Network effects in mobile telecommunications: An empirical analysis

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Abstract

This paper explores the role of network effects in the consumer's choice of mobile phone operator in the UK. For our empirical analysis we use two sources of data: market-level data from OFCOM and micro-level data on consumers' usage of mobile telephones from the survey *Home Online*. We estimate two classes of models which illustrate the role of network effects. The first is a model of the comparative volume of on-net and off-net calls. This finds that the proportion of off-net calls falls as mobile operators charge a premium for off-net calls, but even in the absence of any price differential between on-net and off-net, there is still a form of *pure* network effect, where a disproportionate number of calls are on-net. The second is a model of the individual consumer's choice of operator. This finds that individual choice shows considerable inertia, as expected, but is heavily influenced by the choices of others in the same household. There is some evidence that individual choice of operator is influenced by the number of subscribers for each operator. This second model is estimated in two forms: one where network effects and price effects do not interact and the other where they do interact, as suggested by theoretical considerations. We find that the non-interactive form fits the data better than the interactive form, suggesting again that there are some *pure* network effects at work, independent of price differentials.

JEL classification: D12, L96, M31

Keywords: network effects, social networks, mobile telecommunications, discrete choice

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1 Introduction

It is recognised that network effects can be a powerful source of economic growth (McGee and Bonnici, 2002; Economides, 2003). Due to the self-propelling nature of growth in network markets, market expansion tends to be much faster in network industries than in non-network industries. Network industries, like telecommunications, have been among the fastest growing industries in recent years.

After the seminal article of Rohlfs (1974), and the influential papers of Katz and Shapiro (1985) and Farrell and Saloner (1985), there has been a plethora of theoretical studies into the nature of network effects and by now network effects theory has reached a rather mature state. However, empirical work in this area has been slow to keep track with the advances in theory, and it is only comparatively recently that such studies have appeared in any numbers. Recent empirical studies include Goolsbee and Klenow (2002) on home computers, Berndt et al. (2003) on anti-ulcer drugs, Dranove and Gandal (2003) on DVD-players, Rysman (2004) on yellow pages and Gowrisankaran and Stavins (2004) on electronic payment.

The literature on network effects usually distinguishes between two types of network effects: direct network effects and indirect effects. Direct network effects refer to the case where users benefit directly from the fact that there are large numbers of other users of the same network. In mobile communications, a direct network effect arises when the user can call a larger set of persons. Indirect network effects, on the other hand, arise, because bigger networks support a larger range of complementary products and services. In 2nd generation mobile networks, indirect network effects are only of second-order significance, but they will play an increasing role after the introduction of 3G networks, where usage will be heavily influenced by the availability of data services.

While it is widely acknowledged that network effects are a key feature of telecommunications industries, and indeed that telecommunications networks provide perhaps the leading example of network effects, relatively few studies have analysed the empirical importance and extent of network effects in the telecommunications market. Majumdar and Venkataraman (1998) analyse network effects in the adoption of electronic switching in the US. Gruber and Verboven (2001) have studied the related topic of benefits to standardisation in telecommunications. The UK Competition Commission (2003) examined the role of network externalities in their enquiry on prices for mobile call termination in the UK: here, a stated preference approach has been taken to estimate the value of network externalities. Directly related to our research are the studies from Doganoglu and Grzybowski (2004) on network effects in the German mobile telecommunications market, from Kim and Kwon (2003) on network effects in the Korean market and Grajek (2003) on network effects in the Polish market.

The aim of our research is to empirically analyse the determinants of network effects and its importance for the adoption of mobile telephones and operator choice. To resolve this question, we follow the approach in Swann (2002). There, it is argued that many (or perhaps even, *all*) other users are a potential source of network effects, but some users matter more than others do.

The first question in the analysis of network effects is which is the network that matters to the consumer? The main purpose of traditional (2G) mobile phones is to call other persons and consequently, the network is not only limited to the mobile network, but includes the fixed network as well. In our study, we restrict ourselves to data on the mobile network, which is also supported by the extant literature (see Valletti and Cave (1998)), for two main reasons.

Firstly, the fixed line market is saturated and fixed line penetration in the UK (and in most other industrialised countries) is over 90%. So far, only very few consumers have completely replaced their landline with a mobile phone. In our sample (beginning of 2001), the mobile telephone has replaced the landline completely for only 3% of the respondents, while it somewhat replaced it for another 13%. The number of fixed lines might have exerted an influence in the early years of mobile telecommunications, as it helped to overcome the critical mass necessary for a successful introduction. Afterwards, and in particular for the time of our study, this influence can be assumed to be constant in absolute terms. Furthermore, the integration of fixed and mobile services does not play a big role for consumer choice and a similar influence of landlines can be expected for all operators.

Secondly, some services, such as text messages, have been limited to mobile networks and continue to be a mainly mobile service. In this regard, there is a separate market for mobile and fixed telephony and it can be expected that this will be increasingly important in the future when mobile phones will not only be a device for making phone calls, but for using all kind of services.

To answer the question of which network matters to the consumer, we therefore have to analyse whether the consumer is more interested in the total number of subscribers of an operator or whether (s)he mainly cares about the adoption behaviour of his/ her immediate social network.

For indirect network effects, the interest of the consumer is typically not in the direct interaction with some peers, but rather in the availability of complementary services. Buying a DVD-player, the consumer is interested in the number of titles available for the format. Consequently, the social network rather plays a role as a source of information, but does not drive adoption. As we argued above, the introduction of 3G is likely to change the predominance of direct network effect. Adoption will therefore be partly driven by the availability of services, where it only matters to the consumer how many of them are available and not who is actually using them. However, as our analysis below will demonstrate, the social network does have a very significant effect on adoption decisions in today's GSM-networks.

The paper is organised as follows: Section 2 gives a brief introduction to the mobile telecommunications industry in the United Kingdom and discusses some of its characteristics that are important for our analysis. Section 3 introduces the data that we use. It basically consists of market level data that we obtained from OFCOM and of micro-level data on consumers' usage of mobile telephones from a survey called *Home Online*. Section 4 describes a model of the comparative volume of on-net and off-net calls using aggregated market level data to test whether network effects are present in mobile telecommunications. Section 5 describes a discrete choice model of operator choice using survey data which examines whether network effects also play a role in individual choice of operator. This model is presented in two forms: one where network effects are treated separately from price effects; the other where network effects and price effects are assumed to interact, as suggested by theoretical considerations. Section 6 concludes and describes some priorities for our future research.

2 The mobile telecommunications industry in the UK[†]

The analysis of this paper is conducted based on data from the UK telecommunications industry and more specific on data from the four main GSM-operators Vodafone, O_2, T-Mobile and Orange.[‡]

[†] See Valletti and Cave (1998) for an analysis of the UK market from 1985 to 1998.

[‡] The other two important operators are Virgin, which started at the end of 1999 and uses T-Mobile's network and "3" which started in 2003 and is building up its own 3G-network. At the end of our study period, Virgin had over half a million subscribers, but accounted for less than 2% of the market.

In the United Kingdom, O_2 (Cellnet) and Vodafone started operation in 1985 with analogue mobile networks. There had been relatively slow growth until the entry of T-Mobile (One-to-One) and Orange after 1993 introduced stronger competition to the market. However, the market really took off with the widespread use of prepaid cards, which made mobile telephony attractive for the mass market and especially for low-usage consumers. Although a first prepaid tariff was launched by Vodafone in September 1996, prepaid usage became popular only after mid 1998. As Figure 1 shows, this lead to a period of rapid expansion in the number of subscribers which roughly lasted until early/mid 2001.

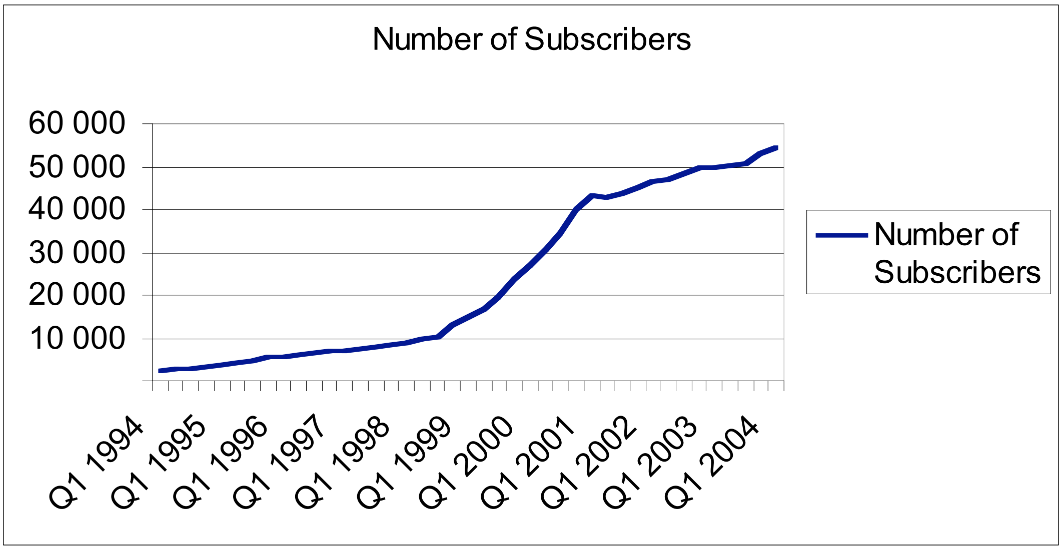

Figure 1 Number of subscribers in the UK

After the burst of the stock market bubble in mid 2001, operators have cleaned up their customer base of inactive consumers (notice the short decline in Figure 1) and have since continued to grow, but this time more gradually and with a stronger focus on increasing the average revenue per user (ARPU) and on upgrading prepaid customers to post-paid customers. Today, operators alone generate around 11 billion GBP of revenues per year. However, as the market is by now reaching saturation with a penetration rate of around 85%, future revenue growth has to come from an increased ARPU rather then from a bigger customer base.

In 2003, "3" introduced the first third generation network in the UK and although demand has not yet met expectations, many expect that 3G-networks will further boost revenues in the mobile telecommunications market.

Especially interesting for our analysis is the development of market shares in the market (see Figure 2). At the end of 1998, the market was dominated by the incumbent operators O_2

and Vodafone, which together accounted for almost 70% of the market. However, by the beginning of 2001 this lead has dissipated and subscriber market shares have been levelled. Today, the market is about equally split between the four GSM operators.[§]

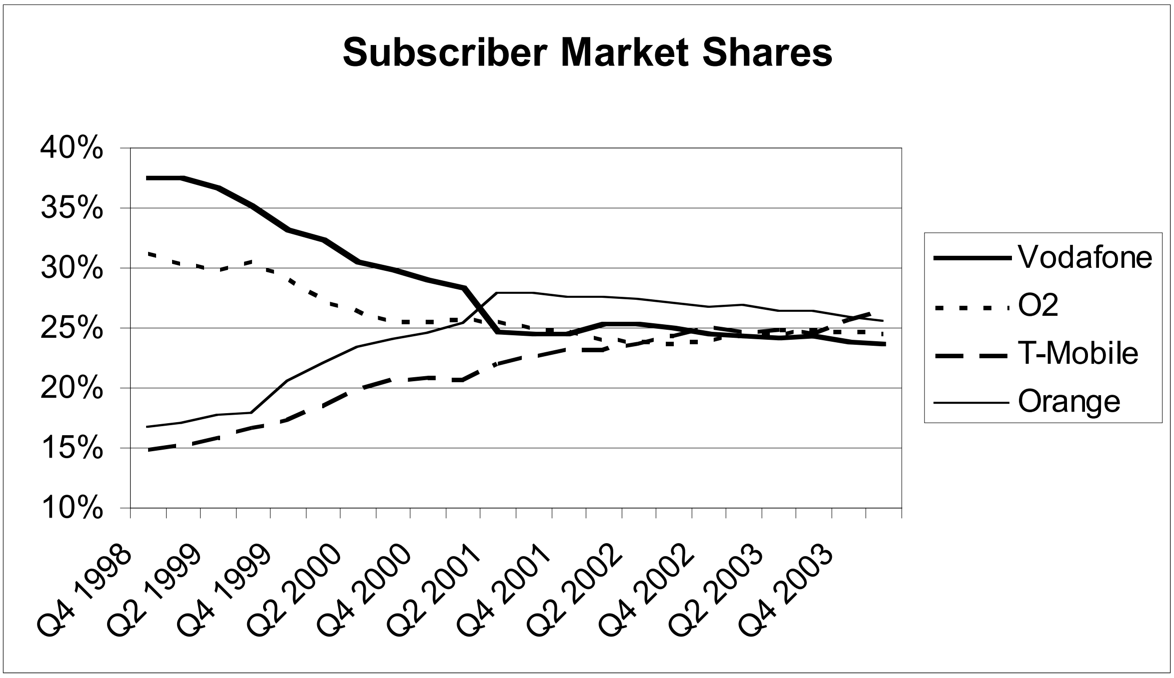

Figure 2 Development of subscriber market shares

The ability of T-Mobile and Orange to catch up with the incumbent operators is somewhat unique to the UK market and is different from, for example, the German market in which the two biggest operators (T-Mobile and Vodafone) still control about 80% of the market and reported stable market shares for the last years. With strong network effects present in the market, one would regard a development like in the UK as unlikely, as network effects result in a strong tendency towards higher market concentration. It could be argued that the development in the UK market is due to the high compatibility between networks. However, as our analysis will show, network effects do play an important role in the adoption of mobile telephones **and** in operator choice.

§ Note that this holds for subscriber market shares. Although there has been a similar trend in revenue market shares, Vodafone still boasts the highest revenue, as its customers generate a higher ARPU.

3 Data

3.1 Data sources

This study uses market data from the UK telecommunications regulator OFCOM (formerly OFTEL) and a survey entitled *Home Online* with data on individual mobile usage. The OFCOM data consists of quarterly time-series market data on number of subscribers, call volumes and revenues. Part of the data is reported on a voluntary basis by the four main UK GSM-network operators: Vodafone, O2, Orange and T-Mobile. Furthermore, OFCOM publishes price data for a variety of user types based on consumer surveys conducted by OFCOM.

The *Home Online* survey was conducted in three waves (October to December 1998, January 2000 and February 2001) by the Institute for Social and Economic Research, University of Essex and was sponsored by BT. The survey data can be accessed from the UK Data Archive (http://www.data-archive.ac.uk/). It consists of data on information and communications technology (ICT) access and usage behaviour from 1000 households and around 2500 individuals from these households that were 16 or older. A subsection of the survey focuses on mobile phone usage and attitudes towards mobile telephony. The most interesting variables for our purpose are information on mobile operator chosen, demographic information (income, age, sex etc.) and household constitution.

The sample of the *Home Online* survey was selected using two-stage clustered sampling with stratification to ensure the inclusion of geographically clustered areas with representation of different social strata close to that of the population. Selection of households was random within these clusters. Interviews were conducted face to face in wave one and by telephone in waves two and three. A full description of the sampling process can be found on the UK Data Archive website.

3.2 Descriptive Statistics

Market penetration has risen considerably in recent years and the strongest growth happened in the period from the end of 1998 to the beginning of 2001, which is also covered by the survey we use. During this period, the penetration rate of mobile telephony in our sample increased from 26.5% to 70.9% (see Table 1). Whereas, users of mobile telephones were still a minority at the end of 1998, mobile phones were almost ubiquitously used two and a half years later. Table 1 compares the market shares observed in our sample with the market shares reported by OFCOM. Market shares are roughly the same, although T-Mobile users are underrepresented and Orange users are overrepresented in the Home Online sample.

	Wave 1		Wave 2		Wave 3	
	Home Online**	Actual (OFCOM)	Home Online	Actual (OFCOM)	Home Online	Actual (OFCOM)
Vodafone	36.0%	37.5%	29.2%	32.3%	25.4%	28.3%
O2	31.4%	31.1%	31.6%	27.2%	29.9%	25.7%
T-Mobile	11.0%	14.8%	15.2%	18.5%	15.6%	20.7%
Orange	18.9%	16.6%	23.9%	22.0%	29.1%	25.4%
Penetration rate	26.5%	27.0%††‡‡	53.7%	46.0%	70.9%	67.0%

Table 1 Market shares and penetration rate

Table 2 presents summary statistics for the individual-specific variables that we use in our regression in Section 5. Apart from household income (HHINC) there is data available for almost every characteristic per observation. Looking at Table 2, it can be stated that at the end of 1998, adopters were superproportionally young, male and from a higher socio-economic group. Furthermore, customers of T-Mobile have a significantly lower household income (and come from a significantly lower socio-economic group§§) than Vodafone customers. On the other hand, O_2 and Vodafone customers are on average older than their counterparts at T-Mobile and Orange, which does not surprise given the longer time in the market for O_2 and Vodafone.

Wave1	Sample (N=1720)	Vodafone (N=164)	O_2 (N=143)	T-Mobile (N=50)	Orange (N=86)
AGE	44.70 (17.94)	39.55 (12.08)	40.53 (13.43)	36.3 (11.99)	34.48 (11.38)
MALE	.46 (.50)	.59 (.49)	.58 (.50)	.54 (.50)	.57 (.50)
MRSCODE	2.72 (1.29)	2.03 (1.07)	2.17 (1.14)	2.41 (1.16)	2.19 (1.00)
HHINC	1997 (1570)	3238 (2088)	2831 (1607)	2238 (1678)	2846 (1357)

Table 2 Demographic statistics for wave 1 (October to December 1998)

** Operator market shares do not sum up to 100% as 12 respondents reported that they have another operator in the first wave.

†† OFCOM penetration rates are based on market research. Aggregated figures can not be used, as some users may subscribe to more than one operator.

‡‡ January 1999

§§ Socio-economic group (MRSCODE) can take on values from 1 (AB) to 5 (E) with 5 being the lowest group.

Similar tendencies persist also in the 2nd and 3rd wave (see Table 3 and Table 4 respectively). Most interesting is that more and more consumers come from lower socio-economic groups and that the predominance of male adopters is getting smaller.

Wave2	Sample (N=1522)	Vodafone (N=236)	O_2 (N=255)	T-Mobile (N=123)	Orange (N=193)
AGE	44.90 (16.83)	39.17 (13.40)	41.29 (14.30)	36.83 (14.92)	41.03 (14.98)
MALE	.45 (.50)	.50 (.50)	.52 (.50)	.43 (.50)	.47 (.50)
MRSCODE	2.91 (1.32)	2.50 (1.16)	2.64 (1.26)	2.80 (1.20)	2.69 (1.16)
HHINC	2008 (3292)	1934 (1406)	3448 (6695)	1675 (1247)	2180 (1131)

Table 3 Demographic statistics for wave 2 (January 2000)

Wave3	Sample (N=1503)	Vodafone (N=262)	O_2 (N=308)	T-Mobile (N=161)	Orange (N=300)
AGE	46.49 (17.29)	43.20 (15.00)	42.20 (15.51)	41.51 (15.67)	41.79 (15.70)
MALE	.45 (.50)	.54 (.50)	.47 (.50)	.47 (.50)	.45 (.50)
MRSCODE	2.94 (1.35)	2.62 (1.25)	2.66 (1.23)	2.92 (1.35)	2.70 (1.21)
HHINC	2089 (2195)	2391(1989)	2781 (3500)	1884 (1410)	2154 (1517)

Table 4 Demographic statistics for wave 3 (February 2001)

4 Market level model of network effects

4.1 Introduction

Network effects in mobile telecommunications are mainly pecuniary and operate through two channels. First, with rising number of users having subscribed to a network, it becomes more attractive for other people also to buy a mobile phone and to subscribe to a/the same network. Second, network expansion drives the usage volume of people already using mobile telecommunications. We would therefore expect that the usage volume of existing subscribers increases with the total number of mobile telephone subscribers. However, this might not be easily detected from aggregate data on call volumes, as later adopters typically use mobile telephones less than early adopters.

Most of the empirical literature on network effects so far focused on the analysis of markets with indirect network effects (like CD-Players and CDs, VHS-recorders and cassettes etc.). Mobile telecommunications is at the moment still characterised by a prevalence of direct network effects, which makes an estimation of network effects more complicated. A first approach could be taken by regressing past network size on current network size. However, network size and prices are closely interrelated, as bigger network sizes drive down prices (economies of scale) and lower prices increase demand. This makes this approach to measuring network effects prone to estimation errors. Furthermore, there are also no good instruments readily available for prices. Input prices, for example, arguably play a smaller role than in other industries and these prices are also difficult to measure due to economies of scale and fast technological advances in the supplier market.

Mobile networks are highly compatible with each other and the network effects that exist in the market are typically induced by network operators through higher prices for off-net than for on-net calls. As network effects operate through prices, a second possibility to detect network effects is to compare the call volume increases for on- and off-net calls separately.[***] If the induced network effects work, we can expect a stronger increase in on-net than in off-net call volumes with an increasing price differential. This again has two reasons: Firstly, users might be aware that off-net calls are more expensive than on-net calls and try to limit the frequency and length of off-net calls, for example, by switching to landlines for longer calls. Secondly, users might choose operators in order to be on the same network as most of their peers. This effect might not have been very strong in the early years of mobile

[***] Off-net calls are calls made to other mobile networks. Landlines are not included in the analysis.

telephony when the majority of calls were made to landlines, but can be expected to have grown with rising potential mobile calling partners with an increase in subscriber numbers.

4.2 The Model

The model developed below describes the ratio of off-net to on-net calls, using OFCOM data. In particular, the model compares the actual ratio of off-net to on-net calls, and the ratio we would expect if calls from one operator were spread evenly across the other operators' networks.

Suppose that there are four operators (i = 1,…,4) and that the market share of each operator is given by m_i. Suppose that the actual pattern of calls between networks is given by the following matrix (where w_{ij} is the share of volume of calls from network i to network j):

		To Network:			
		1	2	3	4
Calls from Network:	1	w_{11}	w_{12}	w_{13}	w_{14}
	2	w_{21}	w_{22}	w_{23}	w_{24}
	3	w_{31}	w_{32}	w_{33}	w_{34}
	4	w_{41}	w_{42}	w_{43}	w_{44}

Table 5 Observed Shares (by volume of calls)

If there are no differences in prices for off-net and on-net calls and if the calls from one operator's network are spread evenly across the other networks (in proportion to the sizes of these networks) then we can calculate the expected pattern of calls as follows:

		To Network:			
		1	2	3	4
Calls from Network:	1	$m_1\, m_1$	$m_1\, m_2$	$m_1\, m_3$	$m_1\, m_4$
	2	$m_2\, m_1$	$m_2\, m_2$	$m_2\, m_3$	$m_2\, m_4$
	3	$m_3\, m_1$	$m_3\, m_2$	$m_3\, m_3$	$m_3\, m_4$
	4	$m_4\, m_1$	$m_4\, m_2$	$m_4\, m_3$	$m_4\, m_4$

Table 6 Expected Shares (by volume of calls)

Now we do not have actual data on all the elements in the first matrix, but we do have data on the actual volume of on-net calls and the actual volume of off-net calls. If we express these as percentages of the total volume of calls, then we see from the first matrix that the actual proportion of on-net calls is given by:

$$Vol_{on}^{actual}(\%) = \sum_{i=1}^{4} w_{ii} \tag{1}$$

and the actual proportion of off-net calls is given by:

$$Vol_{off}^{actual}(\%) = \sum_{i=1}^{4} \sum_{\substack{j=1 \\ j \neq i}}^{4} w_{ij} \tag{2}$$

From the second matrix, we see that the expected proportion of on-net calls is given as:

$$Vol_{on}^{expected}(\%) = \sum_{i=1}^{4} m_i m_i \tag{3}$$

and the expected proportion of off-net calls is:

$$Vol_{off}^{expected}(\%) = \sum_{i=1}^{4} \sum_{\substack{j=1 \\ j \neq i}}^{4} m_i m_j \tag{4}$$

Table 7 shows the matrix of expected call patterns relating to the first period for which we have data on this decomposition.

	Vodafone (Market Share 36.7 %)	O_2 (Market Share 29.9 %)	T-Mobile (Market Share 15.8 %)	Orange (Market Share 17.6 %)
Vodafone (36.7 %)	13.5 %	11.0 %	5.8 %	6.5 %
O_2 (29.9 %)	11.0 %	8.9 %	4.7 %	5.3 %
T-Mobile (15.8%)	5.8 %	4.7 %	2.5 %	2.8 %
Orange (17.6%)	6.5 %	5.3 %	2.8 %	3.0 %

Table 7 Expected Shares (by volume of calls) 2nd quarter 1999 †††

††† Subscriber market shares are used for calculating this matrix.

If there are no network effects present, we would expect the actual on-net call volume percentage to be close to the sum of the main diagonal percentages. In our case the expected value is 27.9 %. In other words, we would expect far more off-net calls than on-net calls.

The calculated expected call volumes can then be compared with the observed volume of on- and off-net calls as reported by OFCOM. For the 2nd quarter 1999, we find for example that 51.1 % of all mobile terminated calls are on-net. Figure 3 shows the development of on- and off-net calls since the beginning of 1999. Whereas about an equal amount of on- and off-net calls were made in the beginning, the on-net call volume increases considerably faster afterwards.

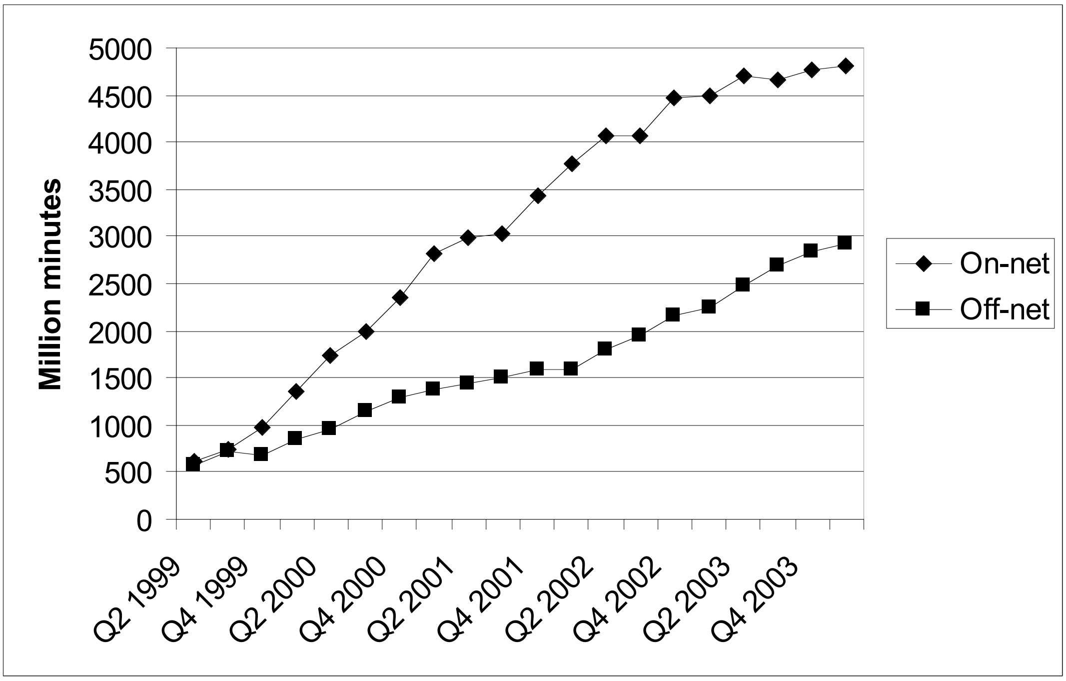

Figure 3 Development of on- and off-net call volumes

Figure 4 depicts the development of the ratio between prices for off-net calls and for on-net calls. In early 1999, off-net calls were about twice as expensive as on-net calls (19 pence per minute compared to 10 ppm). Two years later, off-net calls were about five times more expensive (26 ppm compared to 6 ppm). Afterwards, a decrease in the price ratio can be observed, but prices for off-net calls were still about three times higher in early 2004 (16 ppm compared to 5 ppm).

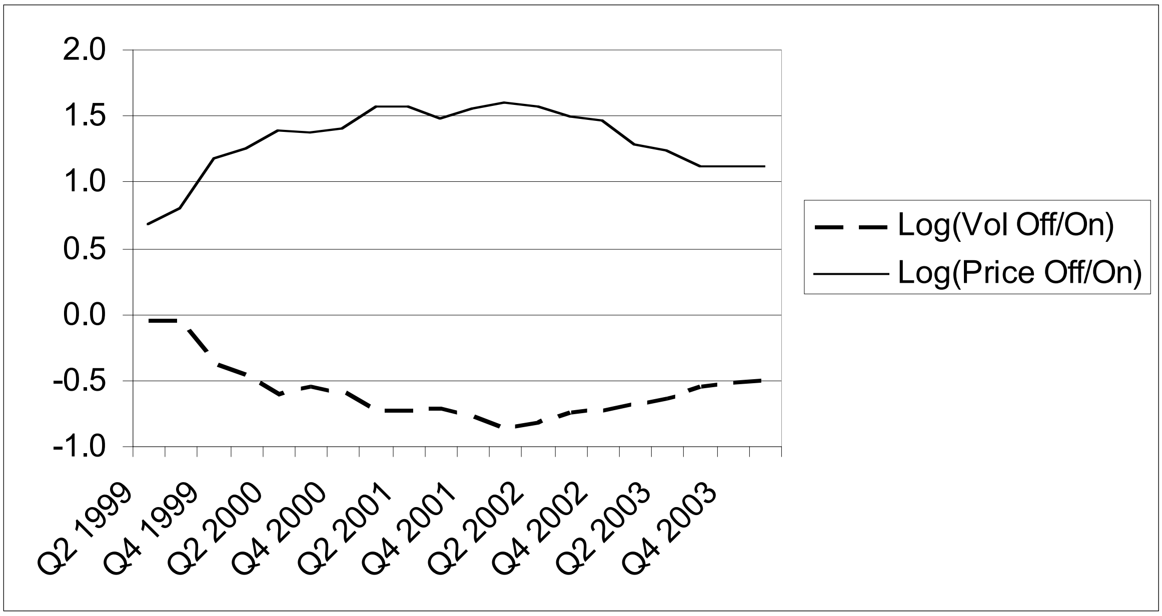

Figure 4 Prices and the ratio between off- and on-net calls

We then examine the relationship between actual and expected call volumes in the following regression:

$$\log\left\{\frac{Vol_{off}}{Vol_{on}}\right\}^{actual} - \log\left\{\frac{Vol_{off}}{Vol_{on}}\right\}^{expected} = \alpha - \beta_1 \log\left\{\frac{P_{off}}{P_{on}}\right\} \tag{5}$$

This demand function is a very simple one. It takes no account of income or quality (e.g. network coverage and reliability). However, it is arguable that neither of these vary much over the short period from which this sample is drawn. Moreover, even if call volumes in total increase with income, it is not clear why income should have much effect on the ratio of off-net to on-net calls.[‡‡‡]

The parameter β_1 is a sort of price elasticity (relating to the premium for off-net calls). It describes how the off-net share is expected to fall as the premium for off-net calls rises. If there is no premium for off-net calls, then the ratio P_{off}/P_{on} is 1, and hence the right hand side of equation (5) reduces to α. If there is only a direct effect of prices on off-net calls, then we would expect α to be zero. If however, α were negative, that would imply that even in the absence of any price differential between off-net and on-net calls, a disproportionately large number of calls are on-net. This would be suggestive of a pure network effect, unrelated to the existence of price premia for off-net calls.

‡‡‡ We might however expect this ratio to depend on quality – for example, if the reliability of on-net calls is higher than the reliability of off-net calls.

4.3 Estimation results

A regression based on equation (5) is less likely to suffer from a strong simultaneity bias than would a regression using total network size as the dependent variable. Table 8 (Model 1) shows the results of this model using OLS.

	Model 1	Model 2	Model 3
Constant α	-.419 (.12) ***	-.274 (.095) **	-.356 (.042) ***
Log (P_{off} / P_{on})	.945 (.096) ***	.460 (.107) ***	.856 (.032) ***
y_{t-1}		.482 (.075) ***	
t			-.017 (.001) ***
No. Observations	20	19	20
R^2	0.843		0.985
F-test	96.66	130.38	538.56
Durbin-Watson (2,18)	.175	Not applicable	1.562
Alternative DW F / Prob. > F		0.511 / 0.4859	
Breusch- Godfrey F / Prob. > F		0.625 / 0.4414	

Figure in brackets are standard errors

** Significant at 5% level; *** Significant at 1% level

Table 8 Regression results for off-/on-net call volumes

The DW statistic indicates that there might be a problem with autocorrelation in the model. To account for a possible dynamic misspecification of the model, we include the first lag of the dependent variable in the regression and test:

$$y_t = \log\left\{\frac{Vol_{off}}{Vol_{on}}\right\}^{actual} - \log\left\{\frac{Vol_{off}}{Vol_{on}}\right\}^{expected} = \alpha - \beta_1 \log\left\{\frac{P_{off}}{P_{on}}\right\} + \beta_2 y_{t-1} \quad (6)$$

The results are shown in Table 8 (Model 2). As the error term is heteroskedastic, we used Newey-West robust standard errors. Using the alternative Durbin-Watson and the Breusch-Godfrey-test, we now can not reject the null hypothesis of no serial correlation. The price elasticity β_1 is much lower than in Model 1, but is still highly significant. The value of .460

means that a one percent increase in the price premium for off-net calls leads to a .460 percent reduction in the dependent variable. The long-run effect of the price ratio is given by $\frac{\beta_1}{1-\beta_2} = .888$, which is very close to the estimated coefficient β_1 of model 1. In short, the observed ratio of off-net to on-net calls is reasonably sensitive to the price premium for off-net calls. The significant lag of the dependent variable demonstrates the inertia present in the consumers' adoption process towards price changes. This could be due to imperfect information and the switching costs present in the market.

Even more interesting than the interpretation of β_1, however, is the interpretation of α. α is significant and negative, which means that even if there is no price premium for off-net calls, there would still be a disproportionately large share of on-net calls. This suggests that there is a pure network effect here, unrelated to price.

Visual inspection of the simple regression from model 1 (see Figure 5) also suggests a third model. In general, there is a very good fit between the fitted and the observed values for the period during which the price ratio increases and for the period during which the price ratio falls again. However, most of the early values lie above the fitted line and most of the later values below, which suggests that there might be a time trend. Reestimating equation (5) and including a time trend, leads to the results displayed in Table 8 (Model 3).

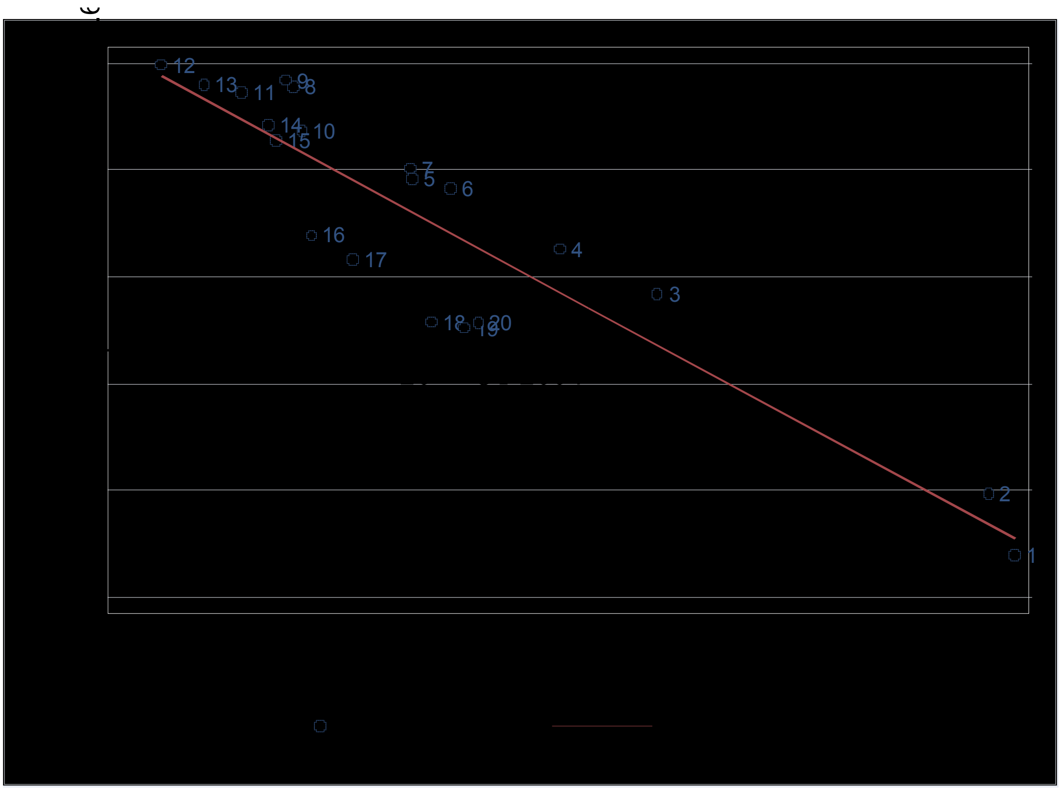

Figure 5 Fitted and observed values for on-/off-net calls

All coefficients are highly significant and the overall fit is best. The DW-statistic is just outside the 95%-confidence interval (1.10;1.54) and the error term is homoskedastic. The significant time coefficient suggest that over time, we would expect the ratio of off-net to on-net calls to grow. The time coefficient can be seen as a proxy for an underlying process of users aligning their operator choice with their peers. We can not forecast how long this process will work, but this process might not be easily revertible due to the switching costs present in mobile telecommunications. In other words, even after the price differential has vanished, we would expect a far higher share of calls to be on-net than off-net.

One limitation of our analysis of market level data is obviously given by the limited number of observations available to us. Because we have data on individual adoption of mobile telephony available, we can further probe into the determinants of network effects in mobile telecommunications, which will be done in the following section.

5 Network effects and operator choice

5.1 Introduction

Section 4 has shown that network effects play a role in the extent to which consumers make on- and off-net calls. We have suggested that consumers try to avoid high costs of off-net calls by coordinating operator choice with their peers. A further indication that network effects are important for operator choice is given by Moore and Rutter (2004, 92). They find that the most common reason why users choose their operator (named by 30% of the respondents) is because friends or family use the same operator.[§§§]

Number of adopters living in a household	Number of operators chosen per household			
	1	2	3	Total
1	373	0	0	373
2	320	152	0	472
3	56	75	18	149
4	20	4	12	36
Total	769	231	30	1030

Table 9 Number of operators per household compared to total number of adopters per household (wave 3)

To get an intuition of the importance of intra-household coordination, Table 9 compares the number of operators per household to the total number of adopters per household. For wave 3, we altogether have 1502 respondents that we could include in our analysis. Of these 1502, 472 did not use any mobile operator and are not displayed in Table 9. Furthermore, 373 respondents live in a household with only the respondent having a mobile (many of those are one-person households). For those individuals, we do not have any data regarding their social network. The majority of the rest of the respondents seems to coordinate operators within other household members (see Table 9): Out of the 472 respondents living in households with two mobile users, 320 (68%) use the same operator and only 152 (32%) use different operators. As Table 9 shows, results are similar even if there are more than two adopters within a household.

Table 10 displays the distribution of operators under the assumption that operators are chosen independently within households. For a household with two adopters, we would only expect 124 (26 %) people to live in households with only one operator instead of the 320 people (68 %) observed.

[§§§] Other important factors include network coverage (25%), service package (20%) and cost of calls (15%).

Number of adopters living in a household	Number of operators chosen per household				
	1	2	3	4	Total
1	373	0	0	0	373
2	124	348	0	0	472
3	11	53	86	0	149
4	1	3	20	13	36
Total	509	404	106	13	1030

Table 10 Number of operators per household compared to total number of adopters per household (wave 3) if household members choose independently

As Table 9 and Table 10 show, results are similar even if there are more than two adopters within a household, which is a strong indication that operator choice is coordinated within households. This is also confirmed by a $\chi 2$-test, which yields a test statistic of 1045. With six degrees of freedom, the critical value is 12.6 and the hypothesis of independent choice is very strongly rejected.

In principle, we should expect that network effects in mobile telecommunications are pecuniary. That is, they work through the price system and are induced by the network operators. The main reason why people profit from a bigger network is that there are more people on the same network who can be reached by cheaper on-net calls. Having said that, the results of the last section suggest that there also is a pure network effect that does not directly interact with price differentials.

In general, we would expect the individual's *i* choice of operator to depend on the prices of different services, the quality of different services, the network sizes of different services, and perhaps on the income of consumer *i* and other characteristics of consumer *i*. In what follows, we focus on prices, network sizes and consumer characteristics.

We take two broad approaches. In our first set of estimates (section 5.3) we treat price and network variables quite separately. In the second (section 5.4), we try to capture the interaction between price and network variables. The intuition behind this second approach is as follows. From my (Vodafone) mobile, I can call any other mobile or landline (setting aside issues of geographical coverage). The full network is available to me. This would also be true if I had an Orange mobile. Network effects do not therefore describe the size of the network to which I can connect. Rather, they are a factor determining the cost of the calls I wish to make. If all of the people I wish to call also have Vodafone mobiles, then it is cheaper for me than if they own other phones. For that reason, it is appealing from a theoretical point of view to look at a modelling approach in which price and network effects interact.

5.2 The model

Again, assume that consumers can choose between four different networks. Suppose there are N people (j = 1, …, N), and for any person i, the total length of calls (s)he makes to person j is n_{ij}. Let r(j) describe the mobile operator chosen by person j (r ε {1,…,4}). Let $p_s(r(j))$ describe the cost per minute incurred by someone using operator s in making a call to the network chose by person j. Furthermore, let $C_{is,other}$ be the cost for individual i using operator s for making all other calls (to landlines etc.). Then, the cost to i of making the calls (s)he wishes using operators s= 1, …, 4 is given by:

$$C_{is} = \sum_{j=1}^{N} n_{ij} p_s(r(j)) + C_{is,other} \qquad (7)$$

In practice, we could not expect to know an individual's pattern of calls in such detail. For simplicity, three basic types of calls can be distinguished: off-net calls, on-net calls and other calls. Consequently, the consumer faces a vector of prices, depending on what kinds of calls are made. The induced network effects of mobile telecommunications affect the price difference between on- and off-net calls.

Let $V_{i,mobile} = \sum_{j=1}^{N} n_{ij}$ describe the total call volume that individual i makes to other mobile phones, let $V_{i,other}$ be the volume of other calls (to landlines etc.) and let $r_{s,\text{off}}$ be the percentage of off-net calls. Note that $V_{i,mobile}$ and $V_{i,other}$ do not depend on operator choice, but $r_{s,\text{off}}$ does. Assuming that off-net calls have the same price regardless of which (other) network they terminate in, the total cost to i of making the calls (s)he wishes can be written as:

$$C_{is} = r_{s,off} V_{i,mobile} p_{s,off} + (1 - r_{s,off}) V_{i,mobile} p_{s,on} + V_{i,other} p_{s,other} \qquad (8)$$

We do not have detailed enough data to take into account that the price ratio between on-net and off-net calls may differ between operators. Consequently, we assume that the relation between p_{other}, p_{off} and p_{on} is constant across operators and rewrite equation (8) as:****

$$C_{is} = p_s (V_{i,mobile} \{ r_{s,off} \pi_{off} + (1 - r_{s,off}) \pi_{on} \} + V_{i,other} \pi_{other}) \tag{9}$$

where p_s is a price index per operator and π_{other}, π_{off} and π_{on} are indices capturing the relative price of the three call types. The most interesting parameter here is $r_{s,off}$ the percentage of off-net calls out of the total mobile-to-mobile calls. $r_{s,off}$ varies across operators and person i can minimise C_{is} with the use of two basic strategies:

1. by choosing the operator with the lowest general price level p_s or
2. by choosing the operator, for which $r_{s,off}$ (the percentage of off-net calls) is lowest. The optimal choice for a consumer could be made, if (s)he had perfect information on all the persons j that (s)he wishes to communicate with. That is unrealistic even in a static framework, as it is not conspicuous, which operator is chosen by a particular person. In a dynamic framework neither the network choice of the communication partners nor the communication partners themselves are constant. However, the consumer has two observable proxies influencing the choice: First, the expected network size for each operator. Second, every consumer may have information on network choice of a limited number of family members and close friends.††††

5.3 Estimates for Non-Interactive Model

In a first step, we use the data we have available on the price level per operator p_s, the network size per operator and the data on operator choice of other members of the same household without further specifying the exact structure of the influence of these variables on call expenses. In this first form of the model we treat price and network effects separately. Our dependent variable is operator choice and has four different unordered outcomes.

**** It can be expected that smaller operators gain least by having large price differences between on- and off-net calls, as this would deter consumers from choosing these (smaller) networks. Indeed, this can currently be observed by the pricing scheme used by the 3G newcomer "3", which heavily advertises that there is no difference between on- and off-net calls for some of their tariffs. For the time considered in this study, there is no new entrant into the GSM market and consequently our assumption seems tenable.

†††† A third possibility to reduce total call expenses would be to reduce the length and/or frequency of calls to persons using a different network. This is only a relevant choice factor if this adoption process is not the same for every communication partner. For simplicity, we assume that this process does not affect operator choice.

Therefore, we use a mixed conditional logit / multinomial logit model. On the one hand, we have data on characteristics of the choice. So, for every operator, we have data on the number of subscribers (SUBSCRIBERS), price level (PRICE) and a counter indicating which networks were chosen how often by other members of the same household (HOUSE_NETWORK). This choice-specific data can be used in a conditional logit model as first introduced by McFadden (1973).

Note that there is no quality parameter in our model. The main variables we expect to have an impact on quality are network coverage, international roaming, reliability and customer service. Until 1998, network coverage was lower for Orange and especially T-Mobile.[‡‡‡‡] Likewise, international roaming was possible in far more countries for Vodafone and O_2 users. However, for the period of study and especially for the third wave in 2001, all networks cover over 97 % of the population and international roaming is possible in most countries. Reliability measures the percentage of successful call completion. Especially in the early years of mobile telephony, reliability was lower, because of a shortage of capacity. Reliability typically is higher than 95% (see OFCOM (2000)); the only pronounced difference being a lower reliability of T-Mobile in Scotland and Wales. We therefore conclude that network quality is roughly equivalent between operators and do not include a quality measure in our analysis. This might bias the estimates of the price parameter, but prices are only of second-order importance for our model.

Consumers are highly heterogeneous and there are large differences between highly mobile business users and users who have a mobile just for emergency purposes. We try to account for this variety through the inclusion of individual-specific characteristics in the multinomial logit part of our model. The parameters we included are socio-economic group (MRSCODE), age (AGE) and sex (MALE). Combining the MNL and the conditional logit part results in the following estimation equation (see also Maddala (1983)):

$$\Pr(y_i = \gamma \mid \mathbf{x}_i, \mathbf{z}_i) = \frac{\exp(\gamma \mathbf{z}_{ia} + \eta_a \mathbf{x}_i)}{\sum_{j=1}^{4} \exp(\gamma \mathbf{z}_{ij} + \eta_j \mathbf{x}_i)} \tag{10}$$

where $\mathbf{z}_{ia}$ is the vector of choice-specific characteristics for the four alternatives a and $\mathbf{x}_i$ being the vector of individual-specific characteristics. Note that γ is constant across individuals, whereas η is not. This means that we get a separate estimated coefficient of the individual-specific characteristics for all four choice alternatives.

[‡‡‡‡] Data on network coverage and international roaming are taken from the trade journals *What Cellphone* and *What Mobile*.

The model is estimated separately for each wave. Results for the three waves are similar. Table 11 (Model 1) shows the regression results for the third wave (beginning of 2001).

	Model 1	Model 2	Model 3
HOUSE_NETWORK	1.440 (.077)***	1.275 (0.082)***	
SUBSCRIBERS	.086 (.162)	.138 (.051)***	
PRICE	-.016 (.065)	-.035 (.022)	
$\omega_{household}$			-.016 (.001)***
ω_{other}			.00081 (.00027)***
LAST_CHOICE		2.172 (.109)***	2.209 (.110)***
MRSCODE_O2	.058 (.071)		
MRSCODE_ORANGE	.114 (.072)		
MRSCODE_T_MOBILE	.192 (.088)**		
AGE_O2	.003 (.005)		
AGE_ ORANGE	-.001 (.005)		
AGE_ T_MOBILE	-.014 (.007)*		
MALE_O2	-.332 (.181)*		
MALE_ ORANGE	-.384 (.183)**		
MALE_ T_MOBILE	-.348 (.217)		
No. of observations	1030	1030	1030
Pseudo R^2	0.179	.339	.333
Log L	-1172.6	-944.0	-953.0
LR χ^2 (df)	510.5 (12) ***	968.2 (4) ***	949.8 (3) ***

Figures in brackets are standard errors.

* Significant at 10%-level; ** Significant at 5%-level; *** Significant at 1%-level

Table 11 Determinants of operator choice

The results from the multinomial part of Table 11 (Model 1) reinforce the results obtained from the descriptive statistics in 3.2: there are some significant differences between operators. T-Mobile users, for instance, come from significantly lower socio-economic groups than Vodafone users (the comparison group for the multinomial part) and Orange has significantly more female users than Vodafone.

Most interesting are the results from the conditional logit part. Although SUBSCRIBERS and PRICE have the expected signs, neither is statistically significant. However, the counter

HOUSE_NETWORK capturing the impact of operator choice from other household members on the own operator choice is highly significant.

A very high percentage of people in a household use the same network. If not only network choice but also call volumes are strongly influenced by household members, then this would support our hypothesis from section 4 that network effects play an important role in determining the ratio between off- and on-net calls and that these network effects operate through peers choosing the same network operator in order to minimise the costs incurred by off-net calls.

As an alternative to the above regression model, we use a model where we drop the individual-specific characteristics and instead include a variable (LAST_CHOICE) indicating the operator choice in the previous wave (13 months earlier). This variable probably captures most of the inter-individual heterogeneity, as it can be expected that choice determinants, like for example age, sex, socio-economic group, do not change dramatically from one wave to the next.

This approach also captures some of the inherent inertia in mobile choice: consumers are not completely free to choose their network operator at every wave, because they might be bound contractually and because of other switching costs present in mobile communications (number portability etc.). Table 11 (Model 2) shows the results from this model estimation.

The parameters already used in model 1 have consistent signs and stable coefficients. The estimate for LAST_CHOICE is highly significant and also the HOUSE_NETWORK parameter keeps its high explanatory power. The estimates of the coefficients for PRICE and SUBSCRIBERS are slightly higher in the second model, whereas the standard errors are lower. Although PRICE is still not significant, the SUBSCRIBERS variable is significant at the 1%-level. This would mean that consumers not only take into account the choice of other household members, but also prefer networks with a higher number of subscribers. The estimates for Model 2 resulted in a higher log-likelihood ratio (LR) and a higher R^2 than for Model 1.

There is a wide variety of possible combination of operators used in the same household, but to get a more intuitive idea of how we can interpret the HOUSE_NETWORK results, Table 12 shows the predicted probabilities for a household member choosing O_2 depending on the number of other household member using O_2. The results for the other operators are very similar.

	O_2	Orange	Vodafone	T-Mobile
No other O_2 users in household	23.4%	27.6%	27.7%	21.3%
One other O_2 users in household	52.2%	17.2%	17.3%	13.3%
Two other O_2 users in household	79.6%	7.3%	7.4%	5.7%
Three other O_2 users in household	93.3%	2.4%	2.4%	1.9%

Table 12 Predicted probabilities for choosing O_2[§§§§]

5.4 Estimates for Interactive Model

Finally, we have made some experiments with a modified version of this last model, where the interaction between price and network effects is explicitly captured.

Take all the calls made by a particular user to other mobile users. Let us split these calls into two groups: those made to the household, and those made to all others. For the first group, the cost is proportional to:

$$\omega_{household} = PRICE * \left[HOUSE\_NETWORK_{SAME} + HOUSE\_NETWORK_{OTHER} * \frac{P_{off}}{P_{on}} \right] \quad (11)$$

Where $HOUSE\_NETWORK_{SAME}$ captures the number of household members using the same network and $HOUSE\_NETWORK_{OTHER}$ captures the number of household members using another operator. The assumption is that I am equally likely to call any member of my household, regardless of which mobile operator they use. For the second group, the cost is proportional to:

$$\omega_{other} = PRICE * \left[SUBSCRIBERS_{SAME} * Vol_{ON}(\%) + SUBSCRIBERS_{OTHER} * Vol_{OFF}(\%) * \frac{P_{off}}{P_{on}} \right] \quad (12)$$

Using these two composite variables, $\omega_{\text{household}}$ and ω_{other}, we can estimate a restricted version of the last model:

$$CHOICE = F\left[LAST\_CHOICE ; \omega_{household} ; \omega_{other}\right] \quad (13)$$

[§§§§] The example shows the probabilities, if no other operator apart from O2 is used in the household and if the household member newly adopted a mobile.

The results for this regression are shown in Table 11 (Model 3). It is apparent from inspection of the pseudo R^2 and Log Likelihood that this model does not work as well as that in section 5.3. Moreover, the coefficient for ω_{other} is positive, while we should expect it to be negative and which already suggests that the interactive model does not work satisfactory. A likelihood ratio test comparing the two is complicated because the restricted form (Model 3) is not precisely nested in Model 2. Roughly speaking, however, we can take the large difference of -9.0 in Log Likelihood between Models 2 and 3 as a rejection of the restriction implied in this last form of the model.[*****]

At one level this rejection is a little surprising. It suggests that the intuitively appealing interactions captured above do not fully capture actual choice behaviour. At another level, the result is not entirely surprising. We saw in section 4 that there are pure network effects, unrelated to price differentials between off-net and on-net calls, and the above results reinforce that.

[*****] -2logLR for one restriction is distributed chi-squared with one degree of freedom. We find that the restriction in moving from Model 2 to Model 3 has a rough test statistic of 18.0, and that is significant at the 1% level.

6 Summary

The results obtained from the previous sections give a strong indication that network effects play an important role in mobile telecommunications. This role does not only have an impact on the adoption of the technology per se, but also on the usage of mobile phones and on operator choice. The results from Chapter 4 and the similar quality level of the four operators further suggest that the induced network effect rather than an information contagion process leads to the coordination of operator choice. Furthermore, whereas learning effects played an important role in the computer adoption study of Goolsbee and Klenow (2002) and might also be important for the *adoption* of mobile phones, it is not clear why they should significantly affect *operator choice*.

These results are especially interesting for network operators currently introducing third generation mobile networks. Although network effects will be even more complex for these networks, and will include indirect network effects arising from services offered over the networks, the strong reaction from consumers to changes in the price ratio of off- and on-net calls, suggest that inducing network effects by operators has been a successful strategy. It can in particular be used by the incumbent operators to fend off challenges by the newcomer "3" and also by any operator gaining a lead over the other operators. Furthermore, we have shown how strongly operator choice is coordinated within households. This also suggests that operators gaining an early lead in the 3G market have an advantage over later entrants and that it is important for operators to support this choice behaviour by their customers.

From a regulatory perspective, network externalities have been mainly discussed as a reason for higher termination charges, as users of mobile networks benefit from additional users in every other network (Competition Commission 2003). High termination charges and high costs for off-net calls have been regarded in a recent ruling by the UK regulator OFCOM (OFCOM 2004) as being the result of significant market power that operators have on its individual networks. As our results suggest, the high price of off-net calls can not only be a *result* of market power, but can be a significant *source* of market power, which can especially be used to pre-empt entry by new competitors. If high switching costs are present in mobile telecommunications, this market power would be highly stable once consumers have aligned their operator choice even after the price differential between on- and off-net calls has been lowered.

It can be expected that (social) network effects in mobile telecommunications only get important after a certain network size has been reached (contrary to the case of indirect network effects). This is because in the beginning, most mobile calls were made to traditional landlines. Consequently, Valletti and Cave (1998, 124) have argued that in 1998 network effects did not play a role in mobile telecommunications. Furthermore, it can be assumed (and is supported by the data from the *Home Online* study) that in early years, most people in an adopter's network do not have a mobile phone yet. We therefore would expect that the importance of network effects is increasing over time.

Furthermore, this paper has hopefully shown the richness of impacts caused by network effects. These different impacts are currently only partially explained by the existing economic literature. Especially the standard assumption that network effects grow linearly with network size rests on very strong assumptions (Swann 2002) and is not supported by our empirical evidence. Apart from mobile telecommunications, this might be true for direct network effects in general, where the network effect is based on direct interaction between users.

An interesting area for future research would be to further enhance the knowledge on network effects especially in the area of the micro-foundation of the theory. Models on how social network effects operate and lead to the aggregated results described by traditional network effects theory would be one possibility.

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