverse of the first: the more mobile the consumer, the higher value the first metric will take and the lower value the second metric will take.

The third metric of mobility is Radius. It is similar to the radius gyration and allows two drawbacks of calculating the first metric (CountBS) to be overcome. Similar to HHI, assigning weights makes this metric more resistant to outliers. Using distances when calculating the Radius helps to overcome the underestimation or overestimation of individual mobility, i.e. a situation when individual makes calls from a small number of base stations which are located far from each other and vice versa.

The Radius is calculated as the weighted[5] geometric mean of distances[6] from each base station s of the movement graph of person i in month t to its center of mass.

$$Radius_{it} = \prod_{s} distance_{ist}^{W_{ist}}, \tag{4}$$

where $distance_{ist}$ are distances between base station s of the movement graph of person i in month t and its center of mass.

Unlike the frequently used radius gyration, the proposed metric is not based on Euclidean distance; the haversine formula are used for calculating the distance:

$$distance_s = 6372795 * 2arcsin\sqrt{sin^2\left(\frac{\varphi_c-\varphi_s}{2}\right) + cos\varphi_s cos\varphi_c sin^2(\frac{\lambda_c-\lambda_s}{2})}\ , \tag{5}$$

where φ_c and λ_c are latitude and longitude of the center of mass of the graph of movement in radians, φ_s and $\lambda_s$are latitude and longitude of the s-th point of the movement graph (the base station) in radians.

The advantage of using the haversine formula is a more accurate calculation of distances between 2 objects that are not on a plane, but on the Earth's surface (Lokhvitskiy et al., 2019). Moreover, the proposed metric is calculated not as an arithmetic mean (c.f. the radius gyration), but as a geometric mean of distances. Given that, the proposed metric is resistant to outliers, specifically

[5] Weights are the same as in the HHI approach of mobility measurement. The more used base station has greater contribution to calculation of mobility that fix the problem of outliers in terms of frequency of use.
[6] Using distances fixes the problem of large number of base stations at close distance or small number of base stations at long distance.

to single trips over long distances (Schlink et al., 2010). For instance, the mobility metric calculated in this way will not change significantly in comparison with the radius gyration when dealing with many small trips and single large trip. Similar to the radius gyration, the larger the third metric, the more mobile the person. In order words, the larger the value of third metric the greater the distance a person travels relative to the center of her graph of movements.

In contrast to the radius gyration, the third metric applies the weighting based not on the frequency of the use of a base station, but on the money or time costs of the subscriber. Weights are calculated as in the HHI metric. The less a person's costs for base station *i*, the less weight the distance from this *i*-th base station to the center of mass.

Despite the fact that the last two metrics eliminate the shortcomings of the first, their disadvantage is ignoring human movement features. Two individuals may have the same level of mobility on the second and third metrics, although the trajectories of their movement may be different. In this regard, the first metric, which takes into account all base stations equally, can indirectly take into account human movement features.

Data

Data were collected from a Russian mobile operator for the period from January to November 2012. During the period under review, customers of Russian mobile operators did not have the opportunity to keep their previous phone number when changing service provider. New amendments to the federal law "On communications" were adopted on 31 December 2012 to allow customers to change mobile operator without changing the previous phone number (Federal law No. 253-FZ "On amendments to a federal law "On communications""). Before that, people were forced to pay both high switching costs and the costs arising from informing contacts of the new number. Therefore, in this paper, due to high both monetary and non-monetary costs, we neglect the possibility of switching to another operator and consider switching between tariff plans of the same service provider.

At total of 1,154 mobile phone users of 8 different tariff plans were considered. We assume that an individual chooses one tariff from the set of available tariffs every month. Since not all individuals are represented in each of the 11 months, we observe 7,134 cases of individual choice. Not all tariffs are available for connection every month for the period under review. For example, the tariff plan "Tariff1" was available only from January to May. "Tariff2" was the only tariff that was available throughout the full period. This tariff was chosen as the basic alternative in the model.

101 customers (8.75%) switched to another tariff once during the period, other clients did not change their tariff. As seen in Table 1, about 30% of all customers in the sample used "Tariff6", the

fewest customers used “Tariff3”. Most customers left “Tariff6” and most customers chose “Tariff2” as the replacement tariff.

Tab. 1. The distribution of subscribers by tariffs

	Number of clients on the first available connection date	Number of customers who left the tariff during the period under review	Number of customers who subscribed to the tariff during the period under review
Tariff1	139 (13.71%)	3 (2.97%)	3 (2.97%)
Tariff2	154 (15.19%)	1 (0.99%)	73 (72.28%)
Tariff3	4 (0.39)	0 (0.00%)	0 (0.00%)
Tariff4	205 (20.22%)	11 (10.89%)	0 (0.00%)
Tariff5	220 (21.70%)	10 (9.90%)	22 (21.78%)
Tariff6	308 (30.37%)	73 (72.28%)	0 (0.00%)
Tariff7	25 (2.47%)	0 (0.00%)	0 (0.00%)
Tariff8	98 (9.66%)	3 (2.97%)	3 (2.97%)

The data collected includes information on which tariff plan and which services each person used; how long each call lasted and how much it cost; when and where it was made, the direction (incoming or outgoing) and type of services (text or voice message). Thus, we can calculate detailed monthly consumer expenditure, i.e. how much money he spent on SMS messages and calls within the network. We use monetary costs as control variables.

Any incoming services (including paid services) were completely excluded from the model because they have less influence on the choice of the tariff plan. Firstly, an individual has less control over the volume of consumption of incoming services. Secondly, incoming services are generally not charged for by the mobile operator.

We include only monthly monetary costs of the most popular services among customers in terms of total customer costs for these services in the model. Figure 1 shows that only 10 services are associated with 90% of the costs of the customer base. Among these services, GPRS-Internet is associated with 8.6% of the costs. Prices for internet access are equal for different tariffs, which is why costs for GPRS-Internet are not included in the model. Nor do we take into account long-distance (7.85% of all costs) or international connections (1.82% of all costs), or SMS with increased payment

(2.71% of all costs) due to their significant higher charge per unit. As mentioned, incoming services[7] are not considered due to lack of control over the volume of consumption by a client. Thus, there are 5 services that we take into account when modeling:

- calls within the network;
- calls to numbers of other mobile operators;
- calls to fixed-line telephones;
- SMS messages within the network;
- SMS messages to numbers of other mobile operators.

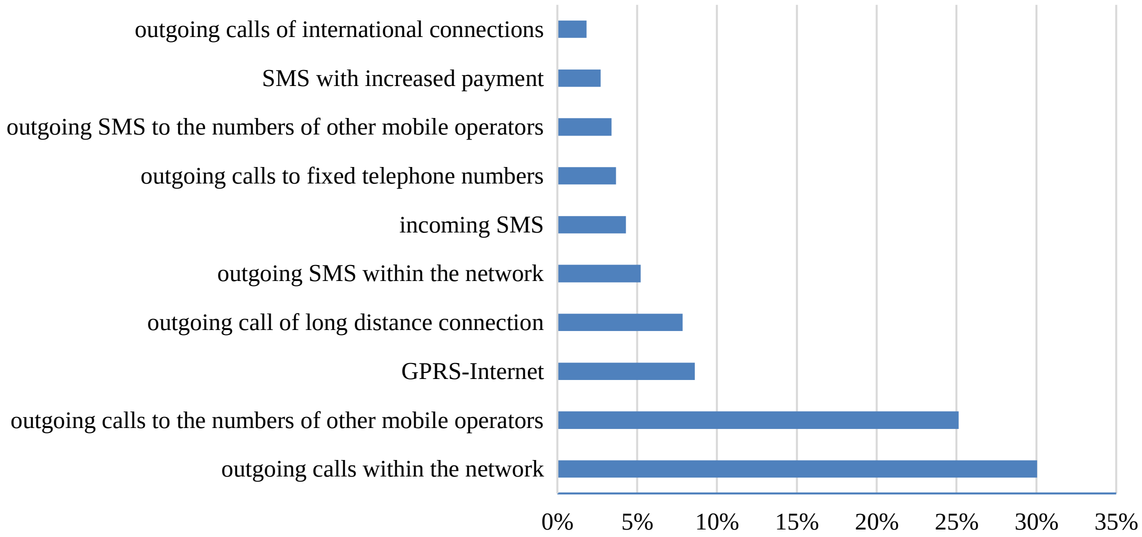

Fig. 1. The cost distribution of the customer base by services

Calls within the network and calls to numbers of other mobile operators are the costliest (Table 2). Calls to fixed-line telephones and SMS messages to the numbers of other mobile operators are the lowest-cost services. A large spread across all 5 services indicates that different customers use different services.

Tab. 2. Descriptive statistics of costs by services

	Mean	Std. dev.
Costs of service 1 (calls within the network), rubles per month	196.439	158.984

[7] In case of 10 services presented in Figure 1, there is paid incoming content SMS that is associated with 4.3% of all costs

Costs of service 2 (calls to numbers of other mobile operators), rubles per month	144.179	163.914
Costs of service 3 (calls to fixed-line telephony), rubles per month	24.792	36.679
Costs of service 4 (SMS messages within the network), rubles per month	33.361	64.548
Costs of service 5 (SMS messages to numbers of other mobile operators), rubles per month	23.80	52.152

In order to use a discrete choice model, it is necessary to calculate the monetary costs that a person would have incurred on alternative tariffs. Assuming that the customer behavior under other tariffs remains unchanged, the alternative monetary costs are calculated using a combination of information about the real volume of consumption each month and the price lists of alternative tariffs (Appendix 1).

The paper focuses on the impact of individual mobility on changing tariff plans. From the data we also know the coordinates of the base stations, which allows us to observe the approximate territorial movements of a subscriber and calculate the mobility metrics. It is assumed that a change in human mobility affects the choice of tariff plan. Table 3 presents the descriptive statistics of the three mobility metrics. “Tariff1” and “Tariff7” are used by customers with the lowest mobility in the sample for all three metrics. Most mobile clients, in terms of HHI and CountBS metrics, use “Tariff2”. Figures 2a–c shows the distributions of the three mobility metrics on “Tariff 1” and “Tariff2”, which differ the most from each other by the mobility of their subscribers. The mobility of subscribers of these tariffs has a different distribution. The chi-square difference test[8] confirms that these tariff plans are chosen by people with different mobility. Therefore, we can state that there is a relationship between the individual mobility and her choice of tariff plan. Thus, our assumption that mobility reflects a person's value attitude and changes her consumption behavior may be true. Accordingly, it is advisable to include this individual characteristic in the model.

Tab. 3. Descriptive statistics of mobility by tariff plans

	CountBS	HHI_Cost	HHI_Dur	Radius_Cost	Radius_Dur
	Mean (Std. dev.)	Mean (Std. dev.)	Mean (Std. dev.)	Mean (Std. dev.)	Mean (Std. dev.)
Tariff1	20.12 (20.57)	0.43 (0.23)	0.41 (0.22)	11591.32 (42866.41)	10689.45 (28865.51)

[8] The test was conducted for the averaged values of each customer mobility metric at 1% significance level.

Tariff2	39.17 (38.98)	0.29 (0.16)	0.24 (0.15)	12418.65 (23970.79)	13396.22 (24486.08)
Tariff3	9.79 (6.22)	0.35 (0.20)	0.36 (0.13)	44520.93 (74366.18)	39347.74 (62056.90)
Tariff4	16.58 (16.60)	0.36 (0.18)	0.37 (0.18)	13154.11 (42416.25)	14329.12 (45393.11)
Tariff5	18.47 (20.24)	0.38 (0.19)	0.36 (0.19)	13032.46 (25176.79)	12180.65 (16983.38)
Tariff6	15.86 (18.58)	0.37 (0.18)	0.34 (0.18)	13211.20 (35091.75)	13576.85 (36909.27)
Tariff7	6.77 (10.66)	0.43 (0.16)	0.36 (0.20)	9839.67 (13906.01)	11513.01 (17094.16)
Tariff8	36.84 (28.23)	0.36 (0.23)	0.33 (0.22)	10855.97 (34977.63)	11189.57 (33215.64)

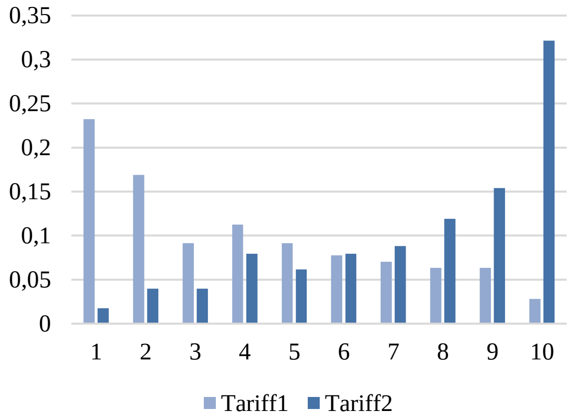

Fig. 2a. Distribution of CountBS by deciles on «Tariff1» and «Tariff2»

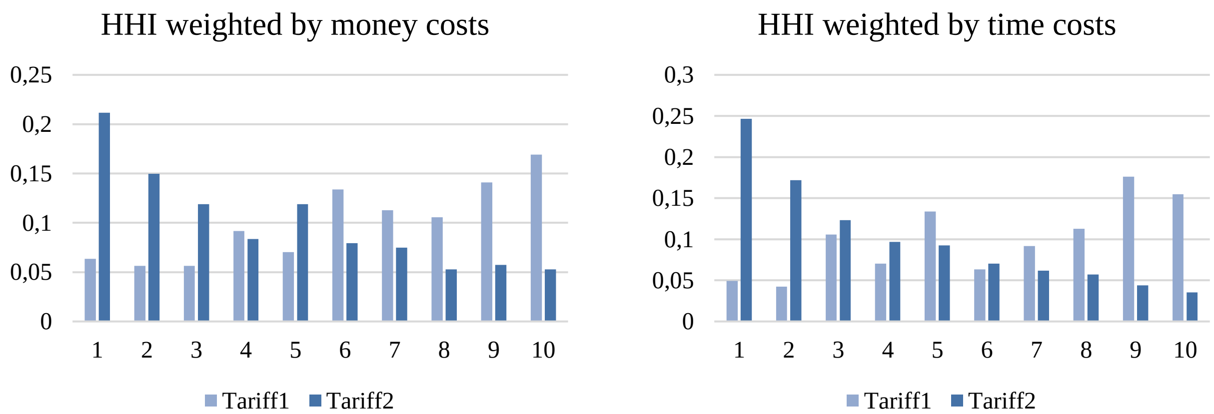

Fig. 2b. Distribution of HHI by deciles on «Tariff1» and «Tariff2»

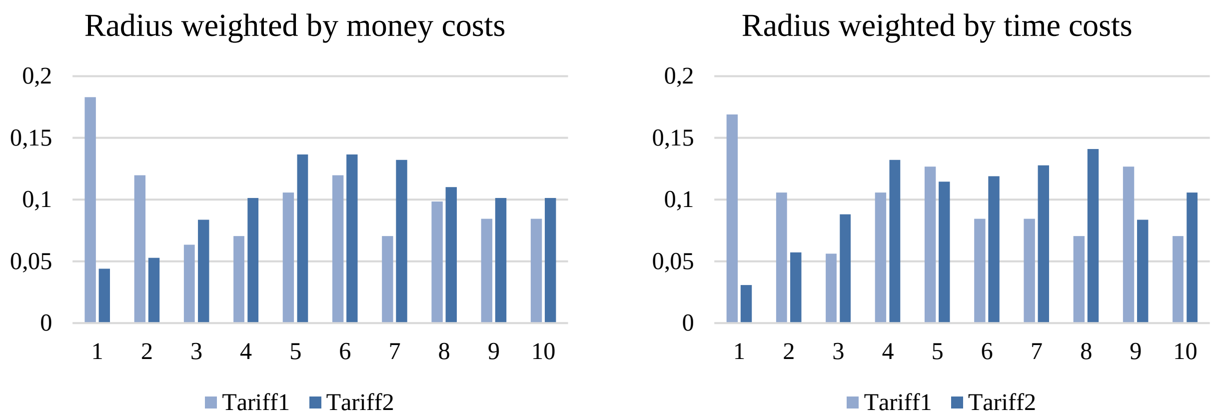

Fig. 2c. Distribution of Radius by deciles on «Tariff1» and «Tariff2»

Methodology

We use a discrete choice model to describe consumer switching between tariff plans (see, for example, Grzybowski and Pereira, 2011; Grzybowski and Liang, 2015; Sobolewski and Czajkowski 2018). It is assumed that each available tariff plan brings utility to a consumer. The value of the utility depends on the characteristics of the tariff and on the characteristics of the individual including mobility. More formally, it is assumed that individual *i* in each period *t* among all available tariff plans *j* = 1, ..., *M* will choose the most preferred tariff:

$$U_{ijt} = x'_{ijt}\beta + \varepsilon_{ijt}, \tag{6}$$

where x'_{ijt} is the vector of regressors observed by individual *i* for alternative *j* at time *t* and ε_{ijt} is a random disturbance.

Let $p_{ijt} \overset{\text{def}}{=} Pr\left\{u_{ijt} = u_{ijt\ k=1,\dots,M}\right\}$. McFadden (1974) shows that if ε_{ijt} is an independent, identically distributed random variable which has a distribution of the extreme values of the first type (Gumbel distribution), then p_{ijt} will be:

$$p_{ijt} = \frac{exp(x'_{ijt}\beta)}{\sum_{k=1}^{M} exp(x'_{ikt}\beta)}, \tag{7}$$

The model is called a multinomial logit model. Its essential limitation is the constancy of the vector of the estimated parameters β for all individuals. On the other hand, the contribution of the same regressor to the utility of the tariff plan is different for different consumers. Therefore, we use a natural generalization of the multiple logit model, that is, a mixed logit model (logit model with random parameters) (Train, 2009; McFadden and Train, 2000). This model assumes that the β parameter varies across individuals, i.e., β is a random value with some distribution:

$$U_{ijt} = x'_{ijt}\beta_i + \varepsilon_{ijt}, \quad (8)$$

$$\beta_i \sim F(\beta_i), \quad (9)$$

$$\beta_i = \beta + \upsilon_i, \upsilon_i \sim N[0, \Sigma_\beta] \quad (10)$$

Model (8)-(9) is a mixed multinomial logit evaluated on panel data by including random effects in the model. A particular case of model (8)-(9) leads to the situation when not all components of vector x'_{ijt} vary across the alternatives. For example, in our case the mobility of individual *i* in period *t* is the constant for all alternatives. Mobility is an individual-specific variable. We know only this characteristic of an individual, the data do not contain sociodemographic characteristics. On the other hand, there are regressors in the model which depend on both the individual and the alternative, for example, the monthly monetary cost of the subscriber by type of service. They are control alternative-specific variables. We refer to monetary costs as the characteristics of a tariff. Costs depend on the price list of *tariff (alternative)* and *individual* levels of consumption. We do not use tariff charges separately as the characteristics of a tariff. There are tariffs with linear pricing and pre-paid tariffs[9] and tariffs with differentiation where charges depend on the past level of consumption. Thus, costs reflect both the price and the volume of consumption. A person, when choosing a tariff, looks not only at the price, but also estimates her approximate volume of consumption. A different volume of consumption implies that a particular tariff is advantageous in terms of costs. Moreover, we include dummy variables for type of tariff and dummy variables for tariffs in the model in order to control for switching costs. We use dummy variables for tariffs as a proxy of switching costs because there is not enough information about the cost of changing tariffs. Switching costs include not only a one-time money subscription fee, but also time costs.

$$U_{ijt} = Mobility_{it} * D_j\gamma_j + Prepaid\delta_1 + Differentiation\delta_2 + D_j\delta_j + Cost_{ijt}\beta_i + \varepsilon_{ijt}, \quad (11)$$

where $Mobility_{it}$ is mobility value of person *i* in month *t*, $Prepaid$ is a dummy variable for prepaid tariff, $Differentiation$ is a dummy variable for tariff with differentiation, D_j is a dummy variable for tariff *j*, $Cost_{ijt}$ is a vector consisting of 5 components which represent the money person *i* spent on tariff *j* in month *t* across different 5 services[10].

[9] The subscription fee is distributed among the services depending on which service is more important for a person, that is, on which he spends more. If a person spends 30% of the costs on SMS, and the rest on calls, then 30% of the subscription fee goes to cost on SMS, and 70% goes to cost on calls.

[10] These services are calls within the network, calls to numbers of other mobile operators, calls to fixed-line telephony, SMS messages within the network, SMS messages to numbers of other mobile operators.

Equation (11) is evaluated by maximum likelihood using the st0133 Stata package/procedure. The evaluation procedure is described in the Stata Journal (The Stata Journal, 2007). Equation (11) assumes the following: the utility of each tariff for the consumer depends on how much money she would have spent on each tariff[11]. The utility also depends on the unobservable characteristics of the tariff, taken into account in the dummy variables for tariffs. The effect of the dummy variable on the utility of the tariff varies depending on the mobility of the subscriber. This reflects the hypothesis that subscribers with different mobility and the same consumption profile have different estimates of the utility of the tariff plan.

We evaluate the model (9)-(11), which takes into account the heterogeneity of people in terms of their sensitivity to changes in the costs of services. It suggests that the coefficients for alternative-specific regressors in this model can be non-fixed. Two people, one of whom mainly makes within-network calls and another sends mostly SMS messages and rarely makes calls, have different price elasticity.

The problem of endogeneity should be mentioned. The choice of tariff plan affects the consumption pattern of an individual and an individual chooses the tariff plan guided by her past and expected future consumption. However, if we consider mobility, the relationship is one-directional. Firstly, we consider base stations located only in Perm Krai. Secondly, mobility affects the choice of a particular tariff plan, but the tariff itself does not affect the level of individual mobility. Thirdly, the characteristics of the tariff do not depend on consumer behavior in space[12]. Moreover, prices of all long-distance and international calls are the same on all tariffs, therefore these services cannot influence the choice of the tariff plan for calls within the region and are excluded from model.

Results

Table 4 presents our mixed logit results[13]. Model (0) is evaluated without a mobility index, and the remaining three models are evaluated with the inclusion of mobility metrics. We include the number of unique base stations (CountBS) as mobility metric in model (1), the mobility metric based on the Herfindahl-Hirschman index (HHI) in model (2), and Radius in model (3).

[11] We observe costs of person for her current tariff from data, in cases of other tariffs we calculate costs of person assuming that her volume of consumption is fixed.
[12] The operator in question had the tariff several years before the period under review, the cost of calls on which depended on the base station used by the subscriber. There was a discount for the base stations selected by the subscriber. However, this tariff was not popular and was soon cancelled. Therefore, it can be assumed that the tariff chosen by the subscriber does not affect her mobility in space.
[13] We show only models that contain mobility metrics weighted by money costs in Table 4 because results of models that contain the same mobility metric, but different ways of weighting are similar. The results of models that used mobility metrics weighted by time costs presents in Appendix 3.

As seen from the evaluation results, the inclusion of the mobility metric improved the quality of the model. First, the mobility of an individual is a significant factor describing the choice of tariff plan. Secondly, according to information criteria, the basic specification without a mobility metric is the worst among the four. In all models, the characteristics of the tariff plan are significant. Based on the coefficients of these characteristics, we can conclude that an increase in the cost of services reduces the probability that an individual will stay with the same tariff. Table 4 indicates that individual mobility is significant in models (1) and (2). The more mobile an individual, the less likely she chooses any of 7 tariff plans in comparison with the base alternative "Tariff2". Therefore, people with greater mobility will tend to subscribe to "Tariff2".

Tab. 4. Results of mixed logit models

		(0)	(1)	(2)	(3)
Costs of service 1	Mean	-0.012^{***}	-0.023^{***}	-0.021^{***}	-0.013^{***}
	Std. dev.	0.046^{***}	0.048^{***}	0.045^{***}	0.042^{***}
Costs of service 2	Mean	-0.007^{**}	-0.004^{***}	0.009^{***}	-0.009^{***}
	Std. dev.	0.058^{***}	0.050^{***}	0.061^{***}	0.069^{***}
Costs of service 3	Mean	-0.004	-0.061^{***}	-0.098^{***}	-0.052^{***}
	Std. dev.	0.194^{***}	0.203^{***}	0.206^{***}	0.166^{***}
Costs of service 4	Mean	0.001	0.006	0.004	0.004
	Std. dev.	0.135^{***}	0.166^{***}	0.105^{***}	0.132^{***}
Costs of service 5	Mean	-0.036^{***}	-0.031^{***}	-0.034^{***}	-0.040^{***}
	Std. dev.	0.185^{***}	0.123^{***}	0.209^{***}	0.194^{***}
Dummy on Tariff3	Mean	-12.256^{***}	-5.479^{***}	-20.642^{***}	-12.879^{***}
Dummy on Tariff4	Mean	-0.168^{*}	-0.089	0.313^{*}	-0.084
Dummy on Tariff5	Mean	4.066^{***}	4.568^{***}	4.641^{***}	4.291^{***}
Dummy on Tariff6	Mean	1.007^{***}	0.622^{***}	1.501^{***}	0.913^{***}
Dummy on Tariff7	Mean	0.471^{*}	5.184^{***}	-2.662^{***}	0.781^{***}
Dummy on prepaid group of tariffs	Mean	1.143^{***}	1.606^{***}	-0.802^{**}	0.774^{**}

Dummy on tariffs with price differentiation	Mean	5.138***	6.647***	3.226***	5.045***
Mobility*Tariff1	Mean		-0.049***	5.475***	1.68e-06
Mobility*Tariff3	Mean		-0.370***	19.272***	1.71e-05
Mobility*Tariff4	Mean		-0.051***	4.495***	8.57e-06
Mobility*Tariff5	Mean		-0.031***	3.784***	4.82e-06
Mobility*Tariff6	Mean		-0.033***	3.838***	6.05e-06
Mobility*Tariff7	Mean		-0.244***	8.974***	-1.6e-05
Mobility*Tariff8	Mean		-0.020***	3.809***	5.86e-07
Number of observations		7134	7134	7134	7134
Information criteria	AIC	10933.95	10642.17	10810.22	10943.76
	BIC	11081.09	10849.90	11017.94	11151.48
R^2 McFadden		0.716	0.724	0.720	0.716
Prob > chi2		0.000	0.000	0.000	0.000

Notes: *, **, *** — Significant at p < 0.1, < 0.05 and < 0.01 accordingly.
Costs of service 1 – calls within the network
Costs of service 2 – calls to numbers of other mobile operators
Costs of service 3 – calls to fixed-line telephony
Costs of service 4 – SMS messages within the network
Costs of service 5 – SMS messages to numbers of other mobile operators

In accordance with the parameter estimates shown in Table 4, the worst model, except the basic model, is model (3). Models (1) and (2) are almost identical in the importance of the coefficients and their signs. Note that the different signs in the coefficients of mobility are interpreted identically, since CountBS and HHI metrics are inverse: the more CountBS or the less the HHI, the more mobile an individual is. Based on the results of the evaluation of models (1) and (2), it can be concluded that mobility relates negatively and significantly to the probability of choosing any of the 7 tariff plans in comparison with the basic alternative ("Tariff2"). However, the obtained mobility coefficients show only a decrease or increase in the probability relative to the basic alternative. It does not resolve the question of what effect mobility has on the choice of an alternative. Therefore, we also have calculated the marginal effects for the model (1), which are shown in Table 5.

The negative marginal effects of "Tariff1", "Tariff3" and "Tariff7" suggest that an increase in mobility decreases the probability of choosing these alternatives. For other tariff plans, the impact of mobility on the probability of choice is positive. Different signs of the model coefficients and the marginal effects are attributed to the distribution of the mobility index on the tariff plans. As seen in

Appendix 2, it is possible to divide the tariffs into three groups: 1) tariffs with a clear predominance of subscribers with low mobility; 2) tariffs with almost uniform distribution of subscribers by mobility; 3) tariffs with a clear predominance of subscribers with high mobility. The third group includes only "Tariff2", which is the basic alternative. Thus, "Tariff2" leads by the share of subscribers with high mobility, which correlates with the obtained negative coefficients of marginal effects: the more mobile the subscriber, the more likely he will choose "Tariff2" and the less likely he will choose other tariffs.

Tab. 5. Marginal effects for mobility metric in model (1)

	Tariff1	Tariff2	Tariff3	Tariff4	Tariff5	Tariff6	Tariff7	Tariff8
CountBS	-0.00083	0.0012	-0.00089	0.00008	0.00096	0.00052	-0.00175	0.00012

Notes: Significant at $p < 0.01$.

The negative marginal effects of "Tariff1", "Tariff3" and "Tariff7", which constitute the group with a predominance of users with low mobility show that the probability of choosing these alternatives drops with increasing mobility. Less mobile people tend to subscribe to these tariffs. If they become more mobile, they will probably switch to another tariff plan. On other tariff plans, the probability of choice increases with increasing mobility, which also correlates with the distribution of mobility on these tariffs.

It can be concluded that mobility is a significant factor determining individual tariff choice. People differ on different tariff plans according to mobility metrics, which means that when the mobility of an individual changes, it is possible to conclude that she will switch to another tariff plan. Therefore, the mobile operator, knowing the mobility and the current tariff of a subscriber, can predict her change of tariff and understand not only the need to keep her, but also how to do so. For example, if a person uses a tariff from the group of tariffs with less mobile subscribers and becomes more mobile, it will be possible to offer her a group of tariff plans corresponding to the new level of mobility.

Such an analysis and prediction may be a powerful competitive advantage. In the telecommunications service industry, tariffs are used as the basis for operator's decision-making. Operators first and foremost use tariffs as an element to meet their profitability criteria. That is why the ability to predict consumer switching with high accuracy is a powerful tool for the effective and profitable management of the tariffs offered by mobile operators.

Conclusion

This paper investigated the choice of tariff plan depending on the level of individual mobility in space. Three methods have been developed for calculating mobility: 1) the number of unique base stations; 2) the approach based on the Herfindahl-Hirschman index; 3) the amplitude of fluctuations around individual center of mass. Since the first metric has two drawbacks, the two other metrics were developed. The second metric allows us to avoid the restriction in the consideration of base stations as equally important. The third metric goes further. Unlike other authors, we use the haversine formula for a more accurate calculation of the distance between two objects on Earth. The use of the geometric mean compared to the arithmetic mean gives greater resistance to outliers. However, the advantage of the first metric over the other two is that it can indirectly take into account human movement features.

Preliminary data analysis showed that people do differ on different tariff plans according to constructed mobility metrics. As for modeling results, the first two metrics are significant. Thus, it can be concluded that the inclusion of mobility metrics in the model improved its quality and that mobility influences consumer choice.

Based on the results, three groups of mobility tariff plans can be distinguished: 1) tariffs with a predominance of customers with low mobility; 2) tariffs with an almost uniform distribution of customers by mobility; 3) tariffs with a predominance of customers with high mobility. This tariff separation can only be observed by the mobile operator, as it follows from the mobility of people, which can only be observed by the operator, but not from the characteristics of the tariff. The probability of choosing the group of tariff plans with a predominance of low-mobile subscribers drops when mobility increases. Less mobile subscribers tend to subscribe to these tariffs. If they become more mobile, they will probably choose another tariff plan. On the other groups of tariff plans, the probability of choice increases with increasing mobility, which also correlates with the distribution of mobility on these tariffs.

If a person becomes more mobile and uses a tariff from the group of tariffs with a predominance of customers with low mobility, it will be possible to assume that she the leaves current tariff. She may then be offered a new tariff plan based on her new level of mobility. If a person becomes more mobile and uses a tariff from group of tariffs with a predominance of customers with medium or high mobility, she will not probably leave the current tariff. Therefore, the mobile operator, knowing the mobility and the current tariff of the subscriber, can predict her change of tariff and understand not only the need to retain her, but also how this can be achieved.

The limitations of this research include the lack of demographic characteristics of subscribers, which may also be important in describing the consumer choice. Secondly, we take into account only intraregional mobility and all the conclusions relate only to this. Analysis of interregional mobility is a task for future research.

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Appendix

Appendix 1

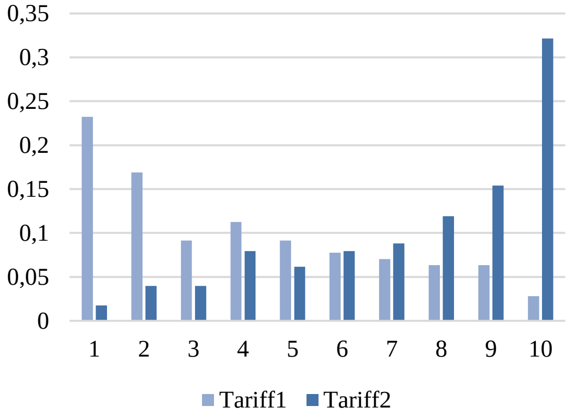
Tab. 1. Price lists of tariff plans

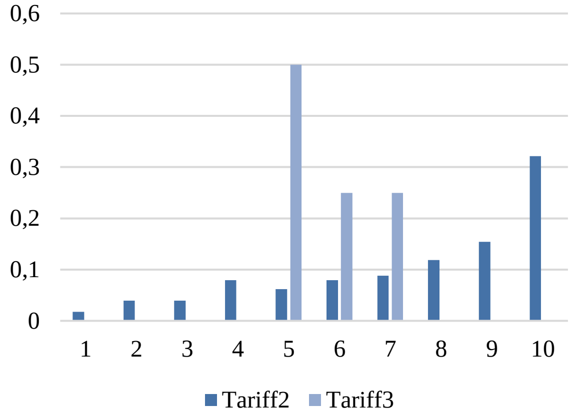
Tariff	Service	Price (rub. per unit of use)
Tariff1	calls within the network;	the first 5 minutes during the day – 1.8, the next – 0.9
	calls to numbers of other mobile operators;	the first 5 minutes during the day – 2.5, the next – 1.25
	calls to fixed-line telephony;	the first 5 minutes during the day – 1.8, the next – 0.9
	SMS messages within the network;	the first 5 SMS per day – 1.5, the next – 0.75
	SMS messages to numbers of other mobile operators.	the first 5 SMS per day – 1.8, the next – 0.9
Tariff2	calls within the network;	monthly costs <2500 rubles – 0.5, > 2500 – 0
	calls to numbers of other mobile operators;	monthly costs <2500 rubles – 1.7, > 2500 – 0
	calls to fixed-line telephony;	monthly costs <2500 rubles – 1.7, > 2500 – 0
	SMS messages within the network;	1.5
	SMS messages to numbers of other mobile operators.	1.8
Tariff3	calls within the network;	3
	calls to numbers of other mobile operators;	3
	calls to fixed-line telephony;	3
	SMS messages within the network;	1.5
	SMS messages to numbers of other mobile operators.	1.8
Tariff4	calls within the network;	1st minute – 2.5, with 2 minutes on 5th – 0, 6th – 1
	calls to numbers of other mobile operators;	1st minute – 2.5, the next – 2
	calls to fixed-line telephony;	1st minute – 2.5, the next – 2
	SMS messages within the network;	1.5
	SMS messages to numbers of other mobile operators.	1.8
Tariff5	calls within the network;	1

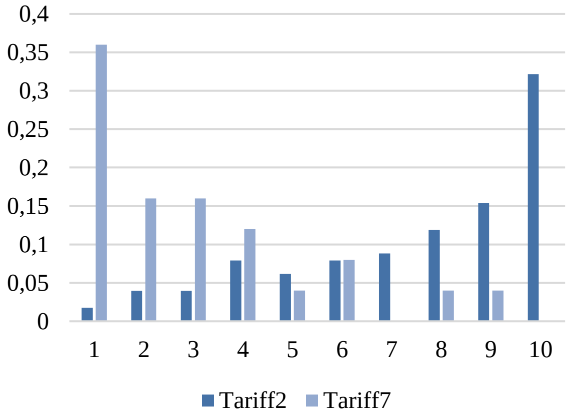
	calls to numbers of other mobile operators;	1.5
	calls to fixed-line telephony;	1
	SMS messages within the network;	1.5
	SMS messages to numbers of other mobile operators.	1.8
	subscription fee	60
Tariff6	calls within the network;	the first 5 minutes during the day– 1.5, the next– 0.75
	calls to numbers of other mobile operators;	the first 5 minutes during the day– 2.7, the next– 1.35
	calls to fixed-line telephony;	the first 5 minutes during the day– 1.8, the next– 0.9
	SMS messages within the network;	SMS per month <150 – 1.5, > 150 – 0.93
	SMS messages to numbers of other mobile operators.	SMS per month <150 – 1.8, > 150 – 1.12
Tariff7	calls within the network;	2
	calls to numbers of other mobile operators;	2
	calls to fixed-line telephony;	2
	SMS messages within the network;	1.5
	SMS messages to numbers of other mobile operators.	1.8
Tariff8	calls within the network;	0.45
	calls to numbers of other mobile operators;	1.45
	calls to fixed-line telephony;	0.45
	SMS messages within the network;	1.5
	SMS messages to numbers of other mobile operators.	1.8
	subscription fee	100

Appendix 2

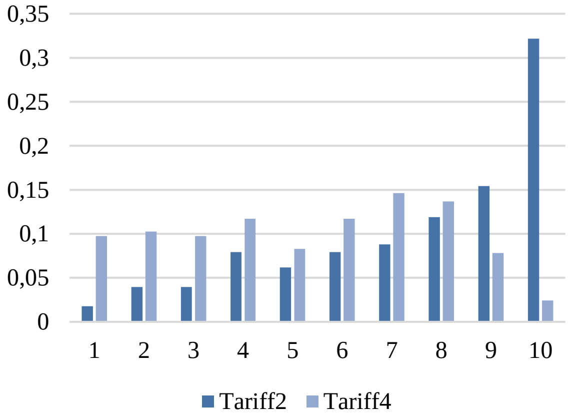
Group 1 – tariffs with a predominance of users with low mobility

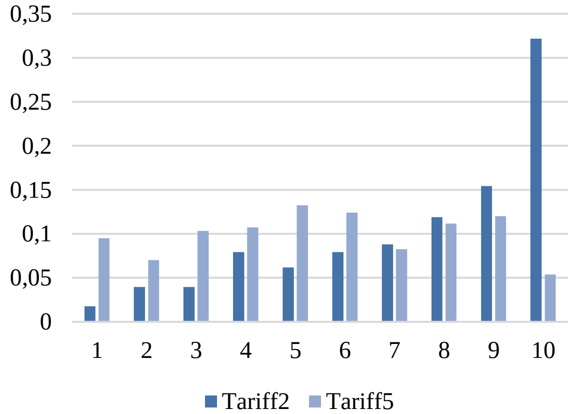


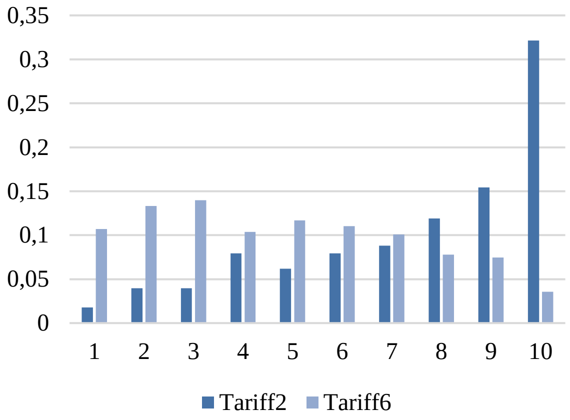


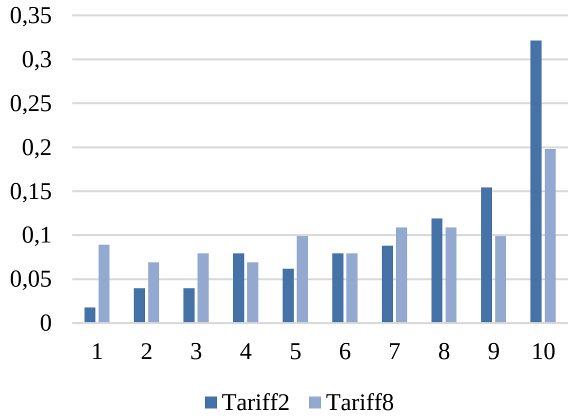


Group 2 – tariffs with almost uniform distribution of subscribers with different mobility









Group 3 – tariffs with predominance of subscribers with high mobility

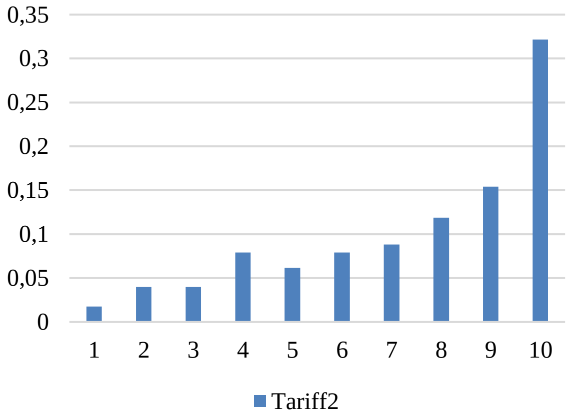


Fig. 1. The distribution of the mobility metric CountBS compared to the base alternative by deciles

Tab. 2. Results of mixed logit models

		(2.1)	(3.1)
Costs of service 1	Mean	-0.023***	-0.012***
	Std. dev.	0.044***	0.044***
Costs of service 2	Mean	0.009***	-0.005**
	Std. dev.	0.060***	0.063***
Costs of service 3	Mean	-0.089***	-0.060***
	Std. dev.	0.194***	0.172***
Costs of service 4	Mean	0.010**	0.002
	Std. dev.	0.171***	0.146***
Costs of service 5	Mean	-0.019**	-0.038***
	Std. dev.	0.121***	0.189***
Dummy on Tariff3	Mean	-17.095***	-12.527***
Dummy on Tariff4	Mean	0.222	-0.080
Dummy on Tariff5	Mean	4.792***	4.321***
Dummy on Tariff6	Mean	1.501***	0.922***
Dummy on Tariff7	Mean	-1.933***	0.821***
Dummy on prepaid group of tariffs	Mean	-1.190***	0.774***
Dummy on tariffs with price differentiation	Mean	3.031***	5.048***
Mobility*Tariff1	Mean	7.000***	1.75e-06
Mobility*Tariff3	Mean	14.051***	1.81e-05**
Mobility*Tariff4	Mean	6.364***	9.15e-06*
Mobility*Tariff5	Mean	5.302***	1.77e-06
Mobility*Tariff6	Mean	5.241***	6.59e-06

Mobility*Tariff7	Mean	8.947***	-3.00e-05**
Mobility*Tariff8	Mean	5.197***	-2.95e-06
Number of observations		7134	7134
Information criteria	AIC	10812.49	10933.54
	BIC	11020.21	11141.26
R^2 McFadden		0.720	0.717
Prob > chi2		0.000	0.000

Notes: *, **, *** — Significant at $p < 0.1$, < 0.05 and < 0.01 accordingly.
Costs of service 1 – calls within the network
Costs of service 2 – calls to numbers of other mobile operators
Costs of service 3 – calls to fixed-line telephony
Costs of service 4 – SMS messages within the network
Costs of service 5 – SMS messages to numbers of other mobile operators

Authors:
Chadov A. L.
National Research University Higher School of Economics (Perm, Russia). Department of Economics and Finance. Senior Lecturer;
E-mail: alchadov20@gmail.com

Shenkman E. A.
National Research University Higher School of Economics (Perm, Russia). Department of Economics and Finance. Senior Lecturer;
E-mail: shenkmanea@gmail.com

Temirkaeva M. R.
National Research University Higher School of Economics (Perm, Russia). Group for Applied Markets and Enterprises Studies. Young Research Fellow;
E-mail: mariatemirkaeva@gmail.com