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Network Structure and Network Effects and Consumer Interaction in Mobile Telecommunications among Students

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Abstract: This study estimates the importance of network effects and the impact of a consumer's social network on her choice of mobile phone provider. The study uses network data obtained from surveys of students in four different classes in the Kurdistan University and Azad University of Sanandaj, Iran. We use the Quadratic Assignment Procedure, a non-parametric arrangement test, to adjust for the particular error structure of network data. The Sample size was 2058 out of that 1340 respondent which is strongly coordinate their choice of mobile phone providers, but only if their provider induces network effects. This suggests that this coordination depends on network effects rather than on information contagion or pressure to conform to the social environment.

Key words: Network effects · Social networks · Mobile telecommunications · QAP

INTRODUCTION

Recently, wireless mesh networks (WMNs) have received incredible research attention in business,engineering, industry and academia [1]. Innovations happen everywhere. How do consumers choose between rival products in a market with network effects? However, some innovative products take off instantly and others take a long time to penetrate the market. A standard assumption of the network effects literature is that it is the overall size of the network that matters to the consumer. In addition, there are many new products that succeed in the early market but ultimately fail to diffuse throughout the whole customer base (Refer to Business Week (8/16/93). In this study we consider a market with network effects, where the benefits of adopting the innovation grow as the number of adopter's increases [2]. Adoption dynamics of such network products or services are quite understood from those of traditional ones. Network products and services are quite difficult to get started and often end up being under-adopted [3]. Network effects play a key role in the adoption of certain types of products, especially interactive communication-type innovations such as telecommunication services [4]. All mobile phone applications especially communication, emergency assistance and entertainment are important to consumers [5]. We directly examine provider choice in a social network and test whether provider choice in a social network is correlated. This work is similar to the Birke & Swann [6]; Bandiera and Rasul [7] in Mozambique. It is widely acknowledged that network effects are a key feature of telecommunications industries and indeed that telecommunications networks provide the leading example of network effects, relatively few studies, like: Dhebar and Oren, [8]; Kim and Kwon, [9] ; Goolsbee and Klenow, [10] ; Saloner and Shepard, [11]; Sun, Xie, & Cao, [12]; Srinivasan, Lilien, & Rangaswamy, [13]; Li, [14]. However, in markets with direct interaction between consumers, like mobile telecommunications, an individual's social network that determines an adoption decision. Mobile networks are highly suited to each other and the network effects that exist in the market are mainly induced by network. Birke and Swann, [15], suggest that the choice of mobile phone provider is strongly coordinated within households and that this effect is more stronger than the effect of overall network size, Manski [16] state that contextual effects and unobserved heterogeneity can

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lead to correlation of choice decisions of network members without network effects being present. Bandiera and Rasul [7] suggest that correlation in their social networks is due to social learning. Likewise, different brands may be attractive to different consumers and brand relation may be clustered among friends who use similar characteristics. For all data on social networks of mobile phone users, we conducted surveys of classes of students at University of Kurdistan and Azad University campus in Sanandaj city of Iran, the universities were chosen because of the different pricing structures in the respective markets. There are two alternatives to the use of individual level data. First, choice behavior can be compared for networks that charge higher prices for off-net calls and networks that do not. We have this opportunity in the Kurdistan University, where the provider *Three* does not charge different prices for on- and off-net calls. The second alternative is to compare choice behavior between different great student with tariff-mediated network effects.

Methodology: The study consists of quantitative case studies of four different classes of students in the Kurdistan University and Azad University of Sanandaj, Iran. In social network studies, most methods have been developed for analyzing networks. It is therefore necessary to analyze the population. In our case, we choose the students in both the universities. The questionnaire consists of two parts. The first part collects demographic information and asks students about their attitudes to and use of mobile phones. In the second part, students were asked to identify the people they communicate. Table 1 shows sample sizes and response rates for the different student. The samples were collected from the undergraduate's students and the respondents rates are above 50 percent in all students. The original data on communication patterns was summarized in symmetric square matrices of N rows and columns, with N being the number of respondents. A "1" in a particular cell of the matrix indicates a communication relationship and a "0" indicates the absence of a communication relationship [6]. As usual for the treatment of network data, diagonal elements are set to zero, the relationship was not mauled.Thus, if A says that she communicates with B, that does not necessarily mean that B also nominates A. However, most relationships are corresponding and we conducted two sensitivity tests by making all relationships symmetric.

Table 1: Sample size and response rates

	First year	Second year	Third year	Fourth year
No of students	333	213	804	708
No of respondents	270	160	440	470
Response rate	81%	75%	53%	64%

Estimation Procedure: For a regression analysis the original matrices were changed the shape of pair relationships between two nodes. We therefore get N (N-1) with one value for each pair:

$$y = \begin{pmatrix} y_{1,2} \\ y_{1,3} \\ \vdots \\ y_{2,1} \\ \vdots \\ y_{NN1,2} \end{pmatrix}$$

Know the element yij indicates whether i nominate j (yij = 1) or not (yij = 0).We can therefore estimate the visible variable model for involving a pairs response models:

$$\begin{aligned} y^*_{ij} &= x\beta + \varepsilon_{ij,} \\ y_{ij} &= 1 \qquad if\, y^*_{ij} > 0 \\ y_{ij} &= 1 \qquad if\, y^*_{ij} \le 0 \end{aligned}$$

However, error terms are not independent, exactly distributed. The correlation between the error terms for pair i,j ($\varepsilon_{i,j}$) and pair k,l ($\varepsilon_{k,l}$) is $\rho_{ij,kl}$ and the general autocorrelation structure for this model is given as[1]:

$$\Omega_{i,j;k,l} = \sigma^2 \begin{array}{c} \\ \varepsilon_{1,2} \\ \varepsilon_{1,3} \\ \vdots \\ \varepsilon_{N,N-1} \end{array} \begin{array}{c} \begin{array}{cccc} \varepsilon_{1,2} & \varepsilon_{1,3} & \cdots & \varepsilon_{N,N-1} \end{array} \\ \begin{pmatrix} 1 & \rho_{1,2;1,3} & \cdots & \rho_{1,2;N,N-1} \\ \rho_{1,3;1,2} & 1 & \cdots & \rho_{1,3;N,N-1} \\ \vdots & \vdots & \ddots & \vdots \\ \rho_{N,N-1;1,2} & \rho_{N,N-1;1,3} & \cdots & 1 \end{pmatrix} \end{array}$$

The observations are not independent, when using network data as is assumed in OLS and logit models. This correlation between observations involving the same nodes stems, for example, from the fact that consumers are more likely to have the same provider as their friends if they use a provider with a high market share in the network. The result shows a positive correlation between observations from the same row or column:

$$\rho_{i,j;k,l} = \begin{cases} 1 & if\ i = k\ and\ j = 1;\ (diagonals\ of\ \Omega) \\ \rho_{i;j,l} & if\ i = k\ and\ j \ne 1;\ (row\ autocorrelation\ parameters) \\ \rho_{j;j,k} & if\ i \ne k\ and\ j \ne 1;\ (column\ autocorrelation\ parameters) \\ 0 & otherwise \end{cases}$$

Table 2: Arrangement of rows and columns (QAP).

(α)					(b)$2 \Rightarrow 1, 4 \Rightarrow 2, 3 \Rightarrow 4, 1 \Rightarrow 3$				
	1	2	3	4		1	2	3	4
1	$X_{1,1}$	$X_{1,2}$	$X_{1,3}$	$X_{1,4}$	1	$X_{2,2}$	$X_{2,4}$	$X_{2,1}$	$X_{2,3}$
2	$X_{2,1}$	$X_{2,2}$	$X_{2,3}$	$X_{2,4}$	2		$X_{4,4}$	$X_{4,1}$	$X_{4,3}$
3	$X_{3,1}$	$X_{3,2}$	$X_{3,3}$	$X_{3,4}$	3	X_1	$X_{1,4}$	$X_{1,1}$	$X_{1,3}$
4	$X_{4,1}$	$X_{4,2}$	$X_{4,3}$	$X_{4,4}$	4	$X_{3,2}$	$X_{3,4}$	$X_{3,1}$	$X_{3,3}$

When parameter estimates are neutral this autocorrelation causes *p-values* to overestimate the significance level of the hypothesis test. Therefore due to observed characteristics (e.g. market shares of providers), it is possible to account for a lot of the correlation there are also unobserved characteristics like price sensitivity that lead to a correlation of error terms. We use the Quadratic Assignment Procedure (QAP) Krackhardt [17], to adjust for incorrect standard errors and to change the order of rows and columns of the original data matrix for the dependent variable and then to re-estimate the original regression model.

Table 2 shows the arrangement procedure: The original matrix on the left is taken and rows and columns are changed the order in the same way. For example, row 2 takes the place of row 1 and column 2 takes the place of column 1. Likewise, row 4 takes the place of row 2 and so on. The right part of Table 2 shows the resulting matrix. By this arrangement procedure, it is ensured that the values that belong together in a row (or column) stay together. This arrangement and re-estimation is said to get an empirical sampling distribution. Finally, the results from the original regression model are compared to the simulated distribution based on QAP and the percentage of cases in which the original or higher values occurred is calculated.

RESULT

Network Structure and Provider Choice: Social networks usefully are analyzed by graphical representations of these networks, in particular in the case of medium-sized networks with a couple of hundred nodes Fig. 1 shows the social network within the Sanandaj students, based on their stated communication patterns.

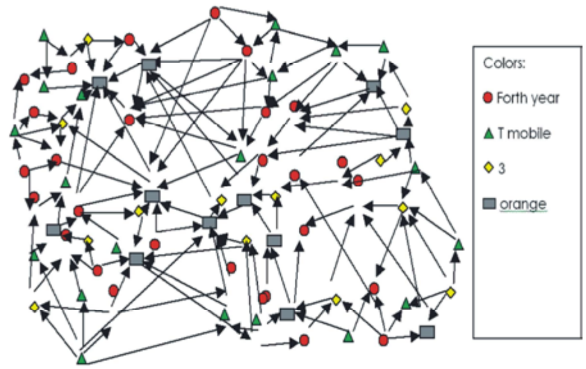

Fig. 1: Interaction network of student (fourth year)

It is a directed graph and arrows show the direction of the nominations from the roster. The graph was created using an embedded algorithm from UCI-NET [18], which is based on the idea of representing the social network graph as a system of mass particles. Nodes are the mass particles that refuse to accept each other and the edges are that put forth an attractive force between nodes. Therefore connected respondents will be grouped together and unconnected respondents will be separated. First, shapes of the objects, shows the degree of the classes and are highly clustered. At the bottom right of the graph, there is a group of other students who even form a separate component and only have communication links within the group. Second, the graph shows a clustering of shadings, which show the main provider chosen and this clearly occurs along class lines. However, there also seems to be a coordination of providers within classes. Within each class group, students that call each other tend to use the same mobile phone provider. One of the most important advantages of a graphical analysis is to develop our directed understanding. In addition we carried out a regression analysis to quantify the degree of coordination of provider choice found in the sample. We estimate a logit model using same provider as the dependent variable. This variable takes on the value 1 if two students use the same provider and 0 otherwise[1]. There are two different types of independent variables.

[1] Some of the respondents in the fourth year student and in particular in first year student had multiple providers and same provider takes any combination of these providers into account. This might potentially bias the estimate downwards. To understand why, take a (fictional) respondent who uses all available providers in a market to be on the same network as all other calling partners. Such a respondent would show up as not coordinating with his friends although he reacts to the induced network effects in the strongest possible way. In the fourth year student although some of the respondents have up to three mobile providers, results are very similar whether we only take the main provider into account or whether we allow for multiple providers. As discussed below in the section discussing the first year student results, estimates measuring the coordination of provider choice are higher in the first year case when we take multiple providers into account.

Table 3: Determinants of choosing the same provider of fourth year student

Dep. Var.: same _ provider	Model 1: QAP regression	Model 2: fixed effects
Friend	0.500 (0.000)***	0.416 (0.000)***
Same course	-0.055 (0.712)	-0.140(0.002)***
Same sex	0.104 (0.028)**	0.062 (0.044)**
Same payment	0.048 (0.424)	0.077 (0.069)*
Constant	-3.138 (0.000)***	-0.731 (0.000)***
No of observations	24,330	24,331
Pseudo-R^2	0.130	0.147
Log likelihood	-11,943.8	-11,718.6

Figures in brackets are p-values for the hypothesis that the coefficient is equal to zero.
* Significant at 10% level.
** Significant at 5% level.
*** Significant at 1% level

Table 4: Calculation of provider coordination measure

	Same_ provider pair	Not Same_ provider pair
Friend	A	B
No friend	C	D

Table 5: Degree of coordination of fourth year student by provider

	Three	O_2	Orange	T-Mobile
Degree of coordination (α)	0.40^{**}	2.10^{***}	1.55	6.95^{***}

X^2-test for the hypothesis that the odds-ratio α is equal to zero.
* Significant at 10% level.
** Significant at 5% level.
*** Significant at 1% level.

Table 6: Predicted probabilities of calling each other

	Not same class	Same class
Not same sex	0.056	0.033
Same sex	0.010	0.065

First, there are pair variables that indicate whether the two nodes that form a pair have certain properties. The variables are same class, same course and friend (respondents call each other on their mobile phone), same sex (nodes have the same gender) and same payment (respondents use the same type of payment: contract vs. pre-paid). Second, we include a set of provider dummies with *three* being the base case. This is necessary as providers have different market shares and it is therefore more likely that two respondents have the same provider if they both use a provider with a high market share. The variables same class, friend and same sex are highly significant and show the expected sign, confirming the graphical analysis from Fig. 1. Two respondents of the same class, who are friends and of the same sex are significantly more likely to use the same provider. Same class and friend have a particularly high significance level and in fact no arrangement resulted in a parameter estimate higher than the observed values from the original regression. Same sex is still significant at the 5 percent level, but the coefficient is far lower than the other two.

Most of the provider dummies are significant as well, which confirms that it is necessary to control for market share. A negative parameter estimate for T-Mobile, for example, reflects the relatively low number of T-Mobile users in the sample and the resulting lower probability that two students both use T-Mobile:

$$y^*_{ij} = x\beta + \alpha_i = \alpha_j = \varepsilon_{ij}$$

$$y_{ij} = 1 \qquad if\, y^*_{ij} > 0$$
$$y_{ij} = 1 \qquad if\, y^*_{ij} \leq 0$$

To check the model, we estimate the following fixed effects model as an alternative:

While α_i and α_j are the fixed effects of the two respondents i and j respectively involved in a pair. For each respondent, Model 2 from Table 3 includes dummy variables for all pairs. Consequently, we have to include N-1 dummies and these dummies cover all systematic individual level effects which have lead to a coordination of provider choice. The estimates for the main coefficients are similar and confirm the results of the original model. If we run the regression separately for different providers, we find a positive coefficient for the friend parameter for all providers but *Three*. To summarize the effect of a communication relationship on provider coordination and compare the degree of coordination between different providers, we can calculate the odds-ratio of a same provider × friendship in cross-table [19, 6]. The odds-ratio of A can be calculated as AD/BC (Table 4) and is independent of the distribution of provider market shares. A can take on values between 0 and +8 and will be 1 when the odds of using the same provider pair are the same whether two respondents are friends or not.

Table 7 (Model 1) shows the results of the regression analysis as described for the fourth year student in Table 3., we asked students to indicate the frequency of interaction for their ties, as it is likely that the strong ties are more likely to affect the outcome [20].We haven't used this information for the first regression of Table 7, where friend just takes the values 0 or 1, so that we can directly compare the fourth year student and third year student results. In general, the parameter estimates are roughly similar between the two studies. As in fourth year same class and friend are strong predictors for same provider in the third year data. In other words, we again find that

Table 7: Determinants of choosing the same provider (third year student)

Dep. Var.: same Provider	Model 1: base Model	Model 2: QAP Friendship Strength	Model 3:QAP Friendship Strength (IM network)	Model 4: QAP Friendship Strength (Combined network)	Model 5: Fixed Effects Friendship Strength
Friend	0.648 (0.000)***	-	-	-	-
Friend1(<once a week)	-	0.701 (0.000)***	0.559 (0.022)**	0.748 (0.001)***	0.522 (0.001)***
Friend2(Once a week)	-	0.578 (0.000)***	0.589 (0.001)***	0.403 (0.017)**	0.533(0.001)***
Friend3 (daily)	-	0.700 (0.001)***	0.838 (0.000)***	0.887 (0.000)***	0.636 (0.003)***
Same course	-0.022 (0.672)	-0.021 (0.695)	-0.021 (0.575)	-0.020 (0.548)	-0.087 (0.483)
Same sex	-0.025(0.254)	-0.025 (0.254)	-0.035 (0.336)	-0.036 (0.105)	-0.033 (0.164)
Same payment	-0.002 (0.959)	-0.002 (0.957)	0.001 (0.966)	0.001 (0.706)	0.0165 (0.755)
Constant	-3.357 (0.000)***	-3.355 (0.000)***	-3.457 (0.000)***	-3.392(0.000)***	-3.978 (0.000)***
No. of observations	18,306	20,033	15,001	20,970	19,936
Pseudo-R^2	0.156	0.156	0.156	0.153	0.173
Log likelihood	-9,971.6	-10,981.4	-73,95.9	-9,968.3	-9,983.3

Figures in brackets are p-values for the hypothesis that the coefficient is equal to zero.
*Significant at 10% level.
** Significant at 5% level.
*** Significant at 1% level.

respondents coordinate their choice of mobile phone provider. Maybe the most interesting difference between the results from the two studies is that the parameter estimate for same class has more than halved. In addition, we do not observe coordination for *Three* users, with the exception of a single *Three* user who is connected to four other *Three* users.

Models 2–5 from Table 7 present the results when including dummy variables for different interaction frequencies. The coefficients for the three friendship parameters are nearly equal in size, which means that students coordinate with their friends regardless of the exact interaction frequency (daily, at least once a week, less than once a week). This means that in the fourth year, friends do not coordinate with each other on an individual basis, but rather with their social network in general. One potential drawback of our network measure is that it might be endogenous, i.e. people who are on different mobile phone networks might decide to use other communication means when interacting with each other to avoid expensive off-net calls. In the third year sample, we asked students with whom they communicated via instant messaging. Instant messaging is one of the communication media that students are likely to use if they would want to avoid expensive off-net calls. 65 percent of all communication links occur both on instant messaging and via mobile phones. Model 3 in Table 7 reports the results for the friendship strength regression using instant messaging the interaction network as the basis for the friendship variables. The number of observation is lower as only 379 out of 440 students communicate via instant messaging. Estimation results are very similar to Model 2 and we therefore conclude that our estimation results are not unduly affected by endogeneity. We further estimated a model combining mobile and instant messaging links assuming that this is the best representation of the underlying friendship network. The results of this regression (Model 4) again are very similar to those obtained without including instant messaging links, which reinforces our confidence that links between students are not endogenous.

The second year student, the class sampled was very homogeneous. There is a bigger number of isolates who do not call any other person in the same class. This difference in network is mainly due to the different education system in the second year, which allows students greater flexibility in choosing their courses. Having said that, there is a core of students that interacts frequently with each other and we can analyze whether these students coordinate providers with each other. Table 8 shows the results of the regression for the second year data. As we do not have enough data to differentiate between communication intensity, we only use a dummy indicating whether two respondents communicate with each other or not. Both the QAP and fixed effects regression lead to negative, but insignificant estimates for the friend parameter. Only the same payment variable and the control dummies for providers are significant. We therefore conclude that the absence of induced network effects in the second year removes the main incentive for coordinating provider choice within the social network. The first year student was conducted at the University of Kurdistan. Most students come from Sanandaj and from nearby (90 percent).The large majority of students used tariffs that price discriminate between on- and off-net calls, the reason why we did not include a dummy variable for this. Three different models for the first year dataset are displayed in Table 9. The first model

Table 8: Determinants of choosing the same provider (second year).

Same provider	Model 1: QAP regression	Model 2: fixed effects
Friend	-0.315 (0.351)	-0.312 (0.165)
Same course	-0.219 (0.247)	-0.253 (0.128)
Same sex	-0.087 (0.580)	-0.123 (0.351)
Same payment	0.130 (0.564)	0.743 (0.014)**
Constant	-2.402(0.011)**	-1.330 (0.003)**
No of observations	2373	2372
Pseudo	0.073	0.074
Log likelihood	-1055.0	-1053.0

Figures in brackets are p-values for the hypothesis that the coefficient is zero. *Significant at 10% level. **Significant at 5% level. ***Significant at 1% level.

Table 9: Determinants of choosing the same provider (first year student)

	Model 1: base estimate	Model 2: close friends	Model 3: fixed effects
Friend	0.433 (0.001)***	-	-
Friend1 (<once a week)	-	0.301 (0.038)**	0.201 (0.110)
Friend2 (once a week)	-	0.345 (0.077)*	0.205 (0.240)
Friend3 (daily)	-	1.342 (0.000)***	1.360 (0.000)***
Same sex	-0.094 (0.267)	-0.096 (0.263)	0.104 (0.049)*
Same payment	0.077 (0.832)	0.086 (0.788)	-0.344 (0.434)
Constant	0.553 (0.160)	0.547 (0.164)	-0.498 (0.361)
No of observations	8186	8186	8186
Pseudo-R2	0.055	0.056	0.162
Log likelihood	-5329.6	-5322.6	-4724.6

Figures in brackets are p-values for the hypothesis that the coefficient is zero.

* Significant at 10% level.

** Significant at 5% level.

*** Significant at 1% level.

is closely related with the models estimated for the other years of studies and includes a friend dummy. The friend parameter estimate in Model 1 is significant as before, but is lower than in the Sanandaj student indicating that coordination might be lower in the first year student sample.

The second model now includes dummy variables capturing the strength of the relationship. As can be seen, the parameter estimate is positive and significant for all communication frequencies, but is 4 times higher for very close friends (daily communication). Students used their mobile phone provider already for an average of over four years and thus coordination seems only likely with very strong contacts. As most students grew up in the vicinity of Sanandaj it is quite reasonable to expect that their communication patterns did not change very drastically with entry into the university and that they only strongly coordinate provider choice with very close contacts. The fixed effects model of Table 9 again confirms the results from the QAP regression.

In contrast to the fourth year student where respondents mainly use multiple providers to take advantage of special offers, the use of multiple providers is more of a coordination mechanism in first year student. Respondents who would have a rather high number of off-net contacts when only taking into account the main provider used, tend to use a second or third provider to be on the same network as their friends. In the first year study, we also analyzed whether students coordinated their provider choice with their family members. Using X^2-test it turns out that students significantly coordinate provider choice with their partners; with their brothers and sisters with their mother, but that this coordination is lower and statistically insignificant with their fathers. The expected value of using the same provider based on the class provider market shares is 36.5 percent, while by comparison, the observed percentages of using the same provider are: partners (75.4 percent), brothers and sisters (52.8 percent), mothers (54.8 percent) and fathers (50.5 percent).

Comparison: Finally, we compare the results from the different studies. We focus again on the degree of coordination as measured by^2 (Table 10) and note that the results are consistent with the one from the different regression tables.

Table 10: Degree of coordination in different classes

Degree of coordination (α)	First year	Second year	Third year	Fourth year
All	1.25**	0.65	1.90***	2.37***
Communicate seldom	1.9	0.63	1.80***	1.84***
Communicate Occasionally	1.13	0.46	1.85***	1.88***
Communicate frequently	3.14***	1.40	2.11***	2.15***

X^2-test for the hypothesis that the odds-ratio _ is equal to zero.

*Significant at 10% level.

** Significant at 5% level.

*** Significant at 1% level.

Table 11: Observed vs. expected % of same provider pair among friends

	First year	Second year	Third year	Fourth year
Observed % same provider	51.0%	13.0%	41.7%	42.4%
Expected % same provider	37.9%	19.89%	22.0%	21.6%
X^2-test	8.2***	2.1	47.82***	108.8***

* Significant at 10% level.

** Significant at 5% level.

*** Significant at 1% level.

The second model now includes dummy variables capturing the strength of the relationship. As can be seen, the parameter estimate is positive and significant for all communication frequencies, but is 4 times higher for very close friends (daily communication). One reason for this finding is the higher state of provider choice in the first year student. Students used their mobile phone provider already for an average of over three years and thus coordination seems only likely with very strong contacts. As most students grew up in the vicinity of Sanandaj, it is quite reasonable to expect that their communication patterns did not change actions with entry into the university and that they only strongly coordinate provider choice with very close contacts. The fixed effects model of Table 9 again confirms the results from the QAP regression. In contrast to the fourth year student, where respondents mainly use multiple providers to take advantage of special offers, the use of multiple providers is more of a coordination mechanism in first year. Respondents who would have a rather high number of off-net contacts when only taking into account the main provider used, tend to use a second or third provider to be on the same network as their friends. Another interesting aspect of coordination in first year is highlighted when comparing coordination by provider. For the first year student we also analyzed whether students coordinated their provider choice with their family members. Using $\times^2$-tests it turns out that students significantly coordinate provider choice with their partners; with their brothers and sisters with their mother, but that this coordination is lower and statistically insignificant with their fathers. The expected value of using the same provider based on the student provider market shares is 35.5 percent, while by comparison, the observed percentages of using the same provider are: partners (75.4 percent) brothers (52.8 percent), sisters (52.6 percent), mothers (56.9 percent) and fathers (51 percent). Finally, we can directly compare the results from the different studies. We here focus again on the degree of coordination as measured by ^{2} (Table 10) and note that the results are consistent with the one from the different regression tables. Another alternative is a comparison of the observed percentages of same provider pair in the samples with the expected values when assuming random mixing of respondents based on student wide provider market shares (Table 11). Both tables show a very strong coordination of provider choice for all students with tariff-mediated network effects. For the second year student we only observe a small and insignificant coordination of providers for very close relationships. Taken as a whole, these observations indicate the main drivers of our results are network effects and not information contagion effects.

DISCUSSION

This study shows that besides peer group effects and information contagion processes, local network effects can be a strong economic source for consumer choice to be interdependent in a social network. As we do not have a time dimension to the data, we cannot decide between provider coordination and the existence of a communication relationship. Although the results in this study appropriate to tariff-mediated network effects, it can be expected that consumer coordination is even stronger if different networks are technologically opposed in character. The research shows that consumers not only coordinate their choice of mobile phone providers within households [6], but also in their wider social network. We also found that this depends on the price difference between on- and off-net calls induced by most providers. This doubts on the traditional assumption in the network effects literature that overall network size rather than local social networks are important for consumer choice. Throughout the paper, we have suggested that two consumers who interact with each other a priori will tend to coordinate their choice of mobile phone provider. However, there are two potential endogeneity problems. First, people could also choose the people they communicate with based on their usage of certain mobile phone providers. Second, people might substitute communicating by mobile phone with other communication media and their social network, as approximated by mobile phone interactions, might be biased towards communications with people using the same network provider. By using a network measure (instant messaging) we have controlled the second effect which is found that the main direction of causality is from friendship to provider coordination. We also note that both directions of causality support our main hypothesis that tariff mediated network effects are at the heart of the observed coordination of provider choice. However, results consistent with the hypothesis that induced network effects is the driving force behind the coordination of provider choice have been found across time and across several student. Consequently our results might rather understate the extent of coordination. Finally, the results described that there are highly relevant to some of the recent policy debates about whether the price discrimination between on-net and off-net calls is anticompetitive and welfare-reducing. Harbord and Pagnozzi [21] suggested that when this on-net/off-net price differential has an important effect on provider choice and/or calling behavior, then this strategic creation of tariff-mediated network effects can be an important strategy for attracting and retaining market share and for discouraging entry by new providers or checking the growth of smaller networks. Our findings show a very important role to tariff-mediated network effects therefore it support the finding of the Harbord and Pagnozzi [21]. However, Birke and Swann, [6] argued that individual choice of provider was much influenced by choices of other family members than total network size and moreover that there had been a trend towards equalization of market shares rather than increasing concentration. These observations suggest that small providers are not necessarily operating at an unbearable disadvantage.

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