The role of network effects and consumer heterogeneity in the adoption of mobile phones: evidence from South Africa

Lukasz Grzybowski

ERSA working paper 522

May 2015

Economic Research Southern Africa (ERSA) is a research programme funded by the National Treasury of South Africa.

The views expressed are those of the author(s) and do not necessarily represent those of the funder, ERSA or the author's affiliated institution(s). ERSA shall not be liable to any person for inaccurate information or opinions contained herein.

The role of network effects and consumer heterogeneity in the adoption of mobile phones: evidence from South Africa

Lukasz Grzybowski*

May 31, 2015

Abstract

In this paper we analyze the role of network effects and consumer heterogeneity in the adoption of mobile phones. We estimate the decision to adopt a mobile phone using panel survey data of South African households between the years 2008 and 2012, which includes interviews with all adult household members. We construct variables which approximate network effects on the household level and find that the greater the number of mobile phones in the household, the greater the likelihood that the other household members will also adopt a mobile phone. Moreover, network effects depend on who in the household adopts a mobile phone. Without within-household network effects the penetration of mobile phones of 76.4% in 2012 would be lower by about 9.9 percentage points. The decision to adopt a mobile phone is also explained by observed and unobserved consumer heterogeneity.

Key Words: Mobile phones; Network effects; Consumer heterogeneity

JEL Classification: L13; L96

*Telecom ParisTech, Department of Economics and Social Sciences, 46 rue Barrault, 75013 Paris, France & School of Economics, Faculty of Commerce, University of Cape Town, Private Bag, Rondebosch 7701, Cape Town, South Africa. E-mail: lukasz@mushroomski.com

1 Introduction

In the last two decades mobile phones became the most important means of remote communication. At the end of 2014 there were nearly 7 billion subscriptions to mobile telecommunications services around the world.[1] In developing countries, where fixed-line telecommunications have not been deployed across the whole territory and especially in the rural areas, mobile phones are usually the only means of remote communication available to people. Mobile phones are also increasingly used as a platform through which services such as mobile banking are delivered. However, since mobile internet is not yet commonly used in the developing countries, the core value of mobile phones still comes from making and receiving calls and from texting, where the greatest share of communications presumably takes place between household members. There are therefore significant network effects from the adoption of mobile phones by household members, i.e., the utility from having a mobile phone should increase when the other household members also adopt mobile phones.

In this paper we analyze the role of network effects in the adoption of mobile phones. We use panel data of South African households including separate interviews conducted among all adult household members between the years 2008 and 2012. This data allows us to test empirically whether the fact that a particular household member has a mobile phone influences the decision by other household members to get a mobile phone. Network effects are approximated by the identity and number of household members who declared having mobile phones. To identify network effects a rich set of individual and household characteristics is included in the estimation such as gender, age, professional activity, household size, the type of dwelling, income and others. Apart from the observed heterogeneity represented by these characteristics we also account for the unobserved heterogeneity. We make use of panel data and estimate individual-specific random effects which are assumed to be normally distributed.

We find that both network effects and heterogeneity matter for the adoption of mobile phones. The greater the number of mobile phones in the household, the greater the likelihood that the other household members will adopt mobile phones as well. Moreover, network effects depend on who in the household has a mobile phone. When the main decision maker has a mobile phone it is less likely that the other household members adopt mobile phones. We argue that this is because

[1] See International Telecommunications Union (ITU) at http://www.itu.int

low-income households may opt for a single mobile phone to be used by all household members to communicate with non-household members. We confirm this by estimating additional regressions for the sub-samples of individuals from poorer and wealthier households. This effect prevails for the poorer households but not for wealthier ones. Without within household network effects the penetration of mobile phones of 76.4% in 2012 would be lower by about 9.9 percentage points.

Our results suggest that the typically observed s-shaped diffusion pattern of mobile phones can be explained by both the presence of network effects and consumer heterogeneity. On the one hand, network effects cause an exponential growth in the number of adoptions after the critical mass is reached (see Cabral (1990) for a theoretical model of the diffusion of innovations with network externalities). On the other hand, an s-shaped diffusion pattern is caused by consumer heterogeneity (see Karshenas and Stoneman (1993)). As our results suggest, there are relatively few consumers with a very high valuation of mobile phones and similarly relatively few with a very low valuation. The valuation of the majority of consumers due to both observed and unobserved factors is close to the average. Hence, when the cost of adoption decreases, mobile telephones are increasingly purchased by consumers with lower valuations which, for normally distributed valuations, results in an s-shaped diffusion pattern.

The remainder of the paper is organized as follows. Section 2 summarizes the previous research on the diffusion of mobile phones and network effects. Section 3 introduces the data. Section 4 discusses the empirical framework. Section 5 presents the estimation results and finally, Section 6 concludes.

2 Literature Review

There is a large body of research on the diffusion of mobile telecommunications services. Most of these studies use aggregate cross-country data. For instance, Gruber and Verboven (2001) estimate a logistic diffusion model for the EU countries and find that regulation and technological progress are important for the growth of the mobile industry. In another paper estimating a logistic diffusion model, Koski and Kretschmer (2005) analyze the effects of regulation and competition on the development of mobile telephony. These studies do not account for the presence of network externalities and, due to the nature of the data, heterogeneity is allowed only across countries. Therefore, they do not explain what causes the estimated s-shaped diffusion pattern.

Another stream of research tests the hypothesis of network effects to explain the diffusion of mobile phones. For instance, Doganoglu and Grzybowski (2007) estimate demand for subscription to mobile services in Germany using nested logit model for aggregate data and acknowledge the importance of network effects in the diffusion process. In another paper, Grajek (2010) finds significant network effects in the Polish mobile telephone industry. Since these studies focus on a single country assuming a representative consumer, they do not allow for the diffusion pattern to be explained by both network effects and consumer heterogeneity. Only consumer-level information observed over time with a good proxy for network effects can disentangle the impact of both effects.

Furthermore, Grajek and Kretschmer (2012) empirically investigate the existence of critical mass in the mobile telephony diffusion and Grajek and Kretschmer (2009) try to identify the network effects by studying mobile phone usage intensity. Based on panel data for operators in 41 countries they conclude that heterogeneity among adopters dominates network effects. Among papers which estimate network effects using individual-level survey data, Kim and Kwon (2003) conclude that Korean consumers prefer carriers that have larger consumer bases. In another paper, Birke and Swann (2006) use household survey data to identify price-mediated network effects in mobile telephony in the UK.

The papers mentioned above study network effects on the market level. However, in telecommunications markets, network effects are in general a local phenomenon, i.e., the main contacts are family and friends who live in the same local area. There are a few papers which study the role of local network effects from a theoretical or empirical perspective. For instance, Sundararajan (2007) develops a theoretical model in which agents, who are connected in a social network, value the adoption of a product by a heterogeneous subset of other agents in their neighborhood. Each agent is located at a node of a graph, knows the nodes that he/she is connected with, but is not informed about the rest of the network structure. Sundararajan shows how in this setup the resulting network of adopters is influenced by the underlying social structure. On the empirical side, Birke and Swann (2005) study the coordination within each consumer's social network based on a survey of students in the UK. They find that the probability that two students have the same operator is higher the more frequently they call one another. In another paper, based on a survey of Italian students, Corrocher and Zirulia (2009) find evidence that consumers take into account local networks when deciding on mobile operators. They also find that consumers are highly heterogeneous with respect to the importance they give to the operators chosen by their friends/family members when choosing which provider to use. Birke and Swann (2010) use student surveys from four different countries and find that individuals' choice of network operator is strongly influenced by the network choices of their local social network and only to a lesser extent by the total number of consumers on the network. Finally, Karacuka et al. (2013) use a survey data of Turkish consumers to analyze the determinants of mobile network subscriptions. They find that consumer choice is significantly affected by the local share of network operators, thereby concluding on the existence of local network effects which may outweigh macro network effects.

There is also a large body of empirical literature which estimates the role of network effects in different industries. Park (2003) and Ohashi (2003) estimate direct network effects using time series data for video recording systems. Other papers estimate direct network effects using regional cross-sectional data, for instance Goolsbee and Klenow (2002) for home computers and Rysman (2002) for Yellow Pages telephone books. Other papers identify indirect network effects by estimating the impact of the variety of complementary products on the utility which consumers derive from the primary product. Gandal et al. (2000) study the diffusion of CD technology and find that the number of CD titles available has an impact on the consumer's willingness to adopt a CD player. Clements and Ohashi (2005) estimate indirect network effects in the US video game market. A discussion of the problems in identifying network effects with high-level time series and cross-sectional data can be found in Gowrisankaran and Stavins (2004). They propose ways to identify network effects in a reduced form model using data on the adoption of automated clearing house technologies by individual banks.

In this paper, we identify direct network effects at the household level after controlling for a rich set of individual and household characteristics and unobserved heterogeneity. Since we use panel data of household members we can estimate individual fixed effects, which represent the propensity to adopt a mobile phone. By estimating both network effects and consumer heterogeneity, we can conclude the role which network effects and heterogeneity play in the diffusion of mobile phones.

3 The Data

Our analysis is based on the National Income Dynamics Survey (NIDS), which is the first nationwide set of panel survey data in South Africa collected by the Southern Africa Labour and Development Research Unit (SALDRU) at the University of Cape Town (UCT), done in three waves: 2008, 2011 and 2012. The data includes information on a representative sample of households and their members living across the country.[2]

The survey combines household-level interviews (administered to the oldest woman in the household) with questionnaires addressed to individual household members. There are separate questionnaires for adults (aged 15 or older) and children (directed to the mother or the caregiver). In this analysis we only consider questionnaires from adult household members.

The first wave of the survey completed in December 2008 includes information on 7,236 households and 16,871 adult individuals. The second wave was completed approximately two years later between May 2010 and September 2011 including 9,134 households and 21,880 adult individuals. The third wave was completed in 2012 including 10,236 households with 22,481 adult individuals. Table 1 shows the number of individuals in three waves used in the analysis and Table 2 the overlapping of individuals across the three waves.

Each questionnaire consists of several modules. Among other questions, the survey collects detailed information on household expenditure and consumption, demographics, education, personal asset ownership and debt, various income sources and intra-household decision-making. Table 3 shows the variables which are used in the estimation and the summary statistics. There is missing information on age and income for some individuals who are dropped from the data in the estimation.

The dependent variable is a 0-1 decision to adopt a mobile phone, which is the declaration of each survey respondent whether he has a mobile phone or not. During the data collection period many individuals adopted mobile phones but there were also some who gave up their mobile connections. The overall penetration in the sample used in the estimation changed from 56.8% in the first wave to 56.9% in the second wave and 76.3% in the third wave. The changes in the level of penetration over three waves across 53 municipalities in South Africa are shown in Table

[2]For description of sampling method see fieldwork manual which is available at http://www.nids.uct.ac.za from where the data was downloaded.

7 in the appendix. There is enough variation in the dependent variable for identifying the effects of both the observed characteristics and the unobserved heterogeneity.[3]

Our main variables of interest are the proxies for network effects. The decision whether to adopt a mobile phone may depend on whether other household members have mobile phones as well because people from the same household communicate with each other more frequently than with others. But the decision may also depend on the overall number of people who could be reached via mobile phone. We model the within-household adoption externality in dependence on the size of the household in the following way. There is no within-household externality for single households but they may overall be more likely to adopt mobile phones to be able to communicate with others. We may therefore observe that single households tend to have mobile phones more often than others. In the households which consist of two adults, the decision of one household member to adopt a mobile phone may have a positive adoption externality on the other household member. In households, which have three adult members, the adoption externality may be different when just one member adopts a mobile phone versus when two members have mobile phones. The expectation is that when two household members have mobile phones, it is more likely that the third member will adopt one as well, as compared to a situation in which only one out of the three household members has a mobile phone. In a similar way, we allow the adoption externality to vary in dependence on the number of mobile phone users in households with four, five, six and seven or more members. Hence, the network effects on the household level are represented by a set of dummy variables denoted by d_{ijk}, which take value of one when the household size of individual i is equal to j and the number of mobile phones used by the other household members is equal to k, where $0 < k < j$, and zero otherwise.

Apart from network effects on a household level, individuals also benefit from communication possibilities with non-household members. However, to identify these network effects one needs to approximate the number of people with whom individuals communicate using mobile phones. One possibility is to use the penetration rate of mobile phones in the municipality where the individuals reside as an approximation (regional network effects). This variable can be constructed

[3]The penetration of mobile phones in South Africa increased between 2011 and 2012 but remained unchanged between 2008 and 2011, while it decreased drastically in many municipalities. We do not have a clear explanation for this decline, which to some extent may be caused by the economic crisis.

from the sample by dividing the number of individuals with mobile phones by the total number of individuals residing in a particular municipality. A potential problem with the identification of regional network effects is that there may be unobserved regional factors which influence the adoption probability of all households in this municipality. For instance, the differences in mobile penetration on a regional level may reflect differences in coverage, on which we lack information. If coverage in certain municipalities was growing faster than in others, the growing number of subscribers at the aggregate level and the increased probability of subscription at the individual level could both be driven by the omitted coverage variable.

The regional fixed factors can be controlled for by means of regional dummies for 53 municipalities in South Africa. But regional network effects cannot be included at the same time due to multicollinearity. We estimated two model specifications. The first one with regional network effects but without regional dummy variables. The second one with regional dummy variables but without regional network effects. Based on the likelihood-ratio test the model with regional dummy variables is preferred over the model with regional network effects. Hence, in this analysis we are only able to account for household-level network effects.

Apart from that the likelihood of adopting a mobile phone may depend on which member of the household has a mobile phone, for which we also account using a set of dummy variables. We create the following dummy variables for the first and second decision-makers. First, a dummy variable is created which measures the impact of having a mobile phone by the first decision-maker on the mobile phone adoption by the other household members, and similarly for the second decision-maker. Another dummy variable measures the impact of having a mobile phone by the first decision maker on the mobile phone adoption decision by the second decision maker, and vice versa.

A potential problem with the identification of within-household network effects may be due to some unobserved household-specific factors having an impact on the adoption decisions of all household members, for instance there may be a general predilection for or against technology at the household level. The within-household network effects variables would then be endogenous. We try to control for these factors by including a large number of individual and household characteristics, including a set of dummy variables for the level of income, which are shown in Table 3. We also control for the unobserved preferences for mobile phones by means of individual random effects. The household-level predilection for a technology should be reflected in high values of individual effects for all members of the household.[4]

4 The Empirical Model

We analyze consumer decision to use a mobile phone. We can model this decision by means of a binomial logit model, where the consumer decides either to have a mobile phone or not. We assume that consumer i derives a linear utility from having a mobile phone at time t given by:

$$U_{it} = X_{it}\beta - \alpha p_{it} + N_{it}\gamma + \xi_i + \epsilon_{it} = V_{it} + \epsilon_{it} \tag{1}$$

where X_{it} denotes a vector of individual and household characteristics, p_{it} is the cost of getting a mobile phone and using the service, N_{it} is a vector of variables representing network effects, ξ_i are unobserved individual-specific preferences for having a mobile phone assumed to be normally distributed and ϵ_{it} is the error term which is assumed to be extreme value distributed. Hence, the choices of the individual are correlated over time due to common unobserved individual-specific component ξ_i.

Since we lack information on the type of mobile phone used by individuals and the cost of usage which may be individual specific, we have to ignore the term αp_{it} and cannot identify the price elasticity of mobile phone adoption. Instead, we allow the average utility to change between waves by means of time dummy variables, which may reflect changes in the level of both price and quality.[5] There may also be network effects on the country level which cannot be identified separately from time dummies. The focus of this analysis is nevertheless on the impact of household-level network effects and consumer heterogeneity on adoption decisions.

Hence, the probability that individual i makes a sequence of choices of having a mobile phone,

[4]Our model does not allow for the correlation of individual-specific effects across household members. An alternative approach to this problem is to estimate a model with household- rather than individual-specific effects. We have estimated such an alternative model specification and found that the impact on the estimation results is negligible.

[5]If all consumers in a given market face the same price, which is often assumed in the empirical studies of mobile telephony, then the price effect will be subsumed in the time dummies.

$y_{it}=1$, in periods $t \in G$ and not having a mobile phone, $y_{it}=0$, in periods $t \in H$, is given by:

$$\begin{aligned}
l_i(\beta,\gamma,\xi_i) &= \prod_{t\in G}\Pr(U_{it}\geq 0)\prod_{t\in H}\Pr(U_{it}<0) \\
&= \prod_{t=1}^{T} F(V_{it})^{y_{it}}(1-F(V_{it}))^{1-y_{it}} \\
&= \prod_{t=1}^{T}\left(\frac{\exp(X_{it}\beta+N_{it}\gamma+\xi_i)}{1+\exp(X_{it}\beta+N_{it}\gamma+\xi_i)}\right)^{y_{it}}\left(\frac{1}{1+\exp(X_{it}\beta+N_{it}\gamma+\xi_i)}\right)^{1-y_{it}}
\end{aligned} \tag{2}$$

where F is the cumulative density function for the logistic distribution of the error term ϵ_{it}. If there is no unobserved individual heterogeneity ξ_i, this is the standard binomial logit probability which enters the likelihood function. With unobserved heterogeneity, it is necessary to integrate the conditional adoption probability $l_i(\beta,\gamma,\xi_i)$ over the distribution of ξ_i:

$$P_i = \int_{\xi} l_i(\beta,\gamma,\xi_i) f(\xi)d\xi, \tag{3}$$

where $\xi_i \sim N(0,\sigma_\xi)$.

Assuming that the decisions of individuals $i=1,...,N$ are independent, the probability that each individual in the sample chooses the sequence of alternatives as observed can be written as the log-likelihood function:

$$\mathcal{L}(\theta) = \sum_{i=1}^{N}\log(P_i) \tag{4}$$

The vector of all parameters which are estimated is denoted by θ. To approximate the integral entering the adoption probabilities P_i given by equation (3) we use a simulation method with R random draws for ξ_i from the normal distribution. The average choice probability per individual is given by:

$$\widehat{P}_i = \frac{1}{R}\sum_{r=1}^{R}\prod_{t=1}^{T}\left(\frac{\exp(X_{it}\beta+N_{it}\gamma+\xi_i^r)}{1+\exp(X_{it}\beta+N_{it}\gamma+\xi_i^r)}\right)^{y_{it}}\left(\frac{1}{1+\exp(X_{it}\beta+N_{it}\gamma+\xi_i^r)}\right)^{1-y_{it}} \tag{5}$$

The maximum simulated likelihood estimator is the value of the parameter vector θ that maximizes the likelihood function $\mathcal{L}$ given by equation (4), after substituting formula (5) into P_i.[6] The model estimated in this paper is more general by allowing for unobserved heterogeneity in addition to observable individual and household characteristics.

[6] The algorithm for estimating a mixed logit model is explained in detail in Train (2003). We estimate the mixed logit model using Stata procedure mixlogit with 50 Halton draws. See Hole (2007) for estimation details.

5 Estimation Results

First, we estimate the logit model for all three waves without taking into account the panel structure of the data, see Table 4. Next, we estimate a mixed logit model with a random coefficient which accounts for the presence of unobserved individual preferences for adoption of mobile phones and therefore considers the panel structure of the data (see Table 5). The main results are very similar in both regressions. The estimates of regional dummy variables are not shown in the tables. The likelihood-ratio test indicates that the mixed logit model in Table 5 with a single random coefficient representing the unobserved heterogeneity of preferences is preferred to the logit model in Table 4. The test statistic is equal to $\chi^2 = -2\ln(L_0/L_1) = -2 \cdot [-26,417 - (-26,064)] = 706$, while the critical value for one degree of freedom is equal to $\chi^2(0.01, 1) = 6.64$. We therefore use the model with random coefficient to interpret the results.

We find that there are significant network effects within the household, where the likelihood of adoption of a mobile phone is positively influenced by the other household members using mobile phones. The greater the number of mobile phones in the household, the greater the likelihood that the other household members will adopt mobile phone as well. We use a set of dummy variables to account for these effects, which depend on the number of mobile users in the households of different sizes, as discussed in the data section. Moreover, network effects also depend on who in the household adopts a mobile phone. Overall, it is more likely that a household member who declared to be the main decision maker has a mobile phone. Also, having a mobile phone is more likely for the household member who is considered to be the second decision maker. Interestingly, when the main decision maker has a mobile phone it is less likely that the other household members adopt mobile phones. Hence, low-income households may opt for a single mobile phone to be used by all household members to communicate with non-household members. Therefore, mobile phones may play the role of fixed-line connections for households which do not have fixed-line access but cannot afford having more than one mobile phone. We test this hypothesis by estimating the model separately for the groups of households with lower and higher income levels. This effects prevails in the estimation for the low income group but becomes insignificant for the group of households with higher income. The possession of a mobile phone by the head of a household has no significant impact on the likelihood of adoption by the second decision maker, but vice versa there is a significant positive impact.

We conduct counterfactual simulations to evaluate how within-household network effects increase the penetration of mobile phones in the population, results of which are shown in Table 6. The levels of mobile penetration, which are predicted by our model are almost identical to the levels which are observed in the sample. The predicted penetrations of mobile phones in the sample are 56.3% in 2008, 56.7% in 2010 and 76.4% in 2012. According to our simulations, if there were no within-household network effects, mobile penetration would be lower by about 7.0 percentage points in 2008, 8.8 percentage points in 2010 and 9.9 percentage points in 2012. Hence, within-household network effects have a strong impact on the diffusion of mobile phones. As we discussed before, apart from within-household network effects, individuals also benefit from communication possibilities with non-household members, for which we do not control in this analysis.

We also find that there is significant heterogeneity in consumer preferences for the adoption of mobile phones. A number of household and individual characteristics significantly influence the valuation of mobile phones, as shown in Table 5. First, the probability of adopting a mobile phone depends on the size of the household. Single households are much more likely to have a mobile phone in general. The likelihood tends to decrease with an increasing number of adult members in the household. The probability is higher for households equipped with TV, computer, car and bicycle, which are in general wealthier households. Interestingly, the probability of adoption does not depend on whether a household has a fixed-line connection. A dummy variable for having a fixed-line is negative but insignificant. Males are in general less likely to adopt mobile phones as well as older people. Compared to black people, whites, Asian and coloured people are less likely to adopt mobile phones. Married people are more likely to have mobile phones as well as people with many children. Individuals without education are less likely to adopt mobile phones, while individuals with at least matric education are more likely. Individuals with some computer literacy are also more likely to adopt mobile phones, as well as individuals who can read or have a driving licence. Being self-employed increases the probability of mobile phone adoption, while individuals who are economically inactive are less likely to have a mobile phone. The probability of mobile phone adoption varies according to profession. There is a significant income effect with households having income between 1,500 and 15,000 South African rands being most likely to have mobile phones. The distribution of preferences according to all these observable characteristics is approximately normal. Finally, we also allow for normally distributed unobserved preferences, which are also found to be significant. The standard deviation around the mean valuation of mobile phone is 1.09.

6 Conclusions

Mobile phones and other network technologies are observed to follow an s-shaped diffusion pattern which may have distinct origins. First, the s-shaped diffusion curve may originate from the presence of network effects, where after reaching a critical mass the adoption grows exponentially until it reaches the level of saturation. But an s-shaped diffusion pattern may also result from normally distributed heterogeneity in the consumer valuation of technology. Some consumers may value mobile telephones more than others due to observed or unobserved characteristics. When the cost of adoption decreases, mobile telephones are increasingly purchased by consumers with lower valuations and at some point the main bulk of consumers with average valuations adopts. In general, both network effects and consumer heterogeneity play a role in the adoption of network technologies. The contribution of this paper is to consider network effects and consumer heterogeneity within a single empirical model.

We use panel data of South African households including separate interviews conducted among all adult household members between the years 2008 and 2012. This data allows us to test empirically whether the fact that a particular household member has a mobile phone influences the decision to adopt a mobile phone by the other household members. Network effects are approximated by the identity and the number of household members who declared having mobile phones. To identify the network effects we include in the estimation a rich set of individual and household characteristics such as gender, age, professional activity, household size, the type of dwelling, income and others. Apart from the observed heterogeneity represented by these characteristics we also account for the unobserved heterogeneity. We make a use of the panel data and estimate individual-specific random effects which are assumed to be normally distributed.

We find that both network effects and heterogeneity matter for the adoption of mobile phones. The greater is the number of mobile phones in the household the more likely it is that the other household members will adopt a mobile phone as well. Moreover, network effects depend on who in the household adopts a mobile phone. When the main decision maker has a mobile phone it is less likely that the other household members adopt mobile phones. We argue that this is because low-income households may opt for a single mobile phone to be used by all household members to communicate with non-household members. We confirm this by estimating additional regressions for the sub-samples of individuals from poorer and wealthier households. This effect prevails for the poorer households but not for wealthier ones. Without within household network effects the penetration of mobile phones of 76.4% in 2012 would be lower by about 9.9 percentage points.

7 References

Birke, D. and G.M.P. Swann, 2005 "Social networks and choice of mobile phone operator," Nottingham University Business School, Industrial Economics Division Occasional Paper Series, No. 2005-14.

Birke, D. and G.M.P. Swann, 2006. "Network effects and the choice of mobile phone operator," *Journal of Evolutionary Economics*, 16(1/2), pp.65-84.

Birke D. and G.M.P. Swann, 2010. "Network Effects, Network Structure and Consumer Interaction in Mobile Telecommunications in Europe and Asia," *Journal of Economic Behavior & Organization*, 76(2), pp.153-167.

Clements, M.T., Ohashi, H., 2005. "Indirect network effects and the product cycle: video games in the US, 1994-2002," *Journal of Industrial Economics*, 53(44), pp.515-542.

Corrocher, N. and L. Zirulia, 2009. "Me and you and everyone we know: An empirical analysis of local network effects in mobile communications," *Telecommunications Policy*, 33(1-2), pp.68-79.

Doganoglu, T. and L. Grzybowski, 2007. "Estimating network effects in the mobile telecommunications industry in Germany," *Information Economics and Policy*, 19(1), pp.65-79.

Gandal, N., Kende, M. and R. Rob, 2000. "The dynamics of technological adoption in hardware/software systems: the case of compact disc players," *RAND Journal of Economics*, 31(1), pp.43-61.

Goolsbee, A., Klenow, P.J., 2002. "Evidence on learning and network externalities in the diffusion of home computers," *Journal of Law and Economics*, 45(2), pp.317-344.

Gowrisankaran, G., Stavins, J. 2004. "Network externalities and technology adoption: Lessons from electronic payments," *RAND Journal of Economics*, 35(2), pp.260-276.

Grajek, M., 2010. "Estimating network effects and compatibility: Evidence from the Polish mobile market," *Information Economics and Policy*, 22(2), pp.130-143.

Grajek, M. and T. Kretschmer, 2009. "Usage and diffusion of cellular telephony, 1998-2004," *International Journal of Industrial Organization*, 27(2), pp.238-249.

Grajek, M. and T. Kretschmer, 2012. "Identifying critical mass in the global cellular telephony market," *International Journal of Industrial Organization*, 30(6), pp.496-507.

Gruber H. and F. Verboven, 2001. "The Diffusion of Mobile Telecommunication Services in the European Union," *European Economic Review*, 45, pp.577-588.

Karshenas, M. and P. Stoneman, 1993. "Rank, Stock Order and Epidemic Effects in the Diffusion of new process technologies: An Empirical Model," *RAND Journal of Economics*, 24(4), pp.503-528.

Karacuka, M., Çatik, A.N. and J. Haucap, 2013. "Consumer choice and local network effects in mobile telecommunications in Turkey," *Telecommunications Policy*, 37(4), pp.334-344.

Katz and Shapiro, 1985 Network externalities, competition and compatibility American Economic Review, 75 (3) (1985), pp.424-440

Kim, H.S. and N., Kwon, 2003. "The advantage of network size in acquiring new subscribers: a conditional logit analysis of the Korean mobile telephony market," *Information Economics and Policy*, 15(1), pp.17-33.

Koski, H., Kretschmer, T., 2005. "Entry, standards and competition: firm strategies and the diffusion of mobile telephony," *Review of Industrial Organization*, 26, pp.89-113.

Ohashi, H., 2003. "The role of network externalities in the US VCR Market, 1978,Äì86," *Journal of Economics and Management Strategy*, 12(4), pp.447-494.

Park, S., 2003. "Quantitative analysis of network externalities in competing technologies: the VCR case," *The Review of Economics and Statistics*, 86, pp.937-945.

Rysman, M. 2004. "Competition Between Networks: A Study of the Market for Yellow Pages," *Review of Economic Studies*, 71, pp.483-512.

Sundararajan, A. 2007. "Local Network Effects and Complex Network Structure," *The B.E. Journal of Theoretical Economics*, 7(1), Article 46.

8 Appendix

Table 1: The number of individuals in the sample

	households	individuals
wave 1	7,236	16,871
wave 2	9,134	21,880
wave 3	10,236	22,481

Table 2: The number of individuals in the sample across waves

		wave 3		
wave 1	wave 2	1	0	sum
1	1	13,691	1,800	15,491
1	0	493	887	1,380
0	1	4,211	2,178	6,389
0	0	4,086	0	4,086
	sum	22,481	4,865	27,346

The numbers should be read as follows. For instance, there were 13,691 adult individuals in all three waves, and 1,800 individuals in waves 1 and 2 but not in wave 3.

Table 3: Summary statistics: three waves

Variable	Obs	Mean	Std	Min	Max	Variable	Obs	Mean	Std	Min	Max
Mobile phone	60110	0.552	0.497	0	1	Fixed-line dummy	60110	0.089	0.284	0	1
Mobile penetration	60110	0.552	0.147	0.002	0.882	Electricity dummy	60110	0.707	0.455	0	1
Region population	60110	522	804	156	6502	TV set dummy	60110	0.647	0.478	0	1
HH=2, mobiles=1	60110	0.152	0.359	0	1	Computer dummy	60110	0.098	0.298	0	1
HH=3, mobiles=2	60110	0.084	0.277	0	1	Private car dummy	60110	0.136	0.343	0	1
HH=3, mobiles=1	60110	0.074	0.262	0	1	Company car dummy	60110	0.043	0.202	0	1
HH=4, mobiles=3	60110	0.044	0.205	0	1	Motorcycle dummy	60110	0.012	0.110	0	1
HH=4, mobiles=2	60110	0.047	0.211	0	1	Bike dummy	60110	0.068	0.251	0	1
HH=4, mobiles=1	60110	0.041	0.199	0	1	Male dummy	60110	0.352	0.478	0	1
HH=5, mobiles=4	60110	0.017	0.130	0	1	Age	51898	38	18	15	106
HH=5, mobiles=3	60110	0.023	0.151	0	1	Race: coloured dummy	60110	0.117	0.321	0	1
HH=5, mobiles=2	60110	0.024	0.152	0	1	Race: Asian dummy	60110	0.010	0.100	0	1
HH=5, mobiles=1	60110	0.021	0.142	0	1	Race: white dummy	60110	0.033	0.179	0	1
HH=6, mobiles=5	60110	0.007	0.080	0	1	Married dummy	60110	0.222	0.416	0	1
HH=6, mobiles=4	60110	0.010	0.099	0	1	Language: Afrikaans dummy	60110	0.138	0.345	0	1
HH=6, mobiles=3	60110	0.010	0.097	0	1	Language: English dummy	60110	0.031	0.173	0	1
HH=6, mobiles=2	60110	0.009	0.096	0	1	Children	60110	0.617	1.142	0	11
HH=6, mobiles=1	60110	0.009	0.095	0	1	Education: no school dummy	60110	0.106	0.308	0	1
HH>7, mobile>6	60110	0.008	0.089	0	1	Education: matric dummy	60110	0.194	0.395	0	1
HH=7, mobiles=6	60110	0.005	0.069	0	1	Computer literacy: high	60110	0.073	0.260	0	1
HH=7, mobiles=5	60110	0.008	0.088	0	1	Computer literacy: low	60110	0.139	0.346	0	1
HH=7, mobiles=4	60110	0.008	0.091	0	1	Driving licence dummy	60110	0.114	0.318	0	1
HH=7, mobiles=3	60110	0.009	0.097	0	1	Reading dummy	60110	0.354	0.478	0	1
HH=7, mobiles=2	60110	0.009	0.093	0	1	Writing dummy	60110	0.348	0.476	0	1
HH=7, mobiles=1	60110	0.008	0.091	0	1	Employment: inactive dummy	60110	0.439	0.496	0	1
Head 1	60110	0.241	0.428	0	1	Employment: employee dummy	60110	0.208	0.406	0	1
Head 2	60110	0.147	0.354	0	1	Employment: selfemployed dummy	60110	0.038	0.190	0	1
Head 1 impact	60110	0.327	0.469	0	1	Job: manager	60110	0.008	0.091	0	1
Head 2 impact	60110	0.214	0.410	0	1	Job: professional	60110	0.025	0.157	0	1
Head 1 impact on head 2	60110	0.093	0.291	0	1	Job: technician	60110	0.009	0.094	0	1
Head 2 impact on head 1	60110	0.094	0.292	0	1	Job: clerk	60110	0.013	0.113	0	1
HH size=1 dummy	60110	0.140	0.347	0	1	Job: services	60110	0.032	0.177	0	1
HH size=2 dummy	60110	0.261	0.439	0	1	Job: skilled	60110	0.007	0.085	0	1
Hh size=3 dummy	60110	0.218	0.413	0	1	Job: craftsman	60110	0.021	0.145	0	1
HH size=4 dummy	60110	0.165	0.371	0	1	Job: worker	60110	0.020	0.139	0	1
HH size=5 dummy	60110	0.101	0.302	0	1	Job: elementary	60110	0.066	0.248	0	1
HH size=6 dummy	60110	0.052	0.222	0	1	Income <=500	54292	0.032	0.175	0	1
HH size=7 dunmy	60110	0.030	0.170	0	1	Income >500 and <=1000	54292	0.074	0.261	0	1
HH size=8 dummy	60110	0.015	0.120	0	1	Income >1000 and <=1500	54292	0.121	0.326	0	1
HH size=9 dummy	60110	0.007	0.086	0	1	Income >1500 and <=2000	54292	0.108	0.310	0	1
HH size>9 dummy	60110	0.011	0.103	0	1	Income >2000 and <=2500	54292	0.095	0.294	0	1
Wave 2 dummy	60110	0.364	0.481	0	1	Income >2500 and <=3000	54292	0.080	0.272	0	1
Wave 3 dummy	60110	0.355	0.479	0	1	Income >3000 and <=3500	54292	0.066	0.248	0	1
						Income >3500 and <=4000	54292	0.052	0.223	0	1
						Income >4000 and <=4500	54292	0.044	0.205	0	1
						Income >4500 and <=5000	54292	0.035	0.183	0	1
						Income >5000 and <=7500	54292	0.112	0.316	0	1
						Income >7500 and <=10000	54292	0.058	0.233	0	1
						Income >10000 and <=15000	54292	0.053	0.225	0	1
						Income >15000 and <=20000	54292	0.027	0.161	0	1

Mobile phone is 0-1 dependent variable. Dummy variables **Mobile penetration** denotes the percentage of individuals with mobile phones in the sample relative to the population of the municipality, which is denoted by **region population**. **HH=j, mobiles=k** take value of one when the household size of individual i is equal to j and the number of mobile phones used by the other household members is equal to k, where $0 < k < j$ and zero otherwise. **Head 1** denotes a dummy variables for the first decision maker in the household and **Head 2** for the second one. **Head 1 impact** is a dummy variables which measures the impact of having a mobile phone by first decision maker on the mobile phone adoption by the other household members, and **Head 2 impact** is analogous for the second decision maker. **Head 1 impact on head 2** is a dummy variable which measures the impact of having a mobile phone by the first decision maker on the mobile phone adoption by the second decision maker, and **Head 2 impact on head 1** is analogous for the second decision maker. **HH size=i** are dummy variables for the size of the household. **Wave 2 and 3** are dummy variables for the second and third wave relative to the first one. The other variables are household and individual characteristics including profession and range of income dummy variables.

Table 4: Logit estimation: three waves

Variables	Est	Std	Variables	Est	Std
HH=2, mobiles=1	0.6784***	(0.050)	Fixed-line dummy	-0.0276	(0.046)
HH=3, mobiles=2	1.0459***	(0.067)	Electricity dummy	-0.0406	(0.029)
HH=3, mobiles=1	0.5238***	(0.060)	TV set dummy	0.4953***	(0.027)
HH=4, mobiles=3	1.2987***	(0.091)	Computer dummy	0.2885***	(0.053)
HH=4, mobiles=2	0.6486***	(0.082)	Private car dummy	0.2826***	(0.044)
HH=4, mobiles=1	0.2640***	(0.081)	Company car dummy	0.3196***	(0.067)
HH=5, mobiles=4	1.4123***	(0.133)	Motorcycle dummy	0.1161	(0.120)
HH=5, mobiles=3	0.8378***	(0.119)	Bike dummy	0.1296***	(0.047)
HH=5, mobiles=2	0.4994***	(0.115)	Male dummy	-0.2460***	(0.026)
HH=5, mobiles=1	0.1006	(0.117)	Age	-0.0118***	(0.001)
HH=6, mobiles=5	1.4412***	(0.207)	Race: coloured dummy	-0.4850***	(0.095)
HH=6, mobiles=4	1.1368***	(0.183)	Race: Asian dummy	-0.6149***	(0.163)
HH=6, mobiles=3	0.7595***	(0.178)	Race: white dummy	-0.6325***	(0.121)
HH=6, mobiles=2	0.2584	(0.179)	Married dummy	0.3293***	(0.031)
HH=6, mobiles=1	-0.1677	(0.183)	Language: Afrikaans dummy	-0.1131	(0.097)
HH>7,mobile>6	2.6490***	(0.230)	Language: English dummy	0.0229	(0.119)
HH=7, mobiles=6	1.2924***	(0.219)	Children	0.1005***	(0.011)
HH=7, mobiles=5	1.5499***	(0.200)	Education: no school dummy	-0.5548***	(0.036)
HH=7, mobiles=4	1.1830***	(0.192)	Education: matric dummy	0.4113***	(0.035)
HH=7, mobiles=3	0.6842***	(0.189)	Computer literacy: high	0.6361***	(0.062)
HH=7, mobiles=2	0.5350***	(0.191)	Computer literacy: low	0.4280***	(0.037)
HH=7, mobiles=1	-0.0195	(0.200)	Driving licence dummy	0.7169***	(0.051)
Head 1	0.7640***	(0.043)	Reading dummy	0.2872***	(0.077)
Head 2	0.4211***	(0.052)	Writing dummy	0.0881	(0.077)
Head 1 impact	-0.1759***	(0.037)	Employment: inactive dummy	-0.5148***	(0.028)
Head 2 impact	-0.0667*	(0.037)	Employment: employee dummy	-0.1794	(0.137)
Head 1 impact on head 2	0.0106	(0.059)	Employment: selfemployed dummy	0.2731***	(0.065)
Head 2 impact on head 1	0.2375***	(0.065)	Job: manager	0.8059***	(0.232)
HH size=1 dummy	2.7944***	(0.208)	Job: professional	0.6571***	(0.173)
HH size=2 dummy	1.5719***	(0.208)	Job: technician	0.7836***	(0.209)
Hh size=3 dummy	1.2877***	(0.209)	Job: clerk	0.6224***	(0.193)
HH size=4 dummy	1.2446***	(0.214)	Job: services	0.7841***	(0.153)
HH size=5 dummy	1.1528***	(0.225)	Job: skilled	0.3714**	(0.173)
HH size=6 dummy	1.0787***	(0.252)	Job: craftsman	0.5096***	(0.154)
HH size=7 dunmy	0.8207***	(0.137)	Job: worker	0.6414***	(0.160)
HH size=8 dummy	0.5204***	(0.146)	Job: elementary	0.3951***	(0.141)
HH size=9 dummy	0.4283**	(0.166)	Income <=500	-0.1008	(0.099)
Wave 2 dummy	0.1256***	(0.027)	Income >500 and <=1000	0.0148	(0.089)
Wave 3 dummy	0.7535***	(0.029)	Income >1000 and <=1500	0.0700	(0.085)
Constant	-1.7924***	(0.234)	Income >1500 and <=2000	0.1440*	(0.085)
			Income >2000 and <=2500	0.1649*	(0.085)
			Income >2500 and <=3000	0.1898**	(0.086)
			Income >3000 and <=3500	0.1592*	(0.088)
			Income >3500 and <=4000	0.1521*	(0.090)
			Income >4000 and <=4500	0.2366**	(0.092)
			Income >4500 and <=5000	0.1189	(0.096)
			Income >5000 and <=7500	0.2075**	(0.083)
			Income >7500 and <=10000	0.1697*	(0.089)
			Income >10000 and <=15000	0.2209**	(0.092)
			Income >15000 and <=20000	0.1407	(0.111)
Obs	51,874				
LL	-26,417				

Table 5: Mixed logit estimation: three waves

HH=2, mobiles=1	0.7699***	(0.061)	Fixed-line dummy	-0.0290	(0.056)
HH=3, mobiles=2	1.2389***	(0.080)	Electricity dummy	-0.0372	(0.036)
HH=3, mobiles=1	0.6369***	(0.072)	TV set dummy	0.5730***	(0.033)
HH=4, mobiles=3	1.5960***	(0.109)	Computer dummy	0.3226***	(0.063)
HH=4, mobiles=2	0.8326***	(0.099)	Private car dummy	0.3305***	(0.053)
HH=4, mobiles=1	0.3458***	(0.097)	Company car dummy	0.3847***	(0.079)
HH=5, mobiles=4	1.7145***	(0.157)	Motorcycle dummy	0.1094	(0.140)
HH=5, mobiles=3	1.0185***	(0.141)	Bike dummy	0.1611***	(0.056)
HH=5, mobiles=2	0.6118***	(0.137)	Male dummy	-0.2785***	(0.034)
HH=5, mobiles=1	0.1067	(0.139)	Age	-0.0129***	(0.001)
HH=6, mobiles=5	1.8081***	(0.245)	Race: coloured dummy	-0.5785***	(0.121)
HH=6, mobiles=4	1.3505***	(0.218)	Race: Asian dummy	-0.6867***	(0.207)
HH=6, mobiles=3	0.9901***	(0.213)	Race: white dummy	-0.6950***	(0.151)
HH=6, mobiles=2	0.3619*	(0.214)	Married dummy	0.3778***	(0.039)
HH=6, mobiles=1	-0.1599	(0.219)	Language: Afrikaans dummy	-0.1262	(0.123)
HH>7,mobile>6	3.2035***	(0.271)	Language: English dummy	0.0245	(0.148)
HH=7, mobiles=6	1.5816***	(0.259)	Children	0.1299***	(0.015)
HH=7, mobiles=5	1.8761***	(0.236)	Education: no school dummy	-0.6966***	(0.048)
HH=7, mobiles=4	1.4338***	(0.227)	Education: matric dummy	0.5122***	(0.044)
HH=7, mobiles=3	0.8571***	(0.223)	Computer literacy: high	0.7076***	(0.073)
HH=7, mobiles=2	0.6054***	(0.224)	Computer literacy: low	0.4939***	(0.044)
HH=7, mobiles=1	-0.0506	(0.235)	Driving licence dummy	0.8106***	(0.062)
Head 1	0.8888***	(0.053)	Reading dummy	0.3365***	(0.091)
Head 2	0.4826***	(0.063)	Writing dummy	0.0979	(0.092)
Head 1 impact	-0.1681***	(0.044)	Employment: inactive dummy	-0.5830***	(0.034)
Head 2 impact	-0.0632	(0.044)	Employment: employee dummy	-0.1717	(0.162)
Head 1 impact on head 2	0.0018	(0.070)	Employment: selfemployed dummy	0.3001***	(0.077)
Head 2 impact on head 1	0.2624***	(0.078)	Job: manager	0.8631***	(0.268)
HH size=1 dummy	3.3217***	(0.247)	Job: professional	0.7300***	(0.203)
HH size=2 dummy	1.8975***	(0.246)	Job: technician	0.8239***	(0.241)
Hh size=3 dummy	1.5336***	(0.248)	Job: clerk	0.6843***	(0.223)
HH size=4 dummy	1.4357***	(0.253)	Job: services	0.8628***	(0.180)
HH size=5 dummy	1.3730***	(0.266)	Job: skilled	0.4329**	(0.206)
HH size=6 dummy	1.2420***	(0.299)	Job: craftsman	0.5737***	(0.182)
HH size=7 dunmy	0.9661***	(0.165)	Job: worker	0.7057***	(0.189)
HH size=8 dummy	0.6127***	(0.176)	Job: elementary	0.4386***	(0.166)
HH size=9 dummy	0.5177***	(0.200)	Income <=500	-0.0733	(0.118)
Wave 2 dummy	0.1626***	(0.031)	Income >500 and <=1000	0.0544	(0.106)
Wave 3 dummy	0.9393***	(0.034)	Income >1000 and <=1500	0.0964	(0.101)
Constant	-2.2293***	(0.280)	Income >1500 and <=2000	0.1949*	(0.101)
Constant STD	1.0916***	(0.030)	Income >2000 and <=2500	0.2232**	(0.101)
			Income >2500 and <=3000	0.2361**	(0.102)
			Income >3000 and <=3500	0.2041**	(0.104)
			Income >3500 and <=4000	0.1979*	(0.107)
			Income >4000 and <=4500	0.2748**	(0.110)
			Income >4500 and <=5000	0.1502	(0.113)
			Income >5000 and <=7500	0.2538***	(0.098)
			Income >7500 and <=10000	0.1952*	(0.105)
			Income >10000 and <=15000	0.2615**	(0.108)
			Income >15000 and <=20000	0.1608	(0.128)
Obs	51,874				
LL	-26,064				

Table 6: Predictions of mobile penetration without network effects

	2008	2010	2012
Sample	56.8%	56.9%	76.3%
Sample predicted	56.3%	56.7%	76.4%
Without household NE	49.3%	47.9%	66.5%

Table 7: Mobile penetration in municipalities in three waves of the survey

Municipality	2008	2011	2012
Alfred Nzo District Municipality	33%	59%	74%
Amajuba District Municipality	66%	47%	82%
Amatole District Municipality	42%	54%	78%
Bohlabela District Municipality	67%	86%	87%
Bojanala District Municipality	65%	65%	85%
Boland District Municipality	54%	56%	62%
Bophirima District Municipality	45%	46%	65%
Cacadu District Municipality	36%	45%	57%
Capricorn District Municipality	62%	69%	84%
Central District Municipality	63%	55%	75%
Central Karoo District Municipality	38%	40%	58%
Chris Hani District Municipality	39%	49%	72%
City Of Cape Town Metropolitan Municipal	65%	61%	79%
City Of Johannesburg Metropolitan Munici	77%	73%	86%
City Of Tshwane Metropolitan Municipalit	87%	70%	89%
Eden District Municipality	57%	48%	75%
Ehlanzeni District Municipality	68%	74%	83%
Ekurhuleni Metropolitan Municipality	77%	80%	94%
Ethekwini Municipality	54%	57%	80%
Frances Baard District Municipality	47%	60%	74%
Govan Mbeki Municipality	66%	74%	86%
Ilembe District Municipality	49%	44%	70%
Karoo District Municipality	48%	53%	67%
Kgalagadi District Municipality	53%	59%	84%
Lejweleputswa District Municipality	59%	56%	78%
Metsweding District Municipality	74%	69%	73%
Mopani District Municipality	53%	64%	79%
Motheo District Municipality	65%	75%	79%
Namakwa District Municipality	41%	40%	54%
Nelson Mandela Metropolitan Municipality	57%	63%	73%
Nkangala District Municipality	68%	74%	82%
Northern Free State District Municipalit	70%	73%	92%
O,R,Tambo District Municipality	40%	44%	70%
Overberg District Municipality	64%	60%	76%
Sedibeng District Municipality	70%	68%	80%
Sekhukhune Cross Boundary District Munic	59%	64%	74%
Sisonke District Municipality	48%	46%	74%
Siyanda District Municipality	47%	53%	68%
Southern District Municipality	61%	55%	75%
Thabo Mofutsanyane District Municipality	64%	57%	83%
Ugu District Municipality	51%	53%	75%
Ukhahlamba District Municipality	44%	58%	75%
Umgungundlovu District Municipality	53%	43%	71%
Umkhanyakude District Municipality	54%	44%	79%
Umzinyathi District Municipality	52%	41%	70%
Uthukela District Municipality	54%	54%	78%
Uthungulu District Municipality	56%	32%	70%
Vhembe District Municipality	59%	69%	84%
Waterberg District Municipality	53%	63%	77%
West Coast District Municipality	65%	45%	68%
West Rand District Municipality	79%	67%	89%
Xhariep District Municipality	49%	57%	66%
Zululand District Municipality	56%	47%	83%
South Africa	57%	57%	76%

There are 53 municipalities in South Africa.

Appendix A

Table A.1: Logit estimation: wave I

Variables	Est	Std	Variables	Est	Std
HH=2, mobiles=1	0.3882***	(0.080)	Fixed-line dummy	-0.1516*	(0.079)
HH=3, mobiles=2	0.6533***	(0.117)	Electricity dummy	0.0555	(0.050)
HH=3, mobiles=1	0.1547	(0.097)	TV set dummy	0.4047***	(0.047)
HH=4, mobiles=3	1.2371***	(0.165)	Computer dummy	0.3173***	(0.099)
HH=4, mobiles=2	0.5678***	(0.138)	Private car dummy	0.2424***	(0.072)
HH=4, mobiles=1	0.1654	(0.130)	Company car dummy	0.4202***	(0.138)
HH=5, mobiles=4	1.7597***	(0.271)	Motorcycle dummy	0.2387	(0.183)
HH=5, mobiles=3	0.5737***	(0.217)	Bike dummy	0.2069**	(0.084)
HH=5, mobiles=2	0.4005**	(0.197)	Male dummy	-0.2729***	(0.046)
HH=5, mobiles=1	0.0849	(0.198)	Age	-0.0138***	(0.002)
HH=6, mobiles=5	0.5297	(0.472)	Race: coloured dummy	-0.5199***	(0.153)
HH=6, mobiles=4	0.4711	(0.358)	Race: Asian dummy	-0.6349**	(0.257)
HH=6, mobiles=3	0.4135	(0.337)	Race: white dummy	-0.4287**	(0.189)
HH=6, mobiles=2	-0.4900	(0.338)	Married dummy	0.3132***	(0.052)
HH=6, mobiles=1	-1.4633***	(0.331)	Language: Afrikaans dummy	-0.0969	(0.154)
HH>7,mobile>6	2.6410***	(0.555)	Language: English dummy	-0.1795	(0.182)
HH=7, mobiles=6	1.1300**	(0.489)	Children	0.0775***	(0.019)
HH=7, mobiles=5	1.2555***	(0.474)	Education: no school dummy	-0.5754***	(0.064)
HH=7, mobiles=4	0.3647	(0.380)	Education: matric dummy	0.4973***	(0.061)
HH=7, mobiles=3	1.0199***	(0.349)	Computer literacy: high	0.5625***	(0.110)
HH=7, mobiles=2	0.2300	(0.352)	Computer literacy: low	0.4107***	(0.066)
HH=7, mobiles=1	0.0470	(0.361)	Driving licence dummy	0.5778***	(0.082)
Head 1	0.5384***	(0.071)	Reading dummy	0.2780**	(0.135)
Head 2	0.1786**	(0.091)	Writing dummy	-0.0483	(0.136)
Head 1 impact	-0.2155***	(0.065)	Employment: inactive dummy	-0.4450***	(0.046)
Head 2 impact	-0.1809**	(0.080)	Employment: employee dummy	-0.2198	(0.308)
Head 1 impact on head 2	0.3507***	(0.121)	Employment: selfemployed dummy	0.3524***	(0.096)
Head 2 impact on head 1	0.3072**	(0.120)	Job: manager	1.2177***	(0.455)
HH size=1 dummy	2.7539***	(0.418)	Job: professional	1.1241***	(0.361)
HH size=2 dummy	1.9219***	(0.418)	Job: technician	1.2441***	(0.434)
Hh size=3 dummy	1.7346***	(0.420)	Job: clerk	1.0036***	(0.372)
HH size=4 dummy	1.5234***	(0.425)	Job: services	1.0353***	(0.334)
HH size=5 dummy	1.4219***	(0.442)	Job: skilled	0.3398	(0.327)
HH size=6 dummy	1.9264***	(0.490)	Job: craftsman	0.5908*	(0.324)
HH size=7 dunmy	0.9512***	(0.345)	Job: worker	0.6266*	(0.334)
HH size=8 dummy	0.8341**	(0.348)	Job: elementary	0.5091	(0.314)
HH size=9 dummy	0.9855**	(0.390)	Income <=500	-0.2533	(0.185)
Constant	-1.3137***	(0.466)	Income >500 and <=1000	-0.1593	(0.176)
			Income >1000 and <=1500	-0.1611	(0.172)
			Income >1500 and <=2000	-0.0536	(0.172)
			Income >2000 and <=2500	-0.0350	(0.173)
			Income >2500 and <=3000	0.0827	(0.176)
			Income >3000 and <=3500	0.0511	(0.178)
			Income >3500 and <=4000	0.2255	(0.185)
			Income >4000 and <=4500	0.0358	(0.189)
			Income >4500 and <=5000	0.1173	(0.203)
			Income >5000 and <=7500	0.1629	(0.170)
			Income >7500 and <=10000	0.1493	(0.183)
			Income >10000 and <=15000	0.2688	(0.186)
			Income >15000 and <=20000	0.4282*	(0.226)
Obs	15,597				
LL	-8,510				

Table A.2: Logit estimation: wave II

Variables	Est	Std	Variables	Est	Std
HH=2, mobiles=1	0.9452***	(0.093)	Fixed-line dummy	-0.0129	(0.074)
HH=3, mobiles=2	1.3263***	(0.115)	Electricity dummy	-0.1735***	(0.050)
HH=3, mobiles=1	0.7861***	(0.103)	TV set dummy	0.6719***	(0.046)
HH=4, mobiles=3	1.4898***	(0.155)	Computer dummy	0.3310***	(0.097)
HH=4, mobiles=2	0.5256***	(0.134)	Private car dummy	0.3130***	(0.080)
HH=4, mobiles=1	0.3204**	(0.129)	Company car dummy	0.2598**	(0.105)
HH=5, mobiles=4	1.4784***	(0.208)	Motorcycle dummy	0.1354	(0.214)
HH=5, mobiles=3	0.9545***	(0.178)	Bike dummy	0.2508***	(0.086)
HH=5, mobiles=2	0.3912**	(0.170)	Male dummy	-0.2266***	(0.044)
HH=5, mobiles=1	-0.1166	(0.167)	Age	-0.0097***	(0.001)
HH=6, mobiles=5	1.7712***	(0.340)	Race: coloured dummy	-0.5412***	(0.180)
HH=6, mobiles=4	1.2425***	(0.279)	Race: Asian dummy	-0.6515**	(0.300)
HH=6, mobiles=3	0.9689***	(0.265)	Race: white dummy	-0.9907***	(0.225)
HH=6, mobiles=2	0.6372**	(0.264)	Married dummy	0.2920***	(0.052)
HH=6, mobiles=1	0.2865	(0.269)	Language: Afrikaans dummy	-0.1660	(0.183)
HH>7,mobile>6	2.6485***	(0.338)	Language: English dummy	0.1029	(0.224)
HH=7, mobiles=6	1.0094***	(0.319)	Children	0.1203***	(0.018)
HH=7, mobiles=5	1.3086***	(0.263)	Education: no school dummy	-0.5694***	(0.063)
HH=7, mobiles=4	1.3788***	(0.251)	Education: matric dummy	0.2927***	(0.056)
HH=7, mobiles=3	0.6001**	(0.248)	Computer literacy: high	0.8406***	(0.111)
HH=7, mobiles=2	0.4571*	(0.247)	Computer literacy: low	0.5100***	(0.063)
HH=7, mobiles=1	-0.2591	(0.257)	Driving licence dummy	0.8573***	(0.089)
Head 1	0.9526***	(0.074)	Reading dummy	0.4405***	(0.124)
Head 2	0.6554***	(0.084)	Writing dummy	0.0415	(0.124)
Head 1 impact	-0.1261**	(0.062)	Employment: inactive dummy	-0.5372***	(0.051)
Head 2 impact	-0.0237	(0.061)	Employment: employee dummy	-0.1516	(0.173)
Head 1 impact on head 2	-0.1880*	(0.099)	Employment: selfemployed dummy	0.2151*	(0.117)
Head 2 impact on head 1	0.1493	(0.108)	Job: manager	0.1360	(0.342)
HH size=1 dummy	2.2143***	(0.269)	Job: professional	0.4241*	(0.239)
HH size=2 dummy	0.8509***	(0.271)	Job: technician	0.5983**	(0.303)
Hh size=3 dummy	0.5282*	(0.273)	Job: clerk	0.1284	(0.298)
HH size=4 dummy	0.7224***	(0.280)	Job: services	0.5629***	(0.199)
HH size=5 dummy	0.6706**	(0.292)	Job: skilled	0.9033**	(0.445)
HH size=6 dummy	0.3284	(0.341)	Job: craftsman	0.3489*	(0.212)
HH size=7 dunmy	0.4675***	(0.177)	Job: worker	0.7244***	(0.223)
HH size=8 dummy	0.1744	(0.200)	Job: elementary	0.4349**	(0.180)
HH size=9 dummy	0.0397	(0.235)	Income <=500	0.0225	(0.158)
Constant	-1.4923***	(0.319)	Income >500 and <=1000	0.1532	(0.136)
			Income >1000 and <=1500	0.2363*	(0.130)
			Income >1500 and <=2000	0.2615**	(0.130)
			Income >2000 and <=2500	0.3002**	(0.130)
			Income >2500 and <=3000	0.2738**	(0.133)
			Income >3000 and <=3500	0.2436*	(0.136)
			Income >3500 and <=4000	0.1972	(0.140)
			Income >4000 and <=4500	0.3867***	(0.144)
			Income >4500 and <=5000	0.1131	(0.155)
			Income >5000 and <=7500	0.2350*	(0.127)
			Income >7500 and <=10000	0.0607	(0.137)
			Income >10000 and <=15000	0.2488*	(0.147)
			Income >15000 and <=20000	-0.0949	(0.178)
Obs	17,570				
LL	-9,255				

Table A.3: Logit estimation: wave III

Variables	Est	Std	Variables	Est	Std
HH=2, mobiles=1	0.5980***	(0.099)	Fixed-line dummy	0.1133	(0.098)
HH=3, mobiles=2	0.8947***	(0.134)	Electricity dummy	0.0897	(0.059)
HH=3, mobiles=1	0.4549***	(0.129)	TV set dummy	0.2676***	(0.055)
HH=4, mobiles=3	1.1398***	(0.194)	Computer dummy	0.1999**	(0.086)
HH=4, mobiles=2	0.7719***	(0.188)	Private car dummy	0.2480***	(0.084)
HH=4, mobiles=1	0.2632	(0.194)	Company car dummy	0.2538**	(0.116)
HH=5, mobiles=4	0.9490***	(0.330)	Motorcycle dummy	-0.0598	(0.265)
HH=5, mobiles=3	0.5651*	(0.321)	Bike dummy	-0.0132	(0.080)
HH=5, mobiles=2	0.3705	(0.323)	Male dummy	-0.2519***	(0.047)
HH=5, mobiles=1	0.2825	(0.339)	Age	-0.0122***	(0.002)
HH=6, mobiles=5	1.6903***	(0.450)	Race: coloured dummy	-0.4591***	(0.172)
HH=6, mobiles=4	1.4496***	(0.437)	Race: Asian dummy	-0.6762**	(0.331)
HH=6, mobiles=3	0.8213*	(0.439)	Race: white dummy	-0.4576*	(0.256)
HH=6, mobiles=2	0.2109	(0.446)	Married dummy	0.4840***	(0.058)
HH=6, mobiles=1	0.5669	(0.470)	Language: Afrikaans dummy	-0.0656	(0.179)
HH>7,mobile>6	2.8931***	(0.784)	Language: English dummy	0.2831	(0.243)
HH=7, mobiles=6	1.6912**	(0.758)	Children	0.1139***	(0.022)
HH=7, mobiles=5	2.0613***	(0.756)	Education: no school dummy	-0.5456***	(0.065)
HH=7, mobiles=4	1.2435*	(0.755)	Education: matric dummy	0.5684***	(0.074)
HH=7, mobiles=3	0.4131	(0.751)	Computer literacy: high	0.4318***	(0.109)
HH=7, mobiles=2	0.9684	(0.762)	Computer literacy: low	0.3317***	(0.063)
HH=7, mobiles=1	0.9627	(0.839)	Driving licence dummy	0.7042***	(0.100)
Head 1	0.7329***	(0.089)	Reading dummy	0.0961	(0.147)
Head 2	0.2961***	(0.105)	Writing dummy	0.2983**	(0.148)
Head 1 impact	-0.2136***	(0.068)	Employment: inactive dummy	-0.5690***	(0.052)
Head 2 impact	-0.0272	(0.062)	Employment: employee dummy	0.6583	(0.545)
Head 1 impact on head 2	-0.0977	(0.101)	Employment: selfemployed dummy	0.2752**	(0.137)
Head 2 impact on head 1	0.2590**	(0.120)	Job: manager	0.8652	(0.752)
HH size=1 dummy	3.7766***	(0.795)	Job: professional	-0.3940	(0.596)
HH size=2 dummy	2.4374***	(0.794)	Job: technician	-0.2271	(0.624)
Hh size=3 dummy	2.1508***	(0.798)	Job: clerk	-0.2979	(0.613)
HH size=4 dummy	1.9513**	(0.808)	Job: services	0.1108	(0.566)
HH size=5 dummy	2.0053**	(0.846)	Job: skilled		
HH size=6 dummy	1.5354*	(0.887)	Job: craftsman	-0.2211	(0.567)
HH size=7 dunmy	1.2663***	(0.331)	Job: worker	-0.1982	(0.570)
HH size=8 dummy	0.8365**	(0.330)	Job: elementary	-0.5880	(0.547)
HH size=9 dummy	0.6314*	(0.336)	Income <=500	-0.2645	(0.215)
Constant	-1.7334**	(0.821)	Income >500 and <=1000	-0.1561	(0.179)
			Income >1000 and <=1500	-0.0805	(0.169)
			Income >1500 and <=2000	-0.0431	(0.167)
			Income >2000 and <=2500	-0.0232	(0.167)
			Income >2500 and <=3000	-0.0149	(0.166)
			Income >3000 and <=3500	-0.0367	(0.167)
			Income >3500 and <=4000	-0.0895	(0.170)
			Income >4000 and <=4500	0.0859	(0.174)
			Income >4500 and <=5000	-0.0053	(0.174)
			Income >5000 and <=7500	0.1007	(0.160)
			Income >7500 and <=10000	0.2110	(0.169)
			Income >10000 and <=15000	0.1682	(0.171)
			Income >15000 and <=20000	0.1160	(0.202)
Obs	18,690				
LL	-8,290				