Estimating Switching Costs in Mobile Telephony in the UK*

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Abstract

This paper employs mixed logit for panel data on British households in years 1999-2001 to estimate the magnitude of switching costs in mobile telephony. There is no empirical evidence, that consumers of mobile services have switching costs when considering to change network operator. The choices of network operators are explained by observed and unobserved heterogeneity in consumers' tastes.

Keywords: mobile telephony, switching costs, random utility, mixed logit.

JEL Classification: C25, D12, L96

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1 Introduction

One-time costs required to terminate current relationship are referred to as switching costs. An important implication of switching costs is that products, which initially were close technological substitutes, cease to remain economic substitutes after the purchase. Thus, ex-ante homogeneous products become heterogeneous ex-post. If any firm wants to convince a customer of the competitor to switch, it has to compensate switching costs through lower prices or higher product value (see Klemperer (1995) for explanation of the sources of switching costs).

Switching costs have a critical impact on choices of consumers and strategies of firms in many industries. Their potential negative consequences for the competition and social welfare are of great concern for regulators. Identifying and measuring switching costs may support the regulation by indicating whether there could be an abuse of market power and inefficiencies in consumers' choices. In particular, mobile telephony is an example of industry, in which consumers are believed to have high switching costs, for instance, due to compatibility costs, transaction costs or search costs. Compatibility costs arise because operators tend to lock handsets to be used exclusively within own network. In this way, firms prevent consumers from switching to another network after getting a subsidized handset. Transaction costs come up because consumers have to change the telephone number when switching network operator. Redistribution of new telephone number to one's social circle requires an effort, which may be viewed as switching cost. Alternatively, the number may be ported, which also can be costly and time consuming for consumers. Finally, search costs arise because consumers have to gather information about other networks.[1]

In fact, the development of mobile telephony in the UK suggests presence of consumer switching costs. Markets shares of 'incumbent' operators and entrants converged in time to almost equal sizes (see Figure 1). This may be the case, if the 'incumbents' BT Cellnet and Vodafone focused on charging higher prices to exploit locked-in consumers. The 'entrants' Orange and One2One could set lower prices to serve, to a larger extend, new consumers and

[1]For detailed discussion see NERA, 2003. "Switching costs".

catch up with 'incumbents' in terms of market shares (see Table 4). Such result is predicted by the theoretical literature on switching costs. Starting from now on, when the industry reached the saturation point and mobile operators equally split the market, high switching costs may allow firms to exploit locked-in consumers.

This paper uses survey data on British households (Home OnLine) to estimate the magnitude of switching costs in mobile industry and assess whether there is a harm for consumer welfare. According to mixed logit estimates for panel data, there is no evidence for switching costs in mobile telephony in the UK. The estimates of switching costs are insignificant for two operators: Orange and One2One, which started providing mobile services with delay, in 1994. The subscribers to BT Cellnet and Vodafone, the first two operators on the market, even benefit when switching to other operators. The choices of network operators are explained by observable and unobservable heterogeneity of tastes. The observable heterogeneity is represented by consumer characteristics, such as sex, age, employment status and household equipment. Furthermore, the probability of switching depends on consumer characteristics, such as age, usage intensity and ways of spending leisure time. This result is consistent with findings in the consumer surveys conducted by the British regulator Oftel.

The next section provides an overview of empirical literature on switching costs. Section 3 briefly presents the mobile telecommunications industry in the UK. Section 4 presents the empirical model, describes the estimation methodology and data. Section 5 discusses estimation results. Finally, section 6 concludes the analyzes.

2 Literature

There is a large body of theoretical literature on switching costs and their effects on consumer choice and competition are well understood (for a review and a list of references see Farrell and Klemperer (2004)). The number of empirical studies is scarcer, which is mainly due to lack of appropriate data sets. Following the methodology used in the report prepared by the National Economic Research Associates for the British Office of Fair Trading, the empirical methods

of estimating switching costs may be divided into direct and indirect.[2] Indirect methods use aggregate data and identify switching costs by estimating cross price elasticities or estimate pricing equations with some proxy variables, which are supposed to influence the magnitude of switching costs. Direct methods use information on individual consumer choices, and measure switching costs in the random utility framework, as employed in this study.

For instance, Kim et al (2003) use aggregate industry panel data to analyze strategic behavior of firms in the presence of switching costs. They find significant estimates of switching costs in the market for Norwegian bank loans. Shy (2003) assumes a static Nash-Bertrand equilibrium and shows how to calculate switching costs using data on prices and market shares. Another range of studies identify switching costs by estimating reduced-form pricing equations. Borenstein (1991) measures the magnitude of switching costs in the U.S. retail gasoline market. Knittel (1997) analyzes the changes in prices for long distance telephone calls in the U.S. after AT&T divestiture in 1984 and explains price rigidity by the presence of search and switching costs. Viard (2002) studies the impact of the introduction of number portability on prices for toll-free numbers in the U.S. He finds that when firms cannot discriminate between old locked-in consumers and new ones, switching costs may have ambiguous effect on prices. Several other empirical studies provide evidence for the presence of switching costs in a range of industries, such as credit cards, electricity, airlines, computer software, television and others (see Farrell and Klemperer (2004) for further references).

However, there are very few studies, which estimate directly consumer switching costs using micro data on individuals' purchase histories. Chen and Hitt (2002) use household data to estimate the magnitude of switching costs and brand loyalty in the online brokerage industry. They find that consumers' switching costs vary across firms, which may control their size through adequate product design and retention strategies. Epling (2002) studies competition in the long distance telephony market in the U.S. after 1996 and finds empirical evidence for heterogeneity in the subscriber switching costs. Consumers with high switching costs end up paying higher

[2]NERA, 2003. "Switching costs".

prices. Shum (2004) estimates switching costs using panel data on households' breakfast cereal purchases. Apart from the economic literature, there is a growing number of related marketing studies on brand loyalty and state dependence in consumer choices.

One important problem, which arises when state dependence of choices is estimated, is that consumers may have unobservable persistent heterogeneous preferences. Heckman (1981) draws a difference between true state dependency and spurious state dependency. True state dependence is a consequence of all observable events, which may be also switching costs and brand loyalty. Spurious state-dependence results from a persistent heterogeneity in the preferences for brands. Consumers may continue buying the same product because it fits better to their idiosyncratic tastes and not due to switching costs. Hence, the parameters representing switching costs may be overestimated when spurious state dependence is ignored. There is a large body of studies, which try to separate true and spurious state dependence. Among empirical studies on switching costs, Chen and Forman (2003) suggest two strategies to identify switching costs from spurious state dependence. They employ an instrumental variable approach and mixed logit estimation, and find high switching costs in the market for routers and switches. Goldfarb (2003) measures loyalty for Internet portals controlling for household-specific heterogeneity by estimating a separate regression for each household. In the present study, mixed logit framework is applied to identify true and spurious state dependence.

3 Mobile Telephony in the UK

At the end of year 2003, mobile telecommunications industry in the UK was represented by five network operators: Vodafone, BT Cellnet (renamed to O2), One2One (renamed to T-Mobile), Orange and Hutchinson 3G. The first four operators provide services in the GSM technology, while Hutchinson 3G is one of the UMTS licence winners and started to provide 3G services in 2003. The first two network operators, Vodafone and BT Cellnet launched their networks in 1985 (analog at first) and were followed by start-ups of two further networks, Orange and One2One in 1994. Until 1994, the network operators were prohibited from supplying services directly to

consumers and had to establish subsidiaries or independent companies for that purpose. Later on, both Vodafone and BT Cellnet were designated by the regulator as having significant market power[3] in the retail market and again were required to provide wholesale airtime to independent service providers, which providing billing and customer care services under own brand names. In this analysis, the choice of consumers is restricted to four network operators.

The regulators of mobile telephony try to reduce firms' power by introducing regulation, which decreases switching costs. The prime way of decreasing transaction costs is by implementing portability of numbers. For instance, in the UK, mobile number portability was introduced in January 1999. However, the amount of switching consumers remained relatively low and even decreased. This may indicate, that transactions and other switching costs are still high. Percentage of ported numbers is also very small. The regulation of handset-locking should decrease compatibility costs. Lack of intervention by the British regulator in this matter is due to a belief, that prohibition of handset-locking would not have any significant impact on the competition and switching behavior.[4] Finally, search costs could be decreased by providing consumers with comprehensive information about all services, which are available on the market. The British regulator supplies consumers with recommendations about the choice of mobile services. There are also plenty of commercial online services, which provide support in making the choice of network operator, tariff and handset. Hence, the search costs may be low compared to transaction costs. According to Oftel's survey, the majority of consumers declared to be satisfied with information, which is available about mobile services.[5]

[3]European Commission, Directive 97/33/EC.

[4]Oftel, Review of SIM-Locking policy, 26 November 2002.

[5]Consumers use of mobile telephony, Q8 February 2002

4 Empirical Analysis

4.1 Estimation Methodology

In the present study, consumer choices of network operators are analyzed by employing the random utility framework developed by McFadden (1974). This approach requires estimation of individual utility functions assuming utility-maximizing heterogenous consumers. The utility function includes observable choice determinants and a stochastic component, which represents unobservable idiosyncratic preferences. Consumer's valuation of a product typically depends on its price and other attributes, and the consumer demographics. When switching costs are present, the previous choice influences current utilities. Switching costs cause a bias in the consumer preferences towards the alternative, which was chosen before. However, the choices of alternatives may be also state-dependent due to a persistent consumer heterogeneity, which is unobserved by the econometricians.

The utility, which consumer i obtains at time t from network operator j out of J available on the market may be written as

$$U_{ijt} = r_j + \alpha p_{ijt} + \beta x_{jt} + \gamma_j z_{it} + \sum_{k=1}^{J} w_k s_{ikt} + \xi_{ij} + \epsilon_{ijt} = V_{ijt}(\xi_{ij}) + \epsilon_{ijt} \tag{1}$$

It is determined by individual service price p_{ijt}, non-price network attributes x_{jt} together with a firm-specific dummy r_j, consumer demographics z_{it} and a set of dummies s_{ikt} to account for switching from alternative k to alternative j. The persistent consumer heterogeneity is represented by ξ_{ij}. Finally, ϵ_{ij} is the idiosyncratic unobservable taste variable, which captures the effects of other unmeasured variables. The parameters in front of consumer demographics γ_j account for observable variation in consumer tastes across network operators. The coefficients of switching dummies w_k represent the disutility, which consumers have to bear when they change network operator. In the formulation (1), the disutility from switching depends on the network from which consumers switch. Each network operator employs a different policy towards switching consumers. For instance, there may be differences regarding the cost of unlocking the handset or porting the number. Moreover, artificial switching costs may vary across networks,

such as an ongoing loyalty program or psychological costs, when consumers are uncertain about the quality of other networks. Alternatively, switching costs could be assumed to be the same across networks. The disutility from switching may also be heterogenous across consumers.

Consumers maximize utility and choose network operator m with the greatest value among all alternatives $U_{im} \geq max_{j \in C_i, j \neq m} U_{ij}$, where C_i is a choice set of individual i. When there is no persistent consumer heterogeneity ($\xi_{ij} = 0$) and the stochastic utility component ϵ_{ijt} is distributed independently, identically extreme value, the choice probabilities simplify to closed-form multinominal logit expressions

$$P_{imt} = P[V_{imt} + \epsilon_{imt} \geq max_{j \in C_{it}, j \neq m} V_{ijt} + \epsilon_{ijt}] = \frac{\exp(V_{imt})}{\sum_{j \in J} \exp(V_{ijt})} \tag{2}$$

The iid assumption about ϵ_{ijt} implies proportional substitution across alternatives and is inappropriate in many situations. In this case, the outside option – fixed line telephony is assumed to be equal substitute to mobile services. The iid assumption enters also for choice sequences made by the consumer over time. Thus, the choice probabilities for panel data are derived exactly in the same way, while in many cases choices may be dependent over time. Ignorance of spurious state dependence may lead to overestimated switching costs w_k.

Mixed logit gets over this constraint by decomposing the unobserved factors into a part that contains all the correlation and heteroskedasticity, and another part that is iid extreme value. The first unobserved component may follow any distribution: lognormal, uniform, triangular, gamma or other. When explanatory variables and density are appropriately specified, any utility-maximizing behavior may be represented by a mixed logit model, in particular both multinominal and nested logit (see Train (2003) for further discussion).[6] In the present case, ξ_{ij} are assumed to have joint normal density. The choice probabilities have no closed-form

[6]In the case of mobile telephony, nested logit represents a plausible pattern of consumer choice. In the first stage, consumers choose between fixed and mobile telephony, or rather between having fixed line only and fixed line together with mobile. Almost all households in the survey had fixed line at home and did not resign after some household members purchased mobile phones. In the second stage consumers select one out of four mobile operators. Thus, the other mobile networks are closer substitutes than fixed line. Nevertheless, the mixed logit estimated in this study is more general than nested logit.

expressions and are given by

$$P_{imt} = \int_{\xi} \left[\frac{\exp(V_{imt}(\xi_{im}))}{\sum_{j \in J} \exp(V_{ijt}(\xi_{ij}))} \right] f(\xi) d\xi \tag{3}$$

Another problem, which arises in estimating dynamic choice models is so called initial conditions problem. The choice probabilities in the first period observed depend on the choices in the earlier periods, which are not observed. The probabilities for the first choice must be somehow determined. The ways of dealing with this problem are addressed by Heckman (1981a, 1981b) and Wooldridge (2002). As argued in the next subsection, which describes the data, the initial conditions issue may be ignored in the present case. This is due to the fact, that for most consumer their first choice of mobile operator is included in the data.

Besides mixed logit, the probability is estimated, that subscriber i to network j will switch operator

$$log \left[\frac{P_{it}(switch)}{1 - P_{it}(switch)} \right] = r_j^s + \alpha^s p_{ijt} + \beta^s x_{jt} + \gamma^s z_{it} + \omega_{ijt} \tag{4}$$

Data is pooled for consumers of all network operators and over time. The probability of switching is linearly determined by service prices p_{ijt}, which may be assumed to be consumer specific, dependent on calling behavior. Consumers differ in usage of mobile services and firms tend to price discriminate according to usage patterns. Hence, there is no single price for all consumers but rather set of prices targeted at segments of consumers. The individual cost of using mobile services may be assumed to be dependent on consumer demographics, and firm attributes according to

$$p_{ijt} = r_j^p + \beta^p x_{jt} + \gamma^p z_{it} + \varepsilon_{ijt} \tag{5}$$

After substituting prices (5) into equation (4), the probability of switching will be dependent only on network attributes and dummies, and consumer demographics.

This paper estimates simple logit model (2), which can be treated as a base model for comparison, simulated mixed logit (3), pricing equation (5) and the logistic regression (4).

4.2 The Data

This analysis is possible thanks to the household panel survey Home OnLine funded by the British Telecommunication Ltd, which is made available for research purposes through the Institute for Social and Economic Research at the University of Essex. The purpose of this survey was to gather individual and household level information about the use of information and communications technologies. The data consists of three annual waves: October-December 1998, January 2000 and February 2001. The first wave comprises 1000 households with response rate of 57%. Households which dropped out in the next waves were replaced by new ones and the household response rate accounted for 75.7% and 67.1% respectively in the second and third wave.

Many respondents did not provide any information about the use of mobile services. For instance, in the first wave 478 individuals declared to have mobile phone and 1315 not to have, out of 2608 in total (penetration rate 26.66%). In the second wave, the respective numbers were 844 and 725 out of 2555 individuals (53.79%), and in the third wave 1106 and 450 out of 2406 individuals (70.99%). According to ITU statistics mobile penetration rates in the UK at the end of respective years were: 25.11%, 45.68% and 72.70%. Thus, the penetration in the group of people who answered the question about mobile subscriptions is accurate. The penetration rates within the total sample account for 18.3% in year 1998, 33% in year 2000 and 46% in 2001. Hence, many consumers who did not mark any answer had mobile phones.

The amount of individuals, which provided information about network operator of their choice in two consecutive years was much lower. In the third wave, out of 2406 individuals 573 declared network operator in both second and third wave and 238 were new subscribers to mobile services, that is declared to be users of mobile services in the third wave but not in the second wave (Table 1). In the second wave out of 2555 individuals these numbers were respectively 239 and 292 (Table 1). Table (2) presents tracking of consumer choices over all three waves. Finally, there are even less individuals, who provided information in all three periods. There were 608 consumers, which declared not to have mobile phone in wave 1, and provided information about

their further choices both in wave 2 and 3. The same refers to only 64 consumers of BT Cellnet, 29 of Orange, 77 of Vodafone and 14 of One2One.[7]

As presented in Table (2), for majority of consumers, the first choice of network operator is contained in the data: 772 consumers had no mobile phone in the first wave and 148 consumers, for which first wave information is missing, had no mobile phone in the second wave. Among the other 202 individuals, which did not provide any information about usage of mobiles in the first wave, about half should not have been subscribed to any network in the first wave. This is because mobile penetration was about 46% in 1999 and 25% in 1998. Still, there is a group of 252 consumers, which declared usage of mobile services already in the first wave. However, in 1997 the penetration of mobiles was around 13-14% compared to 25% in 1998. Thus, within this group around 120 consumers indeed made the first choice in wave 1. Altogether, there may be about 240 consumers out of 1374, for whom their first choice of network operator is not observed. In case of these consumers, there should be no big issue assuming, that their first declared choice is the first choice of network operator at all. In fact, the vast majority of consumers stick to their choices, at least in the short period of time. When the choices are observed since the beginning, the initial conditions problem does not arise and mixed logit may be used to capture state-dependence in dynamic models (see Train (2003)).

To determine factors, which could influence the choice of network operator, one may refer to surveys conducted by Oftel (later renamed to Ofcom). According to the survey from February 2002, around 59% of consumers indicated the cost of using mobile services as the critical choice factor, followed by the coverage and reception quality mentioned by 21%.[8] These factors and, in case of old consumers, the previous choice of network operator should be considered as the main determinants of network choice. However, the differences in coverage and reception quality across network operators are negligible. For instance, Table (3) presents results from Oftel's call success rate survey conducted between October 1999 and March 2000. The differences in

[7]The survey was conducted on a representative sample of British households. The sample used in this study was representative for the whole database, which was checked using comparative statistics.

[8]Consumers use of mobile telephony, Oftel, Q8 February 2002

reception quality over all regions are very small. Furthermore, at the beginning of 1998, BT Cellnet and Vodafone claimed to have covered 99% of the UK population, One2One 93% and Orange 96%. The impact of these factors is equivalent to adding a constant to each utility function, except fixed line, and as such cannot be identified ($\beta x_{jt} = \beta x_t$).

The network operators, which launched their services in 1994, Orange and One2One, tend to charge lower prices than the 'incumbents' BT Cellnet and Vodafone. This is inline with the theory on pricing with switching costs (see Klemperer (1987) and Farrell and Shapiro (1988)). Table (4) presents the prices for representative tariffs for two different usage patterns. The prices vary across consumers due to differences in calling behavior. However, for any consumer i with certain usage pattern, the cost of services provided by BT Cellnet and Vodafone may be assumed to be equivalent, given by αp_{it}.[9] In case of Orange and One2One, this cost is lowered by some constant, that is $\alpha p_{it} - \upsilon$. If this is the case, since only differences in utilities matter, price coefficient α cannot be identified as well. Thus, consumer choice is determined by stand alone value, consumer demographics, switching costs and some unobserved factors, which may be also the spurious state dependence. The firm dummies may differ significantly across networks because of all the factors included, in particular entrants' price discount υ, brand value and network effects. Even though all networks are fully compatible, there may be asymmetric network effects due to the differences in on-net and off-net prices, which make larger networks more attractive. Birke and Swann (2004) use the same Home OnLine survey data together with market-level data on prices and call traffic to identify price-mediated network effects.

In the Home OnLine survey, consumers were asked about the approximate value of quarterly mobile telephone bill and about the average number of calls they make each week. Quarterly bill value represents consumer specific cost of using selected mobile services. Estimating the equation (5), quarterly telephone bill values are used as service prices p_{ijt}, which are regressed on firm dummies and consumer demographics. All individuals, which provided cost information

[9]When some randomness in usage behavior is considered, monthly bill values presented in Table (4) would not be differentiable.

in the second (277) and third wave (235) are pooled together.[10] Some consumers provided cost information in both waves but declared values differ. Outliers are eliminated by choosing consumers, which declared quarterly telephone bills between £10 and £500. In the second wave, 261 consumers provided cost information fulfilling this criteria and in the third wave 215 consumers. Since the impact of network attributes x_{jt} cannot be identified, only firm dummies are estimable. When the assumption on prices is correct, there should be no significant differences in the average quarterly bill values declared by consumers, which are subscribed to 'incumbents' and similarly for consumers of 'entrants'.

The list of consumer characteristics, which may influence quarterly telephone bill values and switching between networks is given in Table (7). In the selection of consumer characteristics, data availability is considered as well as intuitive significance and correlation with declared telephone bills. All these variables may be interpreted as quantitative, except the employment status. Dummies for being employed, retired and full-time student or at school are used in the regression. The unemployment dummy includes all other categories such as: on maternity leave, looking after family or home, long term sick or disabled, on a government training scheme and something else as unemployed. Most variables take ordered discrete values and the negative or positive correlation with quarterly bill value has a plausible interpretation, even though correlation coefficients are rather small. For instance, negative correlation of the variable 'Leisure: meal in restaurant-cafe' and 'Leisure: drink in pub-club' with quarterly telephone bill indicates that people going out more often tend to have higher bills. While people who spend more time on reading books 'Leisure: read books' tend to have lower telephone bills. This is an intuitive result suggesting that people with active social life use mobile services more frequently but the casuality may be also in opposite direction. The same set of variables is used in estimating the logistic switching regression (4).

Finally, there are some consumer characteristics, which may represent observable consumer heterogeneity and determine a match between consumer preferences and service offer of particu-

[10] In the first wave 203 individuals provided quarterly bill values but most relevant explanatory variables are missing.

lar operators. The estimation uses sex, age, employment status and income proxies, such as the number of computers and TV sets in the household (for simple statistics see Table 5). Unfortunately, data on some consumer characteristics, which could explain consumer heterogeneity are not available for all three waves, such as, the number of friends, which are contacted by phone, number of non-local friends and relatives, hours spent on housework and others. These variables also significantly determine choice of network operators when multinominal logit is estimated just for the 3rd wave.

5 Estimation Results

5.1 MNL and Mixed Logit

First, multinominal logit is estimated, assuming that switching costs are the same across networks (specification I in Table (6)). As discussed in the subsection on the estimation methodology, simple logit ignores the presence of persistent heterogeneity but it may be considered as a base model for comparison. True and spurious state dependence should be identifiable by estimating a mixed logit (specification III in Table 6).

In the MNL estimation, all consumer characteristics have plausible signs, for example, the probability of continued fixed line usage decreases for employed individuals and increases for females. Moreover, younger people are more willing to start using mobile services. Members of better equipped households, that is with at least one computer and a greater number of TV sets, are more willing to use mobile services, which may be due to higher income level. There are differences in the coefficient estimates across networks, which should capture part of consumer heterogeneity. Since only differences in utility matter, these estimates are interpreted as the differential effect on the utilities of mobile operators, compared to fixed line subscription.

Network-specific constants capture the average impact on the utility of all factors, that are not included in the model. The utility of the outside option (fixed line telephony) is normalized to zero. Thus, the constants are interpreted as the average impact of all non-included factors on the utility of mobile networks relative to fixed line. The value of mobile telephony is rising over

time, as represented by dummies for waves 2 and 3. When the persistence of tastes is ignored, significant average switching costs are estimated.

In the second specification, switching costs are assumed to differ according to the network, from which consumers switch (specification II in Table 6). As already argued, this may be explained by different contractual and psychological costs. Indeed, there are significant differences in switching costs according to MNL estimation. The consumers of Orange have the highest switching costs and consumers of Vodafone the lowest. The likelihood ratio test can reject the hypothesis, that switching costs do not differ across network operators. The test statistics is equal to $\chi^2 = -2ln\frac{L_0}{L_1} = 120$, while the critical value for 3 degrees of freedom equals to $\chi^2(0.05, 3) = 7.82$.

Next, mixed logit is estimated, in which consumers are assumed to have persistent unobserved brand preferences, given by non-zero ξ_{ij} in the utility specification (1). This implies temporal and intertemporal dependence of choices. The panel data includes three time observations for 768 individuals. For the remaining 606 individuals there are only two time observation. There is significant variation in individual preferences for network operators (specification III and IV in Table 6). The overall fit is much better for mixed logit specification. The likelihood ratio test can reject the hypothesis, that there is no persistent consumer heterogeneity. The test statistics is equal to $\chi^2 = 936$, which is much greater than the critical value for 4 degrees of freedom $\chi^2(0.01, 4) = 13.27$ (specification II against III in Table 6). The estimates of switching costs change drastically, compared to MNL estimates, and become insignificant for the 'entrants', that is Orange and One2One. Surprisingly, switching costs are estimated to be positive for the incumbent operators Cellnet and Vodafone, which implies that subscribers to these network benefit from switching to other operators. This is an unexpected result, which could have explanation only if consumers were paid for switching network operator by the competitors, for instance, by getting free calling time. There is no official information, that such practices were in place in the mobile telephony in the UK. Potentially, this result may be due to misspecification of the model, and in particular due to the assumption on lack of variation in individual price. If the

incumbents, and in particular Vodafone, charged higher prices, consumers would benefit from switching by a decrease in the cost of using mobile services. For a comparison a specification without switching costs is estimated (specification IV in Table 6). The worsened fit suggests presence of true state dependence, as estimated in specification III in Table 6.

5.2 Regression Analysis

Next, quarterly bill values are regressed on consumer characteristics and firm dummies using simple OLS estimation (see Table 8). The variables, which are significant in the pricing regression (5) should be also significant in logistic switching regression (4). The pricing regression suggests that just a few consumer characteristics significantly determine the value of telephone bill (Table 8). The explanatory power of this model is relatively small with $R^2 = 0.34$ and most of the variation remains unexplained. The estimates may be explained in a following way. The set of variables (Class) are dummies representing the frequency of using mobiles. The consumers are divided into six classes depending on the average number of calls per week (1st class are the infrequent users and 6th are the heaviest users). The consumers which declared themselves to be among the heaviest users declared also higher quarterly telephone bills. Moreover, only dummy for Vodafone (Vodafone) turned out to be significant implying that consumers of Vodafone declared to have higher bills than subscribers to other networks. Thus, the services of Vodafone may be on average slightly more expensive – around £9 more in a quarter. Such lack of difference may be some justification for the assumption, that individuals face equal prices across network operators.

Older consumers tend to have lower telephone bills as the age variable (Age) is highly significant and negative. Moreover, the consumers which tend to go out more often, in particular spend more leisure time on eating in restaurants-cafes (Leisurd) and watch live sport (Leisurb), pay higher bills. Finally, consumers which reasoned the purchase of mobile phone as very important (Mpwhy1st), useful for work (Mpwhy2) and personal safety (Mpwhy7) tend to pay higher bills. Consumers which declared that their usage of fixed line services was to a higher extend

replaced by mobile services (Mpuse) pay higher bills. All these results seem to be reasonable. Interestingly, a time dummy, which is supposed to measure a change in quarterly bill values in time is insignificant (3rd wave). Thus, in both waves consumers declared to spend on average the same amount on mobile telephony, even though service prices could decrease.

Finally, the determinants of switching are estimated in the group of consumers, which provided information about mobile operator they use, both in the second and third wave.[11] The estimation results of the logistic regression (4) are presented in (Table 9). Consumers which subscribed to Orange are less likely to switch and consumers of Vodafone more likely, relative to consumers of BT Cellnet. This result is in accordance with the estimates of switching costs. Some variables which were significant in the pricing regression are significant in the switching regression as well. Older consumers are less willing to switch (Age), which is consistent with findings in the Oftel's surveys. Consumers who tend to spend more time on reading books (Leisurg) and on housework (Housewk) are more willing to switch, but also consumers who spend more time on watching live sport (Leisurb) are more willing to switch. Finally, consumers which declared that their usage of fixed line services was to a higher extend replaced by mobile services (Mpuse) are more likely to switch networks. This is also consistent with Oftel's finding that heavier users tend to switch more. A few tests are listed in Table 9 of the null hypothesis, that none of the explanatory variables is related to changes in probability of switching, such as the AIC, Schwartz Bayesian Criterion and Likelihood-Ratio test. The tests do not allow to reject the model.

6 Conclusion

Numerous studies suggest presence of substantial switching costs in mobile telephony. This paper estimates the magnitude of switching costs in mobile industry using mixed logit for panel data on British households in years 1999-2001. There seems to be no evidence for switching

[11] The estimation of determinants for switching between first and second wave is not possible due to missing data but there should be no significant differences.

costs in mobile telephony in the UK. The time-dependence of choice of network operators is due to persistent tastes. The choices of network operators are also explained by consumer characteristics, such as sex, age, employment status and household equipment. These factors account for observable consumer heterogeneity in choices of network operators. Furthermore, in a logistic regression, the probability of switching depends on consumer characteristics, such as age, usage intensity and ways of spending leisure time. This is consistent with findings in consumer surveys conducted by the British regulator Oftel.

One possible explanation for the lack of switching costs is, that the regulation, such as number portability implemented in January 1999 and other, effectively contributed to lowering the cost of changing network operators. The empirical results in this study suggest, that switching costs should not be used as an argument for further regulatory intervention in mobile telephony in the UK.

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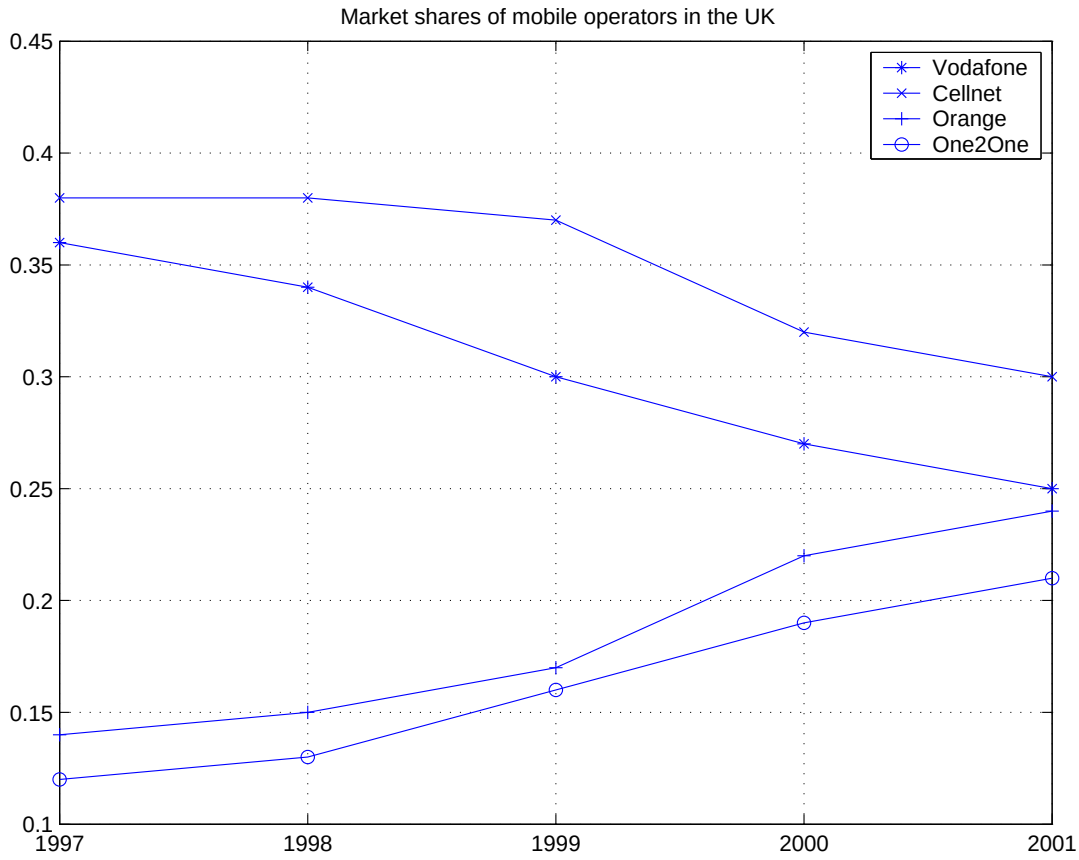
7 Appendix

Table 1: Switching between waves 1/2 and 2/3

Wave 1/2	Cellnet	Orange	Vodafone	One2One	New	Total	Oftel
Cellnet	52	8	8	9	0	77	
	67.53%	10.39%	10.39%	11.69%		32.22%	34.00%
Orange	3	34	0	5	0	42	
	7.14%	80.95%	0.00%	11.90%		17.57%	15.00%
Vodafone	18	9	65	3	0	95	
	18.95%	9.47%	68.42%	3.16%		39.75%	38.00%
One2One	3	0	5	17	0	25	
	12.00%	0.00%	20.00%	68.00%		10.46%	13.00%
Total	76	51	78	34	0	239	
	31.80%	21.34%	32.64%	14.23%		100.00%	
New	99	67	81	45	480	772	
	33.90%	22.95%	27.74%	15.41%		100.00%	
Wave 2/3	Cellnet	Orange	Vodafone	One2One	New	Total	Oftel
Cellnet	148	9	19	13	0	189	
	78.31%	4.76%	10.05%	6.88%		32.98%	32.00%
Orange	9	126	6	3	0	144	
	6.25%	87.50%	4.17%	2.08%		25.13%	22.00%
Vodafone	23	15	112	13	0	163	
	14.11%	9.20%	68.71%	7.98%		28.45%	27.00%
One2One	10	7	3	57	0	77	
	12.99%	9.09%	3.90%	74.03%		13.44%	19.00%
Total	190	157	140	86	0	573	
	33.16%	27.40%	24.43%	15.01%		100.00%	
New	61	83	53	41	320	558	
	25.63%	34.87%	22.27%	17.23%		100.00%	

Figure 1:



Source of data: http://www.ofcom.org.uk

Table 2: Consumer choices over three waves

Wave 1	Wave 2/3	New	Cellnet	Orange	Vodafone	One2One	missing	Total
New	New	230	37	62	37	28	86	480
	Cellnet	5	61	3	4	4	22	99
	Orange	2	2	50	2	1	10	67
	Vodafone	4	9	3	30	6	29	81
	One2One	3	3	2	0	20	17	45
	Total	244	112	120	73	59	164	772
Cellnet	New	2	1	0	0	1	0	4
	Cellnet	1	33	1	4	3	10	52
	Orange	1	1	3	1	0	2	8
	Vodafone	0	2	1	3	0	2	8
	One2One	1	2	0	0	3	3	9
	Total	5	39	5	8	7	17	81
Orange	New	2	1	0	0	0	0	3
	Cellnet	0	1	0	0	1	1	3
	Orange	0	1	17	2	1	13	34
	Vodafone	0	0	0	0	0	0	0
	One2One	1	0	1	0	1	2	5
	Total	3	3	18	2	3	16	45
Vodafone	New	2	0	1	2	0	0	5
	Cellnet	0	10	0	3	1	4	18
	Orange	1	0	7	0	0	1	9
	Vodafone	0	4	6	34	4	17	65
	One2One	0	0	0	0	2	1	3
	Total	3	14	14	39	7	23	100
One2One	New	0	1	0	0	0	0	1
	Cellnet	0	1	0	0	1	1	3
	Orange	0	0	0	0	0	0	0
	Vodafone	0	0	0	3	0	2	5
	One2One	0	0	0	1	7	9	17
	Total	0	2	0	4	8	12	26
missing	New	83	19	20	14	12	0	148
	Cellnet	0	42	5	8	3	0	58
	Orange	0	5	49	1	1	0	56
	Vodafone	0	8	4	41	3	0	56
	One2One	0	5	4	2	21	0	32
	Total	83	79	82	66	40	0	350

Table 3: Call success rate survey

	Held calls	Set-ups	Connect& complete	Held calls	Set-ups	Connect& complete
	Cellnet			One2One		
East Anglia	95.2%	95.9%	99.3%	98.8%	99.4%	99.4%
London	96.6%	98.4%	98.2%	96.0%	97.3%	98.7%
Midlands	97.4%	98.6%	98.8%	97.4%	98.6%	98.8%
Northern England	97.2%	98.5%	98.7%	97.0%	98.5%	98.5%
Northern Ireland	93.8%	96.6%	97.2%			
Scotland	95.4%	98.0%	97.4%	88.0%	91.6%	96.1%
South East Engl.	96.4%	98.3%	98.1%	96.6%	98.4%	98.2%
South West Engl.	96.2%	97.7%	98.5%	96.8%	98.6%	98.2%
Wales	94.8%	96.4%	98.4%	84.7%	88.3%	95.8%
National	96.5%	98.1%	98.3%	95.6%	97.3%	98.3%
	Orange			Vodafone		
East Anglia	98.8%	99.3%	99.5%	98.9%	99.4%	99.5%
London	97.4%	99.0%	98.4%	96.0%	97.2%	98.8%
Midlands	97.6%	98.4%	99.3%	96.8%	98.2%	98.6%
Northern England	98.6%	99.2%	99.5%	96.5%	98.3%	98.2%
Northern Ireland	97.2%	98.2%	99.1%	95.8%	97.0%	98.8%
Scotland	96.1%	96.9%	99.2%	96.3%	98.2%	98.1%
South East Engl.	97.5%	98.4%	99.1%	97.3%	98.6%	98.7%
South West Engl.	97.9%	99.1%	98.8%	97.2%	98.5%	98.7%
Wales	96.7%	97.7%	98.9%	90.4%	93.8%	96.3%
National	97.7%	98.6%	99.1%	96.4%	97.9%	98.4%

Source: Mobile network operators' call success rate survey October 1999 – March 2000, Published May 2000 by Oftel

Table 4: Representative mobile packages in the UK for two different calling patterns

Operator	Package	Fix.	Nat.	Mob.	Int.	SMS	Disc.	Hand	Sum
Basket 1									
Orange	Pre/Just Talk	0.0	12.8	4.5	0.2	2.8	0.0	60.0	80
One2One	Pre/Up2You Std	0.0	15.5	3.4	1.4	0.7	0.0	60.0	81
Cellnet	Pre/Pay & Go	0.0	18.3	4.3	1.4	3.1	0.0	60.0	87
Vodafone	Pre/Pay As U Talk	0.0	18.3	4.9	0.6	8.3	0.0	60.0	92
Basket 2									
Orange	Pre/Just Talk	0.0	40.6	16.9	1.7	3.6	0.0	60.0	123
One2One	Pre/Up2You Std	0.0	48.7	12.7	13.5	2.4	0.0	60.0	137
Cellnet	Pre/Pay & Go	0.0	58.0	16.2	13.5	4.8	0.0	60.0	152
Vodafone	Pre/Pay As U Talk	0.0	58.0	18.6	6.2	10.4	0.0	60.0	153

Source: "International benchmarking study of mobile services and dial-up PSTN Internet access", Oftel, December 2000

Table 5: Descriptive statistics of variables used in simple logit and mixed logit

Variable						
Wave 3	Description	N	Mean	STD	Min	Max
work	employment dummy	1131	0.59	0.49	0	1.0
sex	sex (female=2)	1128	1.56	0.49	1	2.0
age	age	1126	47.29	16.63	16	87.0
compuse	use a computer at home	1131	0.81	0.69	0	8.0
tvnumbr	number of TV sets	1088	2.71	1.26	0	8.0
Wave 2						
work	employment dummy	1374	0.59	0.49	0	1.0
sex	sex (female=2)	1374	1.55	0.49	1	2.0
age	age	1356	45.60	16.86	2	90.0
compuse	use a computer at home	1374	0.78	0.66	0	2.0
tvnumbr	number of TV sets	1360	2.61	1.17	0	7.0
Wave 1						
work	employment dummy	1011	0.58	0.49	0	1.0
sex	sex (female=2)	1011	1.56	0.49	1	2.0
age	age	1011	44.88	16.59	16	89.0
compuse	use a computer at home	1011	0.72	0.67	0	2.0
tvnumbr	number of TV sets	1009	2.53	1.09	0	5.0

Table 6: Simple logit and mixed logit for panel data

		I		II		III		IV	
	Variables	Est.	t	Est.	t	Est.	t	Est.	t
dummies	r Cellnet	-2.036	-5.24	-2.094	-5.39	-4.982	-5.17	-4.388	-5.45
	r Orange	-2.322	-5.77	-2.435	-6.19	-6.885	-7.07	-6.289	-7.03
	r Vodafone	-1.910	-4.70	-1.949	-4.78	-4.685	-4.36	-4.074	-4.48
	r One2One	-2.134	-4.45	-2.244	-4.74	-6.461	-5.53	-5.917	-5.28
randomness	σ Cellnet					4.382	15.16	3.856	15.80
	σ Orange					4.188	12.88	3.838	13.37
	σ Vodafone					5.095	12.61	4.245	14.29
	σ One2One					4.511	11.36	3.968	10.90
time	wave 2	1.918	21.55	1.656	20.70	3.124	15.16	2.864	16.36
	wave 3	2.889	25.56	2.986	26.19	5.411	19.74	4.941	20.93
switching	s	-1.140	13.25						
	s Cellnet			-1.389	-8.62	0.888	2.74		
	s Orange			-2.335	10.15	-0.471	-1.18		
	s Vodafone			-1.028	-6.85	2.063	6.65		
	s One2One			-1.919	-7.18	0.293	0.62		
Cellnet	age	-0.029	-7.25	-0.029	-7.25	-0.061	-6.10	-0.058	-6.44
	sex	-0.523	-3.58	-0.518	-3.54	-1.011	-2.84	-0.898	-2.91
	employed	0.759	5.12	0.807	5.41	1.191	3.67	1.135	3.94
	compuse	0.326	3.32	0.331	3.37	0.338	1.75	0.324	1.84
	tvnumbr	0.361	5.73	0.360	5.71	0.594	4.33	0.521	4.30
Orange	age	-0.030	-7.50	-0.029	-7.25	-0.052	-4.72	-0.049	-4.90
	sex	-0.371	-2.42	-0.352	-2.36	-0.376	-1.06	-0.346	-1.03
	employed	0.719	4.57	0.743	4.82	1.193	3.55	1.171	3.78
	compuse	0.390	3.86	0.386	3.89	0.582	2.92	0.581	3.26
	tvnumbr	0.317	5.11	0.305	5.08	0.498	3.83	0.489	4.04
Vodafone	age	-0.030	-7.50	-0.030	-7.50	-0.070	-5.83	-0.061	-6.10
	sex	-0.584	-3.81	-0.588	-3.81	-1.378	-3.35	-1.320	-3.60
	employed	0.934	5.87	0.997	6.23	1.862	4.92	1.653	4.83
	compuse	0.293	2.71	0.303	2.80	0.387	1.62	0.341	1.55
	tvnumbr	0.292	4.78	0.300	4.83	0.397	2.66	0.374	2.92
One2One	age	-0.041	-8.20	-0.040	-8.00	-0.081	-6.23	-0.073	-6.08
	sex	-0.388	-2.12	-0.373	-2.06	-0.436	-0.96	-0.422	-1.04
	employed	0.489	2.74	0.526	2.97	0.412	1.08	0.494	1.38
	compuse	0.335	2.51	0.339	2.54	0.430	1.65	0.459	1.95
	tvnumbr	0.318	4.67	0.314	4.61	0.491	3.18	0.494	3.45
Log Lik.	N of obs.	3433		3433		3433		3433	
	N of cases	17165		17165		17165		17165	
	Log Lik.	-4050		-3987		-3519		-3547	

Table 7: Descriptive statistics of variables used in pricing and switching regression

Variable	Description	N	Mean	STD	Min	Max	Corr.
Mobbill	Quarterly mobile bill	672	87.70	71.58	12.0	450.0	1.00
Mpcalln	Mobile - average calls per week	672	3.53	1.64	1.0	6.0	0.51
Cellnet	Cellent dummy	672	0.32	0.47	0.0	1.0	-0.05
Orange	Orange dummy	672	0.20	0.40	0.0	1.0	0.05
Vodafone	Vodafone dummy	672	0.32	0.47	0.0	1.0	-0.00
One2One	One2One dummy	672	0.12	0.33	0.0	1.0	0.02
Age	Age	668	40.49	12.85	16.0	77.0	-0.14
Leisurb	Leisure: watch live sport	672	4.51	1.11	1.0	6.0	-0.06
Leisurd	Leisure: meal in restaurants	672	2.84	0.90	1.0	6.0	-0.21
Leisurh	Leisure: drink in pub-club	476	2.95	1.25	1.0	5.0	-0.14
Leisurg	Leisure: read books	672	2.59	1.64	1.0	6.0	0.06
locrang	Non-local friends&relatives	476	3.15	1.61	0.0	5.0	0.08
Housewk	Time spent housework in week	650	8.49	8.36	0.0	70.0	-0.14
Rushd	Rush - tasks around home	476	2.86	1.14	1.0	8.0	0.09
Rushe	Rush - shop for essentials	476	3.35	1.10	1.0	8.0	-0.09
Mpwhy2	Mobile - reason useful for work	536	1.60	0.48	1.0	2.0	-0.26
Mpwhy7	Mobile - reason personal safety	476	1.36	0.48	1.0	2.0	0.32
Mpwhy1st	Mobile - reason 1st important	476	2.29	1.26	1.0	5.0	-0.18
Mpuse	Mobile - replace phone use	672	2.70	0.60	1.0	8.0	-0.27
Mptype	Mobile - payment type	476	2.05	0.57	2.0	9.0	-0.08
Empstat	Current employment situation	672	1.77	1.62	1.0	9.0	-0.11
Employed	Employment dummy	672	0.76	0.42	0.0	1.0	0.16
Retired	Retirement dummy	672	0.09	0.28	0.0	1.0	-0.11
Nowork	Unemployment dummy	672	0.08	0.28	0.0	1.0	-0.14
Student	Student dummy	672	0.05	0.22	0.0	1.0	0.03

Table 8: Determinants of quarterly telephone bills

	Model I			Model II		
Variable	estimate	t-value	sign.	estimate	t-value	sign.
Intercept	197.27	4.86	0.00	199.36	6.49	0.00
Class 2	-0.07	-0.00	0.99			
Class 3	3.43	0.19	0.84			
Class 4	14.00	0.74	0.46	13.39	1.34	0.17
Class 5	20.12	1.05	0.29	18.82	1.80	0.07
Class 6	61.14	3.36	0.00	60.26	7.14	0.00
Orange	9.75	1.12	0.26			
Vodafone	14.22	1.86	0.06	9.14	1.43	0.15
One2One	12.83	1.24	0.21			
Age	-0.48	-1.54	0.12	-0.57	-2.47	0.01
Leisurb	-5.82	-1.84	0.06	-5.41	-1.81	0.07
Leisurd	-13.34	-3.30	0.00	-12.17	-3.29	0.00
Leisurh	0.56	0.20	0.83			
Leisurg	0.74	0.37	0.71			
Locrang	0.47	0.23	0.81	5.35	1.90	0.05
Housewk	0.03	0.08	0.94			
Rushd	-0.74	-0.25	0.79			
Rushe	-1.49	-0.51	0.61			
Mpwhy2	-15.26	-1.81	0.07	-17.15	-2.27	0.02
Mpwhy7	17.15	2.25	0.02	16.21	2.25	0.02
Mpwhy1st	-4.17	-1.53	0.12	-4.09	-1.59	0.11
Mpuse	-11.31	-2.03	0.04	-13.06	-2.52	0.01
Mptype	-3.67	-0.70	0.48			
3rd Wave	-4.12	-0.65	0.51			
Retired	-4.08	-0.34	0.73			
Nowork	-1.50	-0.12	0.90			
Student	-0.39	-0.03	0.97			
R-Square	0.34			0.34		
Root MSE	63.83			62.47		
N used	455			464		

Table 9: Analysis of Maximum Likelihood Estimates

	Model I			Model II		
Variables	Estimate	Wald χ^2	sign.	Estimate	Wald χ^2	sign.
Intercept	1.37	0.97	0.32	-0.38	0.23	0.62
Class 2	0.004	0.00	0.99			
Class 3	-0.33	0.36	0.54			
Class 4	0.23	0.14	0.70			
Class 5	-0.45	0.47	0.49			
Class 6	-0.17	0.08	0.76			
Orange	-0.54	2.66	0.10	-0.63	4.27	0.03
Vodafone	0.53	3.84	0.04	0.48	4.22	0.03
One2One	0.30	0.77	0.37			
Age	-0.02	4.01	0.04	-0.01	5.74	0.01
Leisurb	-0.19	3.23	0.07	-0.18	3.08	0.07
Leisurd	0.06	0.22	0.63			
Leisurh	-0.10	1.08	0.29			
Leisurg	-0.21	7.62	0.00	-0.18	6.59	0.01
Locrang	0.006	0.00	0.93			
Housewk	0.02	3.83	0.05	0.02	4.55	0.03
Rushd	-0.03	0.12	0.72			
Rushe	-0.06	0.32	0.57			
Mpwhy2	-0.47	2.74	0.09			
Mpwhy7	-0.35	1.49	0.22			
Mpwhy1st	0.04	0.23	0.62			
Mpuse	0.32	1.87	0.17	0.30	1.90	0.16
Mptype	-0.04	0.07	0.78			
Retired	0.48	1.86	0.17	0.41	1.60	0.20
Nowork	0.26	0.27	0.59			
Student	-0.11	0.06	0.79			
Model Fit	Intercept	Covariates		Intercept	Covariates	
N used	550			550		
AIC	581.599	585.067		581.599	559.752	
SC	585.909	697.125		585.909	598.542	
-2 Log L	579.599	533.067		579.599	541.752	
L-Ratio	46.53	0.0056		37.84	0.0001	
Score	44.47	0.0096		36.46	0.0001	
Wald	40.19	0.0278		33.67	0.0001	