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Measuring Network Effects in Mobile Telecommunications Markets with Stated-Preference Valuation Methods

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ABSTRACT

This paper demonstrates how stated-preference methods can be applied to modeling consumers' preferences in the field of mobile telecommunications, and to measuring and the valuation of network effects. We illustrate this with a case study of mobile phone operators in Poland. We utilize the Choice Experiment method and present the respondents with hypothetical choices of mobile phone operators, while explicitly controlling for network effects in the form of other users in the same network. Based on the hypothetical choices consumers make we construct a conditional random parameters multinomial logit model to analyze their preferences. This approach allows us to calculate welfare effects associated with alternatives, as well as marginal rates of substitution (and hence implicit prices) of the attributes used to describe the choices, such as operator brand and distribution of family and friends between available mobile networks. The latter constitutes a network effect as consumer's utility is influenced by the number (or ratio) of members of his or her family, friends and other users subscribed to the same operator. Our results confirm the existence of a strong network effect, which is related to the size of the social network group a particular subscriber belongs to, rather than the absolute size of the mobile operator's customer base. We observe that there are two sources of this 'gross' network effect – pecuniary (arising from possible price discounts for on-net calls) and non-pecuniary, and demonstrate a way to disaggregate them. In addition, we find that brand perception and brand loyalty are important determinants of operator choice. Finally, through the application of a non-market valuation method we are able to calculate monetary values of the network effect and brand loyalty, and both turn out to be relatively high. The results might be of a particular interest to mobile phone operators and regulatory authorities – we find that the capacity for vigorous price competition between mobile operators is limited due to significant non-price barriers which mitigate subscribers' mobility in the market. We demonstrate a way to measure these effects in monetary terms based on modeling of consumer preferences.

KEYWORDS

Network effects, mobile telecommunications, brand valuation, stated preference methods, non-market valuation methods, choice experiment, multinomial conditional logit model, preference heterogeneity, random parameters model

JEL CLASSIFICATION

L1; L86; O3

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1. INTRODUCTION

Telecommunications markets are relatively complicated from the economic analysis point of view. There are at least four distinct factors that need to be considered in regulatory and competition models of mobile and fixed-line telephone markets. These are: (i) non-linear pricing in the form of incentive compatible multi-part tariffs, (ii) network effects, (iii) two-sided markets with wholesale level regulation, and (iv) consumer switching costs. In this study we focus on empirical evaluation of network effects.

Economides (1996) argues that telecommunications is a classic example of a two-way network with horizontal compatibility between termination nodes (subscribers). Theoretical literature suggests that in such markets the value of a network access increases with the number of subscribers, constituting a direct network effect. In contrast, in markets with vertical compatibility (e.g. between various components of a hardware-software systems, such as personal computer or a game console; Farrell and Saloner, 1985; Katz and Shapiro, 1985)the consumer's valuation of a good is positively but indirectly, rather than directly, affected by the total number of other users. For instance, hardware users may be influenced by the supply-side economies of scale in software components.[4] This type of externality is a market-mediated indirect network effect. We reference the reader to Farrell et al. (2007) for a comprehensive review of network effects.

There have been a large number of empirical studies which attempted to identify direct and indirect network effects in various markets. Examples include mainframes (Greenstein, 1993), CD and DVD players (Dranove and Gandal, 2003; Gandal et al., 2000), spreadsheets (Brynjolfsson and Kemerer, 1996; Gandal, 1994), and ATMs (Knittel and Stango, 2004, 2006; Saloner and Shepard, 1995).

Much effort has also been devoted to study network effects in telecommunications. Most notably Liikanen et al. (2004) found positive direct network effects between analogue and digital generations of mobile phones as well as within their 2G generation. Doganoglu and Grzybowski(2004) as well as Grajek(2007) found evidence of a very low economic compatibility between different GSM networks, which indicates the presence of strong network effects on the operator level in mobile telephony. They also find that the degree of incompatibility increases with the price discounts for on-net calls. The scale and scope of this impact may depend on many market- and user-specific factors, such as technology, on-net price discounts, the structure of subscriber usage profile, network distribution of their most frequently called parties and many others.

Birke and Swan (2005), and Kim and Kwon (2003) conducted conditional logit analysis on consumer survey data and found a strong relationship between the individual valuation of the

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[4] E.g. the more people buy PS2 game consoles (hardware), the more variety of games (software) will be available in the market at reasonable prices.

operator service and the number of its subscribers. This effect is reinforced by the level of on-net discounts; however, it seems not to be driven solely by price differences. Kim and Kwon (2003) found that network effect is positively related to the total size of the mobile operator's network. They argue that the network effects can be rationalized either be quality signaling or by price discounts for on-net calls. Unfortunately, they do not explicitly verify this hypothesis in their model, since they do not control for price differences between on-net and off-net calls. Birke and Swan (2005) go a step further – they examine the network effect while introducing interaction of price and network size into their model. They find evidence of 'pure' network effect – independent from on-net price discounts. Finally, research by Fu (2004) suggests that in the presence of on-net price discounts and large disproportions of network sizes, a bandwagon effect is observed. The large networks take over a much larger share of new sign-ups, leading to even greater marginalization of smaller operators.

Similar results, under a different methodological approach, were described by Grajek(2007). He estimated a diffusion model using a panel data of the Polish mobile telephony market and found strong network effects leading to an upward sloping demand. His results indicate that network effects are in part price-driven, however, even under flat on- and off-net priceconditions, consumers still perceive networks to a large extent incompatible. As a result consumers prefer their own network to any other. This indicates that network effects might also arise due to learning spillovers and bandwagon effect. Interestingly, Grajek also tested for non-linearity of network effects and found that they exhibit decreasing marginal effects.

Another interesting area of research is the perception of operator brand and its influence on consumer choices. Kim and Kwon (2003) find that the choice of a network is partly affected by an operator's brand.[5]Birke and Swan (2005) provideevidence that the choice of a particular network operator depends on the choices made by the consumer's household members, and on choices the consumer made in the past. This result indicates the brand loyalty effect. In summary, the operators' brands seem to affect utility, and thus consumer choices. As a result, operators seem to be perceived as being differentiated even though they sell functionally identical services or the differences are controlled for. It seems interesting to investigate to what extent this effect can influence choices and possibly add to switching costs.

The previous studies focusing on modeling network effects in telecommunications markets utilized at least three different modeling approaches – the hedonic price method, e.g. Gandal(1994), Brynjolfsson et al. (1996), Knittel et al. (2004), modeling of diffusion, e.g. Grajek(2007), Liikanen et al. (2004), Fu (2004) or conditional multinomial logit model applied to revealed preference data, e.g. Birke and Swan (2005), Kim and Kwon(2003). The last approach seems to be the most advantageous and reliable, as it utilizes data on the individual level and allows for direct modeling of utility functions. However, utilizing revealed preference data does not always allow for the separation of the network effect from the influence of other drivers of consumers' choices, such as switching costs and other biases.

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[5] In their case the effect has been significantly negative for the incumbent (the largest) operator.

We propose a different approach which allows to directly model consumers' preferences, based on hypothetical choices they make if presented with properly prepared alternatives. The application of this stated-preference method is currently a fast-growing technique which is applied in a broad range of fields, including economics of transportation, environment, health, marketing, and policy. It makes possible the eliciting of consumer preferences among new goods, or existing goods with new attributes, which are not necessarily available on the market or for which market data is missing. The great advantage of this method is the ability to systematically and simultaneously study the influence of multiple factors that influence choice behavior. It also offers an advantage in that it was developed to allow for explicitly modeling the importance of multiple experimental factors (choice attributes), while controlling all other factors relevant for consumers' choices (see e.g. Bateman et al., 2004). Our approach enables the formal modeling of utility functions of the consumer, and thus the modeling of network effects while controlling all possible biases inevitably present in market data.

The aim of our study is to propose a new way to identify and measure network effects in mobile telecommunications market. Our paper introduces the stated-preference methodology and illustrates its potential by estimating the strength and monetary value of a pure network effect on a Polish mobile telecommunications market while avoiding pitfalls of earlier studies. We verify a modified version of *existence hypothesis* – we find that the network effect depends not on the absolute size of the operator's customer base, but rather on the presence of family members and friends. Stated-preference methods enable the direct control of how the presence of different groups of subscribers in the same network influences consumer choice. Moreover, we explicitly test the *independence hypothesis* which indicates the presence of 'pure' (non-pecuniary) network effect causing consumers to prefer larger networks even in the absence of price discounts.[6] In addition, thanks to the stated preference approach we are able to test *brand* (perception) *effect* in a direct way – by treating the network brand as an explanatory variable of consumers' choices. We find that the operator's brand affects utility, and thus consumer choice. As a result, operators seem to be perceived as being differentiated even though they sell functionally identical services. Finally, our approach illustrates how to use marginal rates of substitution between different choice attributes to estimate monetary values of these attributes. This way we are able to value marginal network effect and estimate the relative values of operators' brands.

The rest of the paper is organized as follows. In the next section we introduce the stated preference methodology for conducting choice-experiments. In section 3 we briefly describe the structure of mobile phone market in Poland and the empirical study. In section 4 we provide models specification and estimation results. The last section provides discussion and conclusions.

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[6] The independence hypothesis supports the possibility of 'waterbed effect' in mobile markets, which illustrates the following relation – a reduction or elimination of mobile connection termination fees in the wholesale market will likely result in an increase of retail prices Genakos C, Valletti TM 2008. Testing the 'Waterbed' Effect in Mobile Telephony. CEIS Working Paper No. 110..

2. THE METHOD

Researchers in economics have two general data sources for analyses of consumers' preferences – revealed and stated preference data. The former refer to situations where people's choices are observed in real markets and in real market situations. Conversely, stated preference data refer to situations where choices are observed in hypothetical situations. One of the most prominent methods utilizing stated preference data is a choice experiment – creating hypothetical markets, in which consumers are faced with hypothetical choices (Hanley et al., 1998; Hoyos, 2010; Louviere et al., 2006). Since this approach has (to our best knowledge) never been applied in the context of modeling network effects we briefly describe the rationale of this method in this section.

A choice experiment study can be described as one in which potential consumers make choices from mutually exclusive sets of alternatives in a hypothetically constructed scenario. In each choice situation, the choice alternatives are described in terms of different levels of attributes associated with each alternative, and on the basis of experimental design, the alternatives are made to vary between choice situations. By observing the changes in respondents' stated choices with variation in the choice situations, the effects of the attributes on the choices can be derived. In essence, this method allows one to estimate parameters of utility functions of respondents (i.e. to formally model their preferences) whichenables the simulation of their market behavior and welfare changes in case a new product is introduced, and to design an optimal mix of attributes that consumers demand.

Stated preference data are not observed in real markets, but rather collected under the guidance of carefully designed experiments. In the past this raised questions concerning model validity. Nevertheless, research has shown that such concerns are largely unfounded and the methods like choice experiment are now considered mainstream economics (Adamowicz et al., 1998; Burke et al., 1992; Carson et al., 1994; Hanley et al., 1998; Loureiro et al., 2003).

Finally, the choices consumers make allow researchers not only to estimate respondents' willingness to pay for a single good (alternative) but also to estimate implicit prices – respondent's willingness to pay for each level of each attribute, and the ratios at which they are willing to substitute one attribute level for another.

2.1. MODELING DISCRETE CHOICE DATA

2.1.1. RANDOM UTILITY MODEL

The modeling of discrete choice data is built on random utility theory developed most notably by McFadden (1986). It assumes that the utility associated with any state (choice) can be divided into a sum of contributions that can be observed by a researcher, and a component that cannot, and hence is assumed random. Building on Lancaster's theory of consumer choice (Lancaster, 1966), the observed part of utility of a choice alternative is defined as a function of its attributes. This formulation of utility function and choice-specific alternatives leads to the conditional multinomial logit model that allows using observed choices of an individual to compare their utility levels associated with the choice alternatives.

Formalizing, let individual i choose among J alternatives, each characterized by a vector of observed attributes $\mathbf{x}_{ij}$. The utility associated with alternative j is given by:

$$U_i\left(Alternative = j\right) = U_{ij} = \boldsymbol{\beta}'\mathbf{x}_{ij} + \varepsilon_{ij} \tag{1}$$

where $\boldsymbol{\beta}$ is a parameter vector of marginal utilities of the attributes.

It is assumed that individuals act rationally by evaluating all choice alternatives and choose the one from which they derive the greatest utility. By introducing the error term ε_{ij} the modeler assumes utility levels to be random variables, as it is otherwise impossible to explain why apparently equal individuals (equal in all attributes which can be observed) may choose different options.

Random utility theory is transformed into different classes of choice models by making different assumptions about the random term ε_{ij}. When it is usefully assumed to be distributed independently and identically (iid) across individuals and alternatives – Extreme Value Type 1 distribution – the Multinomial Logit Model (MNL) is derived. In this case, the probability that alternative j is chosen from a set of J alternatives that are available for individual i can be expressed as $P\left(j \mid J\right) = P\left(\boldsymbol{\beta}'\mathbf{x}_{ij} + \varepsilon_j > \boldsymbol{\beta}'\mathbf{x}_{ik} + \varepsilon_k\right)$ for all $k \in J$, such that $k \neq j$. This leads to the following convenient probability specification:

$$P\left(j \mid J\right) = \frac{\exp\left(\boldsymbol{\beta}'\mathbf{x}_{ij}\right)}{\sum_{k=1}^{J}\exp\left(\boldsymbol{\beta}'\mathbf{x}_{ik}\right)}. \tag{2}$$

The MNL formulation is usually a starting point for most choice experiment modeling applications, however, it has some important limitations. These arise mainly from rigid assumptions about the distribution of the error term (a diagonal covariance matrix with equal variances) and may result in violation of assumptions by observed choices (e.g. through observed correlation of utilities associated with different alternatives; Hensher et al., 2005; Louviere et al., 2006). Another limitation of the model is preference homogeneity – the assumption that each individual has the same vector of parameters in their utility functions. We will demonstrate below how these limitations can be overcome by relaxing some of the model's rigid assumptions.

2.1.2. PREFERENCE HETEROGENEITY

There have been many attempts to allow for some degree of correlation between alternatives and each of the individual's choices. In particular, these approaches proposed to introduce heterogeneity of consumers' preferences (the fact that consumers have different tastes and hence they may perceive and value the attributes of a good) in different ways. Currently statistical methods to model the heterogeneity of consumers' preferences are being rapidly developed in the literature of choice modeling (e.g. Colombo et al., 2007; Greene and Hensher, 2007; Hole, 2007; Hynes et al., 2008). The state-of-the-art ways to account for preference heterogeneity consist in including socio-economic interactions into conditional multinomial logit models (Brock and Durlauf, 2007), applying covariance heterogeneity nested models (Koppelman and Sethi, 2005), latent class models (Morey et al., 2006), and most notably random parameters conditional models (Hensher and Greene, 2003; McFadden and Train, 2000). The random parameters conditional multinomial logit model (RPL) is currently the most flexible and general approach to model preference heterogeneity. Below we present its general structure.

The random utility expression of an individual's utility function in RPL can be done in the following way:

$$U_{itj} = \boldsymbol{\beta}_i' \mathbf{x}_{itj} + \boldsymbol{\Omega}_{itj} \mathbf{Y}_{itj} + \varepsilon_{itj} . \tag{3}$$

Note that $\boldsymbol{\beta}_i$ is now a vector of individual-specific parameters of marginal utilities of the attributes. Therefore, we explicitly account for each individual i's choices in T choice situations.[7] In addition, let $\mathbf{Y}_{itj}$ be a vector of loadings that map the error component according to the desired structure (and hence allow for generic correlations), and $\boldsymbol{\Omega}_{itj}$ be a vector of stochastic components which follow a distribution specified by a modeler, with zero mean and unknown variance. This new specification of the random term of the utility function allows to include numerous error structures, and hence to account for heteroscedascity, correlation, cross-correlation, and autoregression of error components (Greene and Hensher, 2007; Hensher and Greene, 2003; Train, 2003).

With some loss of generality (assuming that utility function parameters are individual-specific but constant across choice situations)[8], the general random utility model can be expressed in a more concise form:

$$U_{itj} = \boldsymbol{\beta}_i' \mathbf{x}_{itj} + \omega_{itj} , \tag{4}$$

where $\omega_{itj} = \boldsymbol{\Omega}_{itj} \mathbf{Y}_{itj} + \varepsilon_{itj}$. This model is often called random parameters model because utility function parameters are assumed to be random variables following a certain distribution

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[7] In choice experiments an individual is usually confronted with numerous choice-situations whichallows to extract more information from each respondent of the study.

[8] In case choice situations were significantly spread in time, or learning effects were allowed for, this assumption may be relaxed.

specified by the analyst, so that $\boldsymbol{\beta}_i \quad f\left(\mathbf{b},\boldsymbol{\Sigma}\right)$, where $\mathbf{b}$ is a vector of population means of the parameters, and $\boldsymbol{\Sigma}$ is their variance-covariance matrix over the population. Thus, even though each individual has a fixed set of utility function parameters, these parameters are allowed to follow a certain frequency distribution over the population.[9] Finally, an additional extension of the model allows the distributions of the random parameters to be heterogeneous with observed data $\mathbf{z}_i$ – a set of choice invariant characteristics that result in individual heterogeneity. This allows for introducing heterogeneity in both means of the parameters and their variances (heteroscedascity). Formally, $\boldsymbol{\beta}_i \quad f\left(\mathbf{b}+\boldsymbol{\Delta}\mathbf{z}_i,\boldsymbol{\Sigma}+\boldsymbol{\Gamma}\mathbf{z}_i\right)$ where $\boldsymbol{\Delta}$ and $\boldsymbol{\Gamma}$ are vectors of separately estimated parameters that enter the heterogeneous means and variances of the random parameters.

2.1.3. ESTIMATION

In a classical approach a model is estimated via simulated maximum-likelihood methods (Bhat, 2001; Train, 2003). Let individual i's choices in T choice situations be denoted by $\mathbf{y}_i=\left(y_{i1},...,y_{iT}\right)$, where $y_{it}=j$ if $U_{itj}>U_{itk}$, for all $j\neq k$. The conditional probability of observing an individual i stating a sequence y_i of choices, given the fixed values of individual-specific parameters of utility function $\bar{\boldsymbol{\beta}}_i$[10], is given by the product of logit functions:

$$\Lambda\left(\mathbf{y}_i\,|\,\bar{\boldsymbol{\beta}}_i\right)=\prod_{t=1}^{T}\left(\frac{\exp\left(\bar{\boldsymbol{\beta}}_i'\mathbf{x}_{itj}\right)}{\sum_{k=1}^{J}\exp\left(\bar{\boldsymbol{\beta}}_i'\mathbf{x}_{itk}\right)}\right)^{d_{itk}}, \tag{5}$$

where $d_{itk}=1$ if $y_{it}=j$, and zero otherwise.

The unconditional probability of choice is given by the integration of equation (5) weighted by the density distribution of $\boldsymbol{\beta}_i$ over the choice-study sample:

$$P\left(\mathbf{y}_i\right)=\int\Lambda\left(\mathbf{y}_i\,|\,\boldsymbol{\beta}_i\right)f\left(\boldsymbol{\beta}_i\,|\,\mathbf{b},\boldsymbol{\Sigma}\right)d\boldsymbol{\beta}_i, \tag{6}$$

where $f\left(\cdot\right)$ is the multivariate distribution of $\boldsymbol{\beta}_i$ over the sampled population. If covariance terms are not present, Σ is a diagonal matrix.

The log-likelihood function in $\mathbf{b}$ and $\boldsymbol{\Sigma}$ is given by:

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[9] The most frequently used continuous distributions are normal, log-normal, uniform, and triangular. Discrete distributions are also possible – they lead to the latent class model, in which distinct latent groups of individuals have the same utility function parameters.

[10] In MNL model all consumers have the same parameters of their utility function; hence the i index can be skipped. This is not the case when preference heterogeneity is allowed for, see section 2.1.2 for details.

$$\log L = \sum_{i=1}^{n} \ln P\left(\mathbf{y}_i\right). \tag{7}$$

Since the probability $P\left(\mathbf{y}_i\right)$ does not have a closed-form solution it is approximated through simulation $\left(sP\left(\mathbf{y}_i\right)\right)$ – draws[11] are taken from the mixing distribution $f\left(\cdot\right)$ weighted by the logit probability, and averaged up (McFadden and Train, 2000). Hence, the simulated log-likelihood function becomes:

$$s\log L\left(\mathbf{b},\mathbf{\Sigma}\right) = \sum_{i=1}^{n} \ln sP_i\left(y_i\right). \tag{8}$$

This allows a researcher to arrive at maximum-likelihood estimators for $\mathbf{b}$ and $\mathbf{\Sigma}$, which define a distribution of utility function parameters over the population.

2.1.4. WELFARE MEASURES

A consumer's willingness to pay (WTP) for a marginal change in one of the attributes can be computed as marginal rate of substitution between the quantity expressed by the attribute, and income, at a constant utility level (Meijer and Rouwendal, 2006). The concept is equivalent to computing the compensating variation, as applications usually deal with a linear approximation of indirect utility function (Small and Rosen, 1981). Therefore, point estimates of marginal rate of substitution represent the slope of the utility function for the range where this approximation holds.

In choice experiments, as income is often missing from the indirect utility function, the marginal rate of substitution is calculated with respect to minus the cost variable, which is usually included as one of the attributes characterizing alternatives (Jara-Díaz, 1991). Therefore, for a linear utility function, the WTP for a certain level of attribute equals the ratio between the parameter of interest and the minus cost attribute.

A non-trivial problem arises in case both variables are random, and often correlated, as their ratio has an unknown, and possibly bi-modal distribution (Pham-Gia et al., 2006). There is an ongoing research in this field and several solutions to this problem have been proposed (e.g. Hensher and Greene, 2003; Hu et al., 2005; Sillano and Ortúzar, 2005; Train and Weeks, 2005). As the main moments of WTP distributions may not exist (Daly et al., 2010) one can always turn to estimating median WTPs.

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[11] It is usual to use apply quasi-random sampling, e.g. Halton draws, to reduce the simulation variance and to improve the efficiency of the estimation Bhat CR. Quasi-random maximum simulated likelihood estimation of the mixed multinomial logit model. Transportation Research Part B: Methodological 2001;35; 677-693, Hensher D, Greene W. The Mixed Logit model: The state of practice. Transportation 2003;30; 133-176..

2.2. Designing choice experiments

There are numerous ways in which attribute-combinations and alternatives for choice-situations can be prepared. As there are often too many attributes (and their possible levels) to include all possible combinations in a single choice experiment, a so-called fractional factorial design can be used. It consists in including only some combinations of attribute levels in alternatives, usually imposing attribute levels orthogonality and balance (Street and Burgess, 2007; Street et al., 2005).

More recently is has been shown that it is possible to construct non-orthogonal designs which allow for extracting more information from respondents' choices (Sándor and Wedel, 2001). This led to the development of so-called efficient designs for choice experiments, which instead of preparing orthogonal sets of attributes for each choice-set that is presented to a respondent in a choice experiment, designs choice-sets in a way which minimizes the determinant of the asymptotic variance-covariance matrix of the parameters (*D-error*), given the priors of the parameters of a representative respondent's utility function (Scarpa and Rose, 2008).

Since the parameters are usually not all equal to 0, orthogonal factorial designs are not efficient. Researchers usually have some idea of what the priors could be[12]which allows the preparation of choice experiments that reveal more information, and hence improve statistical properties of the final model, or enable the sample to be decreased, which is required for model estimation, and thus reducing the cost of a study.

Finally, the state-of-the-art choice experiments utilize *Bayesian efficient designs*. This consists of utilizing priors which are random variables, rather than fixed coefficients (Sándor and Wedel, 2001). In this case computation of efficient design requires simulation-based integration, as the equation of D-error cannot be solved analytically. The added value of this approach is accounting for uncertainty with respect to parameters' priors, by allowing these priors to be random variables following a probability distribution over a range of plausible values.

After describing the methodology of choice experiments, allowing to formally model consumer's preferences based on the hypothetical choices they make in controlled conditions, we now turn to demonstrating how this approach can be used for the measurement and valuation of network effects.

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[12] It is also common practice to conduct pilot studies which are used for generating priors for the design of a main study.

3. EMPIRICAL STUDY

The Polish mobile telecommunications market is now at maturity, with sim-card penetration at around 110%. There are three incumbent GSM operators and one new entrant operating on the market. The incumbent companies have almost equal market shares and collectively control 95% of the market. Since 2002 these operators have been offering 3G services under similar network coverage.[13] In 2005 UKE (the Polish equivalent of NRA) granted the fourth UMTS license to a new entrant – Play Mobile (P4). Play started its 2G operations in 2007 under national roaming agreement with Plus and 3G services in its own UMTS network. Now P4 has 5% market share in voice services. NRA secured P4 with asymmetric MTR rates. The current level of asymmetry is around 126% but originally it was more than 200%. There are numerous virtual mobile network operators (MVNOs) in the Polish market, however their importance is negligible.

We aimed to model the factors that influence consumers' choices of mobile phone services' providers, based on stated preference study. Such data is usually collected in the form of a survey which is distributed among a sample of target population. A choice experiment survey typically collects socio-demographic data, introduces the choice tasks that are about to follow, and presents each respondent with hypothetical situations, each time asking to indicate the most preferred alternative. In addition, a questionnaire contains mechanisms and information that are included in order to mitigate biases that might be present in hypothetical choice situations (for a comprehensive review of potential biases and ways to mitigate them see e.g. Bateman et al., 2004; Carson et al., 2001).

3.1. DEVELOPMENT OF THE QUESTIONNAIRE

In order to examine potential factors influencing the choice of mobile providers (i.e. the choice attributes), initial qualitative research was conducted. We applied focus group interviews to reduce the number of possible choice attributes to a manageable number of five which consumers paid the most attention to, when choosing their mobile phone's operator.

The first of the attributes used in the study was a brand name of the mobile operator's network. In our preliminary interviews respondents seemed to associate various qualities with different operators (brands). For this reason we have included the four brands of

[13] These are: PTK Centertel (Orange), PTC (Era) and Polkomtel (Plus). PTK Centertel is a subsidiary of Polish Telecom Group – a former monopolist. It was the first mobile operator in Poland. In 1991 PTK launched 1G telephony under NMT-450i and GSM telephony in 1998. PTC is a full subsidiary of T-mobile. Polkomtel is owned by Vodafone and a number of huge Polish state-owned companies. Both companies started to offer GSM services in 1996.

infrastructural MNOs currently operating on the Polish market: Orange, Era, Plus and Play. Virtual operators were excluded from the research, due to their negligible market share.

The next two attributes reflected the price of a call. Operators in Poland do not apply flat rates, but price-discriminate based on call destination.[14] Therefore, we have included two price attributes in our study: on-net price per minute and off-net price per minute. Possible levels of these attributes, which were used to describe the alternatives used in choice sets presented to our respondents, reflected current prices of calls in the market and also levels perceived by participants of focus groups. These were 0.10, 0.30, and 0.50 PLN[15] per minute for on-net calls and 0.30, 0.50, and 0.70 PLN per minute for off-net calls respectively.

The aim of our study was to measure the network effects and their influence on consumers' choices. During the interviews it turned out that an essential attribute that has an impact on the choice of a mobile operator is the presence of specific other subscribers on the same network. However, preliminary qualitative study, as well as some evidence in the literature (Birke and Swann, 2005) indicated that what matters is not the total number of subscribers in the network, but rather the number of people who they most often call, such as family members and friends. Calls to those groups of people generate the major part of network traffic, so their presence on the same network is important for the total cost of calls.

Our qualitative research with the focus groups has shown that the other people whose presence is important for selecting a mobile operator can be divided into three exclusive groups, depending on each respondent's individual emotional relation with them. These three social circles are:

- 'Family' – people such as parents, siblings, partners and other people who are not necessarily a family but are considered to be 'the closest';[16]
- 'Friends' – all persons with whom respondent maintains regular contact, such as friends, acquaintances, and relatives, who were not classified as the 'family';
- 'Others' – all the other people who a respondent contacts irregularly, such as shops, offices, distant friends, or does not contact at all, but are still connected to the same network. This attribute was basically equivalent to each operator's customer base.

As a result, each of the alternatives (possible operators) in a choice situation has been described by the three additional attributes, associated with the percentage of people who they consider their 'family', 'friends' and 'others' who would also be subscribers of the same operator. The first two of these attributes could take the levels of 25%, 50%, and 75%, while the proportion of 'others' in the same network could be 20%, 30%, and 40%.

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[14] This is to some extent justified by the substantial level of mobile termination rates, which cause calls on the same network to cost less than off-the-network calls.

[15] 1 PLN ≈ 0.25 EUR ≈ 0.3 USD

[16] It is important, and was clearly explained in the questionnaire, that the 'family' group does not necessarily consist of family members only, but rather whoever the respondent considers to be 'the closest'. Similarly, some family members could be classified by the respondents to the 'friends' group, if they contacted them less often than other members of 'the closest' group.

The full list of attributes and their possible levels used in the study is summarized in Table 1.

Table 1. The list of attributes used to describe choice alternatives, and their levels

Brand of the operator	• Orange • Era • Plus • Play
On-net price (PLN per minute)	• 0.10 • 0.30 • 0.50
Off-net price (PLN per minute)	• 0.30 • 0.50 • 0.70
% of 'family' using the same operator	• 25% • 50% • 75%
% of 'friends' using the same operator	• 25% • 50% • 75%
% of 'others' using the same operator	• 20% • 30% • 40%

The survey was structured as follows. In the beginning the purpose of the survey was explained and we assured anonymity of each respondent's individual answers. Then questions referring to the current use of a mobile phone followed – type of contract, current mobile operator, and calling profile such as volume of generated traffic and the average monthly bill. In the next part of the questionnaire we introduced the choice tasks to follow – we described the attributes and their possible levels. We clearly defined the groups of 'family', 'friends' and 'others' in the survey. Finally, the choice tasks followed. For each choice situation a respondent was asked to choose an alternative he prefers the most, in terms of the attribute levels that described it. In the last part of the questionnaire we collected socio-demographic data such as age, gender, household size and income of the respondents.

In our study, each respondent was faced with 12 choice tasks, each consisting of 4 alternatives. Each alternative was described with the 5 attributes, specified above. An example of a choice card shown to respondents is given in Figure 1. The choice sets utilized in our study were prepared using Bayesian efficient design (see Section 2.2 for details). To obtain initial estimates (priors) and to verify the qualitative properties of the questionnaire itself we conducted a pilot study on a sample of approximately 50 respondents.

Figure 1. Example of a choice card (translation)

Which of the following mobile phone operators' offers would you consider the best for yourself?

Operator	ORANGE	ERA	PLUS	PLAY
On-net price per minute	10 gr	10 gr	50 gr	50 gr
Off-net price per minute	70 gr	30 gr	70 gr	30 gr
'Family' in the same network	75%	25%	25%	75%
'Friends' in the same network	75%	50%	25%	50%
'Others' on the same network	20%	30%	30%	40%
Your choice	□	□	□	□

The final survey was conducted on a sample of 267 students from the Faculty of Economic Sciences at University of Warsaw. This resulted in 3204 choice observations. Our sample was not representative for any group of mobile users in Poland (other than the students at this faculty), however, we use it for the illustration of how stated preference elicitation and modeling techniques can be used for the analysis of network effects. In addition, some of our findings remain valid irrespective of the representativeness of the sample. In particular this refers to confirming the presence of network effect and analyzing its characteristics. We verify these hypotheses in Section 4 below.

3.2. CHARACTERISTICS OF THE SAMPLE

We now turn to reporting the basic characteristics of our sample data. Even though our sample was not representative, some sample characteristics might be useful in interpreting the results presented in Section 4.

The largest number of students in the test group had a mobile phone operated by Orange (36%), followed by Era (30%), Plus (24%) and Play (10%). These results differ from the overall Polish market shares but this is expected, as the demand for telecommunications services is highly differentiated, and operators introduce strategies which target different segments of the market. The usage profile of telecommunications services in the student group is characterized by low expenditure on telecommunications and a considerably reduced volume of outgoing voice traffic. This makes them relatively less attractive to Plus and Era, who focus on segments with higher intensity of demand. Students are, however, a natural target group for Play who entered the already relatively saturated market, and for Orange, who has an attractive all-around offer.

The usage profile of voice telecommunications services for students is characterized by a relatively low demand for 'paid minutes', small expenditures and a high sensitivity to discounts for on-net calls. Almost 60% of students were subscribers to the postpaid system. The mean monthly bill for all telecommunications services (voice, data, SMS, MMS) was less than 50 PLN.

The usage profile of our sample group indicated that the vast majority of calls are established with a small group of people belonging to the 'family' group (median share of 70%) and a slightly wider group of 'friends'. On average, the 'family' group consisted of 6 persons, while the average size of the 'friends' was 14. We observed the tendency of the members of these two social circles to group with the same operator. Half of the sample students reported to have had at least 50% of the 'family' and 40% of the 'friends' use the same operator. Only in the case of Play the intra-network sizes of both groups were smaller – 30-40% of the 'family' and 10-20% of the 'friends'.

According to our respondents, the most important factor in selecting an operator are the prices for off-net and on-net connections, as well as the share of the 'family' subscribed to the same operator. 80% of respondents declared these factors to be important or very important. In addition, a significant group of respondents (60%) were driven by non-price factors, such as operator brand and the presence of 'fiends' on the same network. Our preliminary finding is that the overall size of the operator's network was considered irrelevant. This indicates that the magnitude of network effect may depend mainly on the size of the group with which a respondent maintains close and constant social relations. We verify this finding quantitatively in the next section.

The declared prices of on-net and off-net connections averaged 0.27 and 0.46 respectively. The price differentiation between the operators was relatively small. Era was declared by its users to be the cheapest, with price per minute of 0.24 and 0.40 PLN, respectively, for on-net and off-net calls per minute. Analogous connection prices charged by the other operators were perceived to be on average 0.26 and 0.47 PLN (Plus), 0.28 and 0.48 PLN (Orange) and 0.32 and 0.44 PLN (Play). Compared to the 'big three', Play represents a pricing strategy of a 'late entrant' who has to build its customer base by taking over subscribers from mature competitors. For this strategy to be successful, Play has to compensate for negative network effect by lowering off-net calls.

4. RESULTS

The stated preference choice data was used to formally model consumers' preferences. Several model specifications were used. For illustration, we start with presenting the simplest – the multinomial logit model.

In what follows, we've assumed the following general form of the utility function of the respondents:

$$\begin{aligned} U_i &= \beta_{ORA} ORA + \beta_{ERA} ERA + \beta_{PLU} PLU \\ &+ \beta_{P_{ON}} P_{ON} + \beta_{P_{OFF}} P_{OFF} + \beta_{FAM} FAM + \beta_{FRI} FRI + \beta_{OTH} OTH \, , \\ &+ \beta_{P_{ON} FAM} P_{ON} FAM + \beta_{P_{ON} FRI} P_{ON} FRI + \beta_{P_{ON} OTH} P_{ON} OTH + \varepsilon_i \end{aligned} \tag{9}$$

where :

- ORA, ERA and PLU are dummy variables representing alternative specific constants associated with each operator (Play is assumed the reference point). These variables control for properties of the operators, such as quality of service, brand perception etc., not controlled for by other attributes of presented alternatives;
- P_{ON} and P_{OFF} represent on-net and off-net price respectively;
- FAM, FRI and OTH represent the percentage of people from the 'family', 'friends', and 'others' respectively, subscribed to the same operator;
- β are parameters associated with respective variables.

4.1. THE MULTINOMIAL LOGIT MODEL

The results of the MNL model are given in Table 2. We begin by noting that almost all explanatory variables turn out to be significant determinants of choice. Although the parameter values do not have direct interpretation, their signs and relative values reflect how different factors influence respondents' choices (their utility, and hence the probability of choosing a certain alternative).

Coefficients of alternative-specific constants (ORA, ERA, PLU) indicate that respondents prefer to subscribe to one of the 'big three' networks rather than to Play, *ceteris paribus*. Their relative values indicate that Orange is the most preferred, followed by Era and Plus.

The coefficient of on-net price per minute is not statistically significant. This is likely a result of P_{ON} entering the model through interactions with FAM, FRI, and OTH at the same time, hence the effect of a higher on-net price is already controlled for by these interactions. The coefficient of off-net price is significant and negative, as are two of the interaction coefficients. This indicates the negative influence of price on utility, and hence on the probability of choosing an alternative with higher prices. The interpretation of interaction terms is this – the more ‘family’ or ‘friends’ on-net and the higher the on-net price (at the same time), the lower the utility is.

The coefficients associated with the percentage of people from the ‘family’, ‘friends’, and ‘others’ groups indicate their influence on choice probabilities. Clearly, the percentage of the members of the ‘family’ group is the most significant determinant of choice, with the coefficient for the ‘friends’ over two times smaller. The coefficient associated with the percentage of ‘others’ in the same network is not significant what indicates that the market share of an operator is not an important determinant of consumers’ choice – which matters is the presence of people with whom close relations are maintained.

Table 2 – The results of the multinomial logit model

	Coefficient	Standard error
β_{ORA} – services operated by Orange	0.7673***	0.0751
β_{ERA} – services operated by Era	0.6541***	0.0948
β_{PLU} – services operated by Plus	0.4992***	0.0834
P_{ON} – on-net price	2.1452	1.2744
P_{OFF} – off-net price	–4.6035***	0.1801
FAM – % of ‘family’ using the same operator	4.3185***	0.4711
FRI – % of ‘friends’ using the same operator	2.1704***	0.3479
OTH – % of ‘others’ using the same operator	0.9170	0.8340
$\beta_{P_{ON}FAM}$ – interaction of on-net price and % of ‘family’ using the same operator	–7.6874***	1.6952
$\beta_{P_{ON}FRI}$ – interaction of on-net price and % of ‘friends’ using the same operator	–6.1711***	1.3581
$\beta_{P_{ON}OTH}$ – interaction of on-net price and % of ‘others’ using the same operator	–1.8476	3.1794

Log likelihood function	–2730.4483
Pseudo-R^2	0.3511
AIC (normalized)	1.7670
BIC (normalized)	1.7884

***, **, * – Significance at 1%, 5%, 10%

The above simple model was used to illustrate how the results can be interpreted. It is interesting to briefly summarize some of these first results, however. We observe the presence of a strong network effect – the presence of the people a respondent maintains close social relations with (‘family’, ‘friends’) significantly increases the attractiveness of an offer. This effect is irrespective of the potential cost savings, since their interactions with the on-net price are controlled for. Therefore, what we observe is a ‘pure’ (non-pecuniary) network effect. In contrast, the presence of ‘others’ in the same network does not influence respondents’ choices in a significant, systematic way.

4.2. THE RANDOM PARAMETERS LOGIT MODEL

In the next step we relax some of rigid assumptions of the MNL model. We have tested several model specifications allowing for the incorporation of preference heterogeneity. The best performing model, both in terms of goodness-of-fit indices (Akaike and Bayesian Information Criteria) as well as its predictive power, was a random parameters multinomial logit model in which all the attributes’ parameters were assumed to be normally distributed random variables. We allowed for correlations between these random parameters, which proved to be highly significant. In addition, we accounted for the panel structure of our dataset (since each respondent faced 12 choice-sets) by introducing random effects type of treatment – additional random term for all observations from the same individual. Finally, we introduced observed individual heterogeneity in alternative specific constants (ORA, ERA, PLU). The means of these random parameters’ distributions were assumed to be functions of individual-specific explanatory variables[17] – the brand of currently subscribed operator (SQ_{ORA}, SQ_{ERA}, SQ_{PLU}).

Table 3 shows the results for our final, random parameters logit model.[18] The introduction of individual heterogeneity and a more complex error structure drastically increases model performance. This is visible as the large increase in the values of log-likelihood function, and pseudo-R^2, with a decrease of AIC and BIC indices, in comparison with the MNL model.

We start the analysis with the panel B of Table 3. The statistical significance of all the coefficients indicates that standard deviations of the random parameters are significantly different from zero, and hence that the variables should indeed be modeled as random. This is a strong evidence of unobserved preference heterogeneity.

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[17] As reported by a respondent.
[18] Should the reader be interested in inspecting the correlation between the parameters, we report the estimates of the elements of lower triangular of Cholesky matrix (i.e. products of Cholesky decomposition of the variance-covariance matrix of coefficients) in Annex 1.

Table 3. The results of the random parameters model

	(A) Means of normally distributed random parameters		**(B)** Standard deviations of normally distributed random parameters	
	Coefficient	Standard error	Coefficient	Standard error
β_{ORA} – services operated by Orange	0.8451***	0.1446	0.9806***	0.1411
β_{ERA} – services operated by Era	0.4053**	0.1631	0.8078***	0.1498
β_{PLU} – services operated by Plus	0.2045	0.1487	0.4654***	0.1308
P_{ON} – on-net price	0.6590	2.5626	4.9151**	2.2560
P_{OFF} – off-net price	–8.3644***	0.4948	6.5545***	0.4468
FAM – % of 'family' using the same operator	6.3468***	0.8340	6.1437***	0.6458
FRI – % of 'friends' using the same operator	4.1570***	0.6794	4.7318***	0.5058
OTH – % of 'others' using the same operator	0.2320	1.5389	4.8208***	1.2196
$\beta_{P_{ON}FAM}$ – interaction of on-net price and % of 'family' using the same operator	–11.2236***	2.5238	12.7225***	2.1544
$\beta_{P_{ON}FRI}$ – interaction of on-net price and % of 'friends' using the same operator	–8.8433***	2.7947	11.3908***	1.9729
$\beta_{P_{ON}OTH}$ – interaction of on-net price and % of 'others' using the same operator	–2.7651	5.9869	19.2064***	4.4508
(C) Covariates of means of random parameters				
SQ_{ORA} – currently subscribed to Orange (covariate of β_{ORA})	0.71067***	0.18641	–	–
SQ_{ERA} – currently subscribed to Era (covariate of β_{ERA})	0.77649***	0.18049	–	–
SQ_{PLU} – currently subscribed to Plus (covariate of β_{PLU})	1.14241***	0.17862	–	–

Log likelihood function	–2186.4648
Pseudo-R^2	0.4917
AIC (normalized)	1.4608
BIC (normalized)	1.6166

***, **, * – Significance at 1%, 5%, 10%

Interpreting the coefficients given in panel A should now be done together with the coefficients in panel C – covariates of means of normally distributed random parameters. They all have expected signs and relative values, and their interpretation coincides with that given to the MNL model parameters. The dummy variables associated with the brand of currently subscribed network (SQ_{ORA}, SQ_{ERA}, SQ_{PLU}) are very significant explanatory variables of the means of alternative specific constants' distributions (β_{ORA}, β_{ERA}, and β_{PLU} respectively). This is an indicator of strong brand loyalty – the consumers currently subscribed to an operator prefer this operator to others, even in their hypothetical choices, and even if the prices and the presence of the 'family' and 'friends' are controlled for. This effect is the strongest for current Plus users, and is similar for Era and Orange ($SQ_{PLU} > SQ_{ERA} > SQ_{ORA}$, see panel C for details). Once this effect is controlled for, we can see that Orange seems to be the brand which is mostly appreciated for its latent characteristics (e.g. quality of service), while Era is almost twice less appreciated and Plus is not significantly different from Play ($\beta_{ORA} > \beta_{ERA} > \beta_{PLU}$) .

As before, the off-net price has a significant and negative coefficient, as is the on-net price, entering through interactions with the 'family' and 'friends'. The market share of an operator ('others') does not seem to significantly contribute to explaining consumers' choices, even if interacted with on-net price.

4.3. VALUATION OF NETWORK EFFECTS

We now turn to estimating the monetary value of network effects, i.e. to calculating implicit prices of the attributes associated with network effects. This can be done by calculating the marginal rate of substitution of monetary parameters – in our case the price of off-net calls – for an attribute of interest.

Panel A of Table 4 shows median implicit prices in terms of average price per minute, along with associated standard deviations. These were generated using parametric bootstrapping following Krinsky and Robb (1986). Since our price parameter was also random we have followed the simulation method similar[19] to that proposed by Hu et al. (2005); in order to avoid 'exploding' implicit prices, when a random price parameter was very close to zero we averaged over 10^4 draws of each parameter, for each round of Krinsky and Robb draws from parameter distributions.

The results in panel A of Table 4 can be interpreted in the following way. The median value of Orange and Era brands for the subscribers of these networks, in comparison with Play, is an equivalent of a 10.10 and 4.85 cent PLN increase in price per minute, respectively. This is a net effect, as we control for the commitment effect – the fact that our participants seemed to prefer brands which they were currently using. Additional illustration is provided if the results are expressed in terms of additional cost of monthly mobile phone bill. This is done in panel B of Table 4. The results show that having a phone in the Orange network, as compared to the Play network is worth an additional 17.75 PLN increase of an average monthly bill, all else being equal. Similarly, the value of having Era as an operator, in comparison with Play, was

[19] Since our parameters were correlated, we took draws from multivariate normal distribution, rather than multiple draws from normal distribution of parameter.

8.52 PLN a month. These results show that consumers perceive mobile phone operators differently, in spite of the functional similarity of their services.

Table 4.Implicit prices of the choice attributes

	(A) Increase of price per one minute of off-net connection [cPLN]		(B) Increase of an average monthly bill [PLN]	
Attribute	Implicit price	Standard error	Implicit price	Standard error
β_{ORA}	10.1037***	1.6961	17.754***	2.9804
β_{ERA}	4.8457**	1.9613	8.5148**	3.4463
β_{PLU}	2.4452	1.7854	4.2967	3.1372
FAM	0.7588***	0.0973	1.3333***	0.1709
FRI	0.4970***	0.0751	0.8733***	0.1319

***, **, * – Significance at 1%, 5%, 10%

Similarly, we were able to calculate implicit prices for the network effects – increasing the ratio of ‘family’ and ‘friends’ who are using the same network. Each percentage point increase of the ‘family’ using the same operator was wortha 0.76 cent PLN increase in the price of an off-net minute of call. The equivalent value for ‘friends’ was almost 0.50 cents PLN. In terms of an increase of a monthly bill these attributes are equivalent to an additional 1.33 or 0.87 PLN respectively. These results demonstrate the presence of a very strong network effect – with an increasing quantities of goods (number of close persons using the same operator) consumers are willing to pay higher prices per minute or higher bills. Hence, the network effect causes a reduction of price elasticity of demand for minutes. This result is valid even though savings due to cheaper on-net calls are controlled for, and hence constitutes a non-pecuniary network effect.

The reasons for this ‘pure’ network effect, as proposed by Grajek(2007), and Kim and Kwon (2003) are quality signaling and conformist behavior of consumers. Our findings – strong network effects in close social groups – are supportive for both explanations, as we usually observe conformist behavior in close social group as well as quality or norm signaling via membership of the people who are an important point of reference.

5. Discussion and conclusions

In this study we demonstrate the existence of a network effect in the Polish mobile phone market. We observe that the choice of an operator is strongly determined by a presence of the people a consumer contacts most often, and is in the closest relationships. This result occurs even if potential cost savings, due to lower on-net price per minute, are controlled for. Therefore we conclude that we observe a direct, non-pecuniary network effect. The possible reasons for this 'pure' network effect are quality or norm signaling and conformist behavior of consumers, especially with regard to groups of a small social distance.

Thanks to utilizing the stated-preference approach we were able to observe that the network effect is stronger for the persons a consumer considers to be closer or contacts more often (e.g. family members) than for more loose relationships (e.g. friends). We found that this effect is far stronger than the size of the total base of an operator's users ('others'), which did not turn out to significantly contribute to the choice of an operator.

The presence of a network effect is in line with the findings of Birke and Swan (2005), Fu (2004), and Kim and Kwon (2003). However, we show that this effect depends on the number of people a consumer calls most often, rather than all subscribers to a network. In addition, unlike Birke and Swan (2005) we observe a significant interaction of the on-net price and the presence of 'family' or 'friends' in the same network. We thus conclude that the network effect is partly driven by on-net price discounts and partly by non-pecuniary effects, which we call the 'pure' network effect. We argue that our results are more reliable as they do not suffer from other uncontrolled influences, the revealed data may suffer from. These include e.g. the switching cost that, as other studies have shown, to large extent determines which operator is used (Birke and Swann, 2005; Grajek, 2007).

We found that consumers displayed relatively strong preconceptions of operators' quality of service. This was manifested through the value consumers' placed on their brands, irrespective of other attributes of choice which, thanks to utilizing a choice experiment technique, could be freely altered and hence controlled for. A similar study targeted at representative samples of other populations could lead to the valuation of mobile phone operators' brands in total.

Another interesting observation we were able to make was a significant impact of the status-quo operator on each respondent's choices. It seems that our respondents displayed a strong loyalty to their present operator, even in hypothetical choices. This effect was not symmetrical – the loyalty to some operators was stronger than to the others. This interesting auto-selection mechanism increases switching costs, despite mobile number portability introduced in recent years.

Our study proposes a new way to identify and measure network effects in mobile telecommunications market. We introduce the relevant methodology and demonstrate its use. The stated preference approach allows to freely change relevant attributes' levels and hence control for all the factors that might be relevant for consumers' choices, and avoid biases present in revealed (market) data. This bottom-up approach allowed us to formally model consumers' utility functions and therefore measure and provide monetary values of network effects, and other factors relevant for mobile operator choices.

Through the utilization of random parameters multinomial logit model we were able to account for preference heterogeneity. This turned out to be a significant improvement in our model specification indicating that there is a strong heterogeneity in terms of perception of all the major determinants of operator choice – brand, on-net and off-net call price, and the presence of other groups of users of the same operator.

From the perspective of regulatory policy the independence of network effects and price effects may bring important conclusions. We provide empirical evidence that the network effects may not disappear with the abolition of interconnection rates and introduction of a flat (non-differentiated) rates for a call. Therefore, operators can try to discount network effects and brand commitment by increasing price of calls for end users. In response to such behavior, regulatory authorities should seek to further reduce switching costs and enforce high standards of service across networks. The explicit modeling of non-pecuniary network effects, utilizing proposed methodology, may be of interest to the national equivalents of NRA in each country, as they would find it worthy to consider regulatory mechanisms for retail prices based on actual costs of services.

In conclusion, our study lays foundations for future research of network effects. Although we have applied the methodology to a non-representative study group, we have demonstrated the potential of this method for applications to modeling network effects on other markets, other groups of consumers, and for regulatory policy. We also argue that our findings about the nature of network effect, brand perception and brand loyalty remain valid for other groups of users, even if their values may differ.

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Annex 1. Lower triangular of Cholesky matrix for the RPL model with random price parameter (standard errors given in parentheses)

	β_{ORA}	β_{ERA}	β_{PLU}	P_{ON}	P_{OFF}	FAM	FRI	OTH	$\beta_{P_{ON}FAM}$	$\beta_{P_{ON}FRI}$	$\beta_{P_{ON}OTH}$
β_{ORA}	0.9806*** (0.1411)	–	–	–	–	–	–	–	–	–	–
β_{ERA}	-0.4960*** (0.1616)	0.6376*** (0.1527)	–	–	–	–	–	–	–	–	–
β_{PLU}	-0.3715*** (0.1431)	-0.2802** (0.1311)	0.0054 (0.1266)	–	–	–	–	–	–	–	–
P_{ON}	0.2775 (1.9167)	1.2520 (1.8524)	-4.5483* (2.3944)	1.3513 (2.0477)	–	–	–	–	–	–	–
P_{OFF}	0.4252 (0.3863)	-1.1383*** (0.3679)	2.5808*** (0.4798)	5.7951*** (0.4395)	1.1134 (0.6809)	–	–	–	–	–	–
FAM	-0.0878 (0.8821)	0.5826 (0.7851)	-5.7885*** (0.6493)	0.6699 (0.6684)	-0.0764 (0.7991)	1.8535*** (0.6090)	–	–	–	–	–
FRI	-0.4181 (0.6743)	-0.9554 (0.6881)	-0.5013 (0.7591)	-2.1116*** (0.7094)	-1.9407*** (0.7384)	-2.3132*** (0.5696)	2.7340*** (0.4821)	–	–	–	–
OTH	2.1570 (1.3727)	0.8223 (1.3761)	-1.7376 (1.8010)	0.3232 (1.5152)	0.0342 (1.0672)	-1.6254 (1.0912)	3.1652*** (0.9303)	1.4578 (1.0518)	–	–	–
$\beta_{P_{ON}FAM}$	0.4428 (2.8682)	-5.3445** (2.5144)	9.9524*** (2.2829)	-1.8153 (2.0747)	0.0004 (2.5786)	-3.5637* (2.0676)	0.5043 (0.9864)	0.1226 (1.3720)	4.2173*** (0.8965)	–	–
$\beta_{P_{ON}FRI}$	2.0869 (2.0628)	0.4866 (2.3768)	3.9645 (2.4499)	6.5854*** (2.2789)	4.5994** (2.0597)	1.9007 (1.8252)	4.8035*** (1.6544)	-2.7330** (1.1629)	2.6332*** (0.9251)	1.9560** (0.9280)	–
$\beta_{P_{ON}OTH}$	-8.5417* (4.9834)	-0.7646 (5.0327)	6.5103 (6.6414)	-4.4196 (5.4872)	4.9633 (4.2552)	7.8578* (4.0340)	-10.139*** (3.2820)	6.3362 (4.1523)	-1.0218 (1.8229)	1.2403 (1.5551)	1.2250 (1.5100)

***, **, * – Significance at 1%, 5%, 10%