# How competitive are markets for telecommunications services in South Africa?

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## 1 Introduction

The demand for mobile voice telecommunications services in South Africa is estimated in this paper, in order to identify whether customers are responding to lower prices from challenger networks (Cell C and Telkom Mobile), or whether consumers are not responding. Consumers might not be responding for a variety of reasons, such as a lack of access to incumbent network (MTN, Vodacom) infrastructure and on-net discounting off retail prices by incumbent networks.

In addition, own-price and cross-price elasticities of demand for mobile voice services are likely to be quite different in South Africa where the fixed line network has significantly less coverage, and where prepaid subscribers account for the vast majority of subscribers. Prepaid subscribers are likely to be more price sensitive than postpaid subscribers. We would expect therefore that own-price elasticities of demand would be reasonably elastic and that mark-ups for prepaid customers would therefore be low. If the mobile operators are able to price discriminate between prepaid and postpaid subscribers, this would explain how they have been able to cover their fixed costs in achieving full population coverage in a developing country like SA.

This paper presents results for prepaid subscribers. First, a brief overview of the literature is provided, followed by a description of the methodology followed, and the dataset used. Results are then presented, and these are followed by conclusions.

## 2 Literature review

A number of papers have been written on the demand for telephony services. Vogelsang (2010) provides a review of this literature. Studies on market-level own price elasticities of demand show relatively inelastic demand for mobile services (elasticities of between $-0.183$ and $-0.5$) (Vogelsang, 2010), which suggests that there is competition among mobile operators (since operators are not pricing at monopoly levels). Similarly, fixed line elasticities of demand are low and close to zero for access charges (Vogelsang, 2010). Own price elasticities of demand for fixed line usage charges are also low and are greater than $-1$ (Vogelsang, 2010).

An important feature of these studies is that they ought to take into account both access and usage charges (Hausman *et al*, 1993), which some (but not all) do, as Vogelsang (2010) points out. Furthermore, considerable lengths are sometimes taken to try to generate differences in access charges which usually do not vary significantly over time within countries (Ward and Woroch, 2010).

Grzybowski & Pereira (2007) find own-price firm-level elasticities of between $-1.7$ and $-6.4$ for mobile operators in Portugal. These relatively high levels of own-price elasticities imply relatively low mark-ups, and therefore limited market power of individual operators.

Garbacz and Thompson (2005) measure market-level elasticities among a number of developed and developing countries, and find market-level elasticities of between $-0.183$ for developing, and $-0.447$ for developed countries.

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There are also several papers on demand for telecommunications services in individual developing countries. Narayana (2008), for example, estimates demand for telephony services in India. He finds market-level elasticities of demand for mobile services of $-0.284$ for access charges, and $-10.39$ for usage charges. In addition to access and usage prices, Narayana (2008) used income, family size, age, education, caste and occupation as explanatory variables.

Ward & Zheng (2012) find market-level elasticities of demand for mobile telephony of between $-0.3$ and $-0.7$. They studied demand for mobile services in 31 provinces in China between 1998 and 2007, and used ARPU as their proxy measure for price, relying on prices in neighbouring provinces as instruments for price in any given province.

In summary, the existing literature on the demand for mobile telecommunications services suggests that markets are reasonably competitive, with relatively low market-level elasticities of demand (Vogelsang, 2010). This literature is somewhat inconclusive, however, partly due to the fact that finding high quality price data for different countries is difficult given the complexities of telecommunications prices (installation, access and usage prices), service quality and the variety of mobile services that are bundled with tradition mobile voice services.

An additional feature of the literature is that supply side considerations are not taken into account: developed countries have existing fixed line networks that are largely depreciated, while developing countries do not (Vogelsang, 2010). Fixed lines may be more significantly cheaper in developed countries as a result of this, which might lead to greater competition for mobile operators from fixed line operators, resulting in lower elasticities of demand for mobile services. This means that own-price firm-level elasticities of demand in developing countries might be quite different to those in developed countries.

This paper will extend the literature on demand for voice telecommunications services, and will thus add to the debate on estimating demand for mobile services, by using two unique datasets: the All Media Products Survey (AMPS) and unique pricing datasets (described below).

# 3 Methodology

Demand for mobile voice services will be estimated using a discrete choice framework. There are several behavioural modelling approaches to estimating discrete choice models of demand for consumer level data (Davis & Garces, 2010). These include multinomial logit, conditional logit, generalised extreme values (including nested logit), mixed logit and probit. Some of these models have closed form solutions, including multinomial logit and nested logit, while other models, including mixed logit and probit, require simulation (Train, 2009). The most widely used model for estimating discrete choice models of demand is the conditional logit model, an extension of the multinomial logit (MNL) model (Mcfadden, 1973). A MNL model will be estimated as follows:

Consumer $i$'s utility derived from product $j$ is given by:

$$U_{ij}(p_j, r_j, z_i; \theta) = V_{ij}(p_j, r_j, z_i; \theta) + \epsilon_{ij} \tag{1}$$

where $p_j$ and $r_j$ are the price and intrinsic value, respectively, of product $j$ and $z_i$ is a vector of characteristics of consumer $i$. There is a vector of parameters to be estimated, $\theta$, and a stochastic error term $\epsilon_{ij}$.

All estimates are relative to the outside option, which is choosing no service at all.

Consumer $i$ will choose product $j$ over product $k$ if $U_{ij} \geq max_{j \neq k, k \in C_i} U_{ik}$ where $C_i$ is the choice set. This occurs with the following probability:

$$P_{ij} = Pr[V_{ij} + \epsilon_{ij} \geq max_{j \neq k, k \in C_i} V_{ik} + \epsilon_{ik}] \tag{2}$$

We assume that $\epsilon_{ij}$ are independently and identically distributed (IID) across individuals and alternatives and follow a type I extreme value distribution and have a scale parameter $\sigma_\epsilon$. This means that the choice probability can be solved using the logit formula, given by:

$$P_{ijt} := Pr[j|p_i t, .] = \frac{exp(V_{ijt})}{\sum_{k \in C_i} exp(V_{ikt})} \tag{3}$$

**Table 1: Prepaid, postpaid and hybrid customers (AMPS, 2010 - 2013)**

| package | 2010 | | 2011 | | 2012 | | 2013 | | Total | |
|---|---|---|---|---|---|---|---|---|---|---|
| | No. | % | No. | % | No. | % | No. | % | No. | % |
| 0. None | 5,143 | 20 | 3,974 | 16 | 3,431 | 14 | 3,106 | 12 | 15,654 | 16 |
| 1. Contract | 3,821 | 15 | 2,702 | 11 | 2,835 | 11 | 2,863 | 11 | 12,221 | 12 |
| 2. Pre-paid | 16,196 | 64 | 17,191 | 69 | 17,286 | 69 | 17,824 | 70 | 68,497 | 68 |
| 3. Hybrid | 0 | 0 | 1,216 | 5 | 1,545 | 6 | 1,633 | 6 | 4,394 | 4 |

where $p_j$ is the vector of prices for each product $j$ that consumer $i$ may choose from.

In order to estimate equation 3, log-likelihood will be used. The probability that a consumer selects the choice observed is: $\Pi_j P^{y_{ij}ij}$, where $y_{ij} = 1$ if consumer $i$ chose product $j$ and $y_{ij} = 0$ otherwise.

### 3.1 Estimating elasticities

A key outcome of the demand estimation process is the ability to calculate price elasticities of demand. For the multinomial logit model, the elasticity of demand for product $j$ with the respect to price of product $k$ for consumer $i$, is denoted as follows:

$$\varepsilon_{ijk} = \frac{\partial P_{ij}}{\partial p_{ik}} \frac{p_{ik}}{P_{ij}} \tag{4}$$

where the probability that consumer $i$ chooses product $j$ is captured as $P_{ij}$.

Next, we calculate the partial derivative of the probability, $P_{ij}$, that consumer $i$ chooses product $j$ with respect to the price of product $k$, $p_{ik}$:

$$\frac{\partial P_{ij}}{\partial p_{ik}} = \begin{cases} -\alpha P_{ij}(1 - P_{ij}) & \text{if } k = j \\ \alpha P_{ij} P_{ik} & \text{otherwise.} \end{cases} \tag{5}$$

This allows us to calculate elasticities:

$$\varepsilon_{ijk} = \begin{cases} -\alpha p_{ij}(1 - P_{ij}) & \text{if } k = j \\ \alpha p_{ik} P_{ik} & \text{otherwise.} \end{cases} \tag{6}$$

# 4 Data

### 4.1 All media products survey

The All Media Products Survey (AMPS) is used to estimate elasticities. AMPS is a survey of more than $25,000$consumers on a rolling 12 month basis, and contains a number of variables on telecommunications service choices and use, and demographic information.

Prepaid customers and voice services are analysed here. Prepaid customers account for approximately two thirds of the AMPS sample (see Table 1). The variability in consumer choices of operators (Table 2), voice prices and demographic factors, including age, gender and income (Tables 3 and 4), will be exploited to estimate elasticities of demand for voice services. The analysis presented below pools the results of the AMPS surveys in $2010 - 2013$.

The overall number of mobile subscribers grew between 2010 and 2013, as did the proportion of people that belonged to a network.[1] Nonetheless, the market shares of connected prepaid subscribers did not change significantly over the sample period. Vodacom's prepaid market share remained approximately constant at 45% over the period, while MTNâĂŹs market share declined slightly from 42.5% in 2010 to 41.7% in 2013 (see Table 2).

The AMPS survey disproportionately samples Whites, Indians, Coloureds and higher income groups. The results presented below are unweighted, and therefore do not compensate for this sample bias.

[1]The proportion of AMPS respondents that said they do not have a cellphone service fell from 20% in 2010 to 12% in 2013.

Table 2: **Operator market shares, prepaid customers (AMPS, 2010 - 2013)**

| selected | 2010 | | 2011 | | 2012 | | 2013 | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | No. | % | No. | % | No. | % | No. | % | No. | % |
| 0. No service | 5,143 | 24 | 3,974 | 19 | 3,431 | 17 | 3,106 | 15 | 15,654 | 19 |
| 1. Telkom Mobile | 0 | 0 | 0 | 0 | 89 | 0 | 115 | 1 | 204 | 0 |
| 2. Cell C | 1,983 | 9 | 2,200 | 10 | 2,001 | 10 | 2,241 | 11 | 8,425 | 10 |
| 3. MTN | 6,875 | 32 | 7,057 | 33 | 7,221 | 35 | 7,405 | 35 | 28,558 | 34 |
| 4. Virgin Mobile | 40 | 0 | 32 | 0 | 47 | 0 | 40 | 0 | 159 | 0 |
| 5. Vodacom | 7,298 | 34 | 7,902 | 37 | 7,928 | 38 | 8,023 | 38 | 31,151 | 37 |

Table 3: **Average age by operator chosen (AMPS, 2010 - 2013)**

| selected | 2010 | 2011 | 2012 | 2013 | Total |
|---|---|---|---|---|---|
| 0. No service | 43 | 45 | 46 | 46 | 45 |
| 1. Telkom Mobile | | | 38 | 38 | 38 |
| 2. Cell C | 33 | 34 | 35 | 35 | 34 |
| 3. MTN | 35 | 36 | 36 | 37 | 36 |
| 4. Virgin Mobile | 37 | 38 | 37 | 43 | 39 |
| 5. Vodacom | 38 | 39 | 39 | 39 | 39 |
| **Total** | 38 | 39 | 39 | 39 | 39 |

Table 4: **Average income by operator chosen (AMPS, 2010 - 2013)**

| selected | 2010 | 2011 | 2012 | 2013 | Total |
|---|---|---|---|---|---|
| 0. No service | 6,044 | 6,734 | 7,109 | 7,429 | 6,728 |
| 1. Telkom Mobile | | | 13,333 | 14,727 | 14,119 |
| 2. Cell C | 10,260 | 10,651 | 10,962 | 12,426 | 11,105 |
| 3. MTN | 8,881 | 9,432 | 9,281 | 9,833 | 9,365 |
| 4. Virgin Mobile | 14,939 | 13,917 | 16,826 | 14,840 | 15,266 |
| 5. Vodacom | 10,969 | 11,441 | 11,417 | 12,129 | 11,502 |
| **Total** | 9,051 | 9,809 | 9,936 | 10,670 | 9,862 |

**Table 5: Prepaid operator prices (2010 - 2013)**

| operator | 2010 | 2011 | 2012 | 2013 | Maximum |
|---|---|---|---|---|---|
| Telkom Mobile | 1.22 | 1.22 | 1.22 | 0.75 | 1.22 |
| Cell C | 1.50 | 1.33 | 0.99 | 0.99 | 1.50 |
| MTN | 1.20 | 1.10 | 0.99 | 0.84 | 1.20 |
| Virgin Mobile | 1.66 | 1.49 | 1.49 | 0.99 | 1.66 |
| Vodacom | 1.29 | 1.12 | 1.03 | 0.82 | 1.29 |

The average ages and incomes of each of the operators varies considerably. Consumers that choose no service are significantly older (43âĂŞ46 over the period, ) and poorer (monthly incomes of between R6,000 and R7,000) than consumers that choose a mobile service (Table 3). Cell CâĂŹs customers are on average younger than MTN and VodacomâĂŹs customers, and VodacomâĂŹs customers are on average older than those of the other operators.

Prepaid voice prices are used from ResearchICTAfrica and from the press. Each of these prices is then matched to the relevant year for the relevant operator in the AMPS dataset. There is a considerable debate about prepaid prices in South Africa. We have used the lowest available off-net price for Telkom Mobile, Virgin Mobile and Cell C, since these networks have relatively smaller market shares and most calls are therefore likely to be off-net (see Table 5).

For MTN and Vodacom, we used blended average outgoing voice prices, calculated from their annual reports. This was necessary because most calls on the MTN and Vodacom networks are likely to be on-net and will benefit from dynamic discounts. While Vodacom reports an average prepaid price, MTN does not. In order to ensure that the datasets are comparable, we used blended prepaid and contract prices for both MTN and Vodacom. Since the bulk of customers and minutes are on prepaid, it is likely that this will provide a reasonable proxy for blended prepaid prices.

# 5 Results

The multinomial logit model estimates the demand for a product or service relative to an outside option, such as not buying the service at all. In this case, the demand for prepaid services is being estimated, and the outside option is to not buy a prepaid service (i.e. the consumer may buy a contract or hybrid service, or not buy a service at all). A more fully developed approach would be to nest options for consumers, in two stages: in the first stage, consumers decide on whether to buy a prepaid, contract or hybrid package, and in the second stage choose an operator. The prices for contract and hybrid products is not currently available, and so this deeper âĂŸnested logitâĂŹ approach will be estimated in future research. Further extensions also require attention, including taking into account the role of internet access on consumer choices, and other factors that might influence consumer decisions.

The results presented here are nonetheless useful, and provide an indication of the extent of competition in the market. The conditional logit estimation results are shown on Table 6 below. The main point to note is that the estimated price parameter has the expected sign (negative) and we can reject the null hypothesis that it is equal to 0 at least at the 1% level of significance. Similarly, we can reject the null hypothesis that the estimated parameters for the operator dummies are 0 at least at the 1% level of significance (their interpretation, in respect of elasticities is provided below).

The estimation results are robust to the specification of the model. Three models are specified on Table 5: the first contains the impact of consumer choice of operator only, the second includes the interaction of price on age, income and gender, and the third includes interaction terms for age, gender and income on operator choice. These interaction terms account for any impact that age, gender and income separately have on price and operator choice. For example, it might be the case that younger people have a preference for Cell C or that older people less price sensitive. These interaction terms are intended to account for these variations in the dataset. The co-efficient on price terms is consistently of the correct sign (negative) and is statistically significant at the 0.1% level of significance. The co-efficients on all of the interaction terms are also statistically significant, save for the impact of gender on Telkom Mobile and Virgin Mobile, which

**Table 6: Estimation results - conditional logit**

| | m1 | m2 | m3 |
|---|---|---|---|
| | b/t | b/t | b/t |
| choice | | | |
| price | -1.050*** | -0.483*** | -1.042*** |
| | (-21.89) | (-9.13) | (-21.09) |
| TelkomMobile | -3.182*** | -3.238*** | -3.024*** |
| | (-36.11) | (-36.29) | (-14.28) |
| CellC | 0.651*** | 0.570*** | 1.623*** |
| | (10.88) | (9.28) | (22.20) |
| MTN | 1.775*** | 1.717*** | 2.730*** |
| | (32.29) | (30.44) | (42.61) |
| VirginMobile | -3.113*** | -3.248*** | -2.902*** |
| | (-29.83) | (-30.71) | (-12.20) |
| Vodacom | 1.986*** | 1.899*** | 2.385*** |
| | (32.81) | (30.58) | (34.46) |
| page | | -0.019*** | |
| | | (-46.61) | |
| pmale | | -0.236*** | |
| | | (-15.55) | |
| pincome | | 0.000*** | |
| | | (43.44) | |
| age1 | | | -0.021*** |
| | | | (-5.18) |
| age2 | | | -0.035*** |
| | | | (-42.13) |
| age3 | | | -0.028*** |
| | | | (-48.84) |
| age4 | | | -0.020*** |
| | | | (-4.29) |
| age5 | | | -0.019*** |
| | | | (-34.84) |
| male1 | | | -0.056 |
| | | | (-0.39) |
| male2 | | | -0.209*** |
| | | | (-7.53) |
| male3 | | | -0.351*** |
| | | | (-17.11) |
| male4 | | | -0.433** |
| | | | (-2.69) |
| male5 | | | -0.269*** |
| | | | (-13.28) |
| income1 | | | 0.000*** |
| | | | (14.70) |
| income2 | | | 0.000*** |
| | | | (35.88) |
| income3 | | | 0.000*** |
| | | | (29.96) |
| income4 | | | 0.000*** |
| | | | (14.72) |
| income5 | | | 0.000*** |
| | | | (44.44) |

**Table 7: Voice prices for Telkom Mobile, Cell C, MTN, Virgin Mobile and Vodacom (conditional logit model 1**

| provider | 1. Telkom Mo Max elast | 2. Cell C Max elast | 3. MTN Max elast | 4. Virgin Mo Max elast | 5. Vodacom Max elast | Total Max elast |
|---|---|---|---|---|---|---|
| 1. Telkom Mobile | -1.05 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| 2. Cell C | 0.11 | -1.03 | 0.11 | 0.11 | 0.11 | 0.11 |
| 3. MTN | 0.33 | 0.33 | -0.65 | 0.33 | 0.33 | 0.33 |
| 4. Virgin Mobile | 0.00 | 0.00 | 0.00 | -1.34 | 0.00 | 0.00 |
| 5. Vodacom | 0.37 | 0.37 | 0.37 | 0.37 | -0.64 | 0.37 |
| **Total** | 0.37 | 0.37 | 0.37 | 0.37 | 0.33 | 0.37 |

might be a result of the relatively small sample sizes of the latter two variables.

Own-price elasticities for Model 1 are reported on the diagonal of the table below, and cross-price elasticities are provided in the other cells. The co-efficient on price is similar for models 1 and 3, and it turns out that the sum of the price co-efficients on model 2 (once the co-efficients on the interaction terms are multiplied by the age, income and gender variables) add up to almost the same price co-efficient as that estimated in models 1 and 3. This means that the elasticities calculated are robust to each of the specified models. Note that an important feature of the multinomial logit model is the Independence of Irrelevant Alternatives assumption. This means that any other operator entering the market would take market share equally from each of the existing operators. One outcome of this is that the cross-price elasticities of demand for any given operator are identical with respect to each other operator.

Own-price and cross-price elasticities of demand are reported on Table 7 below. For example, if Vodacom were to raise its prices by 1%, this would cause a reduction in the probability of Vodacom being chosen by consumers of 0.64%. The first important result is that MTN and VodacomâĂŹs own-price elasticities of demand ($-0.65$ and $-0.64$) are considerably less elastic than Telkom Mobile and Cell CâĂŹs elasticities of demand and Virgin Mobile (all less than $-1$). This suggests that MTN and VodacomâĂŹs customers are not especially sensitive to price, particularly when compared to Virgin Mobile and Cell CâĂŹs customers.

Secondly, by far the greatest competitive constraint is brought by MTN and Vodacom, followed by Cell C. An increase in price of 1% by Telkom, Cell C, or Virgin, for example, would result in an increase of 0.34% of the probability of subscribers choosing MTN, and a 0.37% increase in the probability that subscribers choose Vodacom. This compares, for example, to a 1% increase in prices by MTN or Vodacom resulting in an increase in the probability that consumers choose Cell C of only 0.11%, and an increase in the probability that consumers choose Virgin Mobile or Telkom Mobile of only 0%.

This means that Cell C, while it does play a role in competing with Vodacom and MTN, plays a considerably more limited role than MTN and Vodacom competing with one another does. There are very low cross-price elasticities of demand between any of the operators and Telkom Mobile and Virgin Mobile, which means they play a very limited role in constraining MTN and Vodacom. This is consistent (though does not provide direct evidence of) tariff-mediated network effects through on-net discounts and  or a lack of network access provided by the incumbent networks.

## 6 Conclusion

It appears as though price competition has broken out among the mobile operators, particularly for prepaid services. In order to assess the extent to which the mobile operators do indeed constrain one another, we have estimated the demand for prepaid mobile services, using the All Media Products Survey (AMPS) dataset on consumer choices, and using publicly available prepaid prices from operator annual reports, press articles and data collated by Research ICT Africa.

The results of this analysis suggest that MTN and Vodacom have considerably lower own-price elasticities of demand (i.e. their customers are less price sensitive) than Cell C, Telkom Mobile and Virgin Mobile have, which suggests that MTN and Vodacom wield greater market power than Cell C, Telkom Mobile and Virgin Mobile. Secondly, consumers respond to price increases mostly by switching to Vodacom and MTN (there are considerably higher cross-price elasticities of demand associated with these two operators than with the others), suggesting that while the incumbent operators constrain one another to some extent, the other operators do not constrain MTN and Vodacom significantly. A price increase by MTN or Vodacom results in only a small number of subscribers moving towards Cell C, and almost none moving towards Telkom Mobile or Virgin Mobile.

This suggests that, while competition has broken out for prepaid voice services, there may be exclusionary conduct in the market, including through tariff-mediated network effects through on-net discounting by the incumbents and  or a lack of access to incumbent networks.

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