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The Impact of Mobile Phones on Change in Employment Status in South Africa*

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Abstract

In this paper we analyse whether having a mobile phone impacts chances of getting employed. We use five waves of panel data from the National Income Dynamic Survey (NIDS), which was conducted in South Africa between years 2008 and 2017. In the estimation we include a vector of observable individual and household characteristics and account for unobserved heterogeneity amongst individuals. The estimation results suggest that mobile phone ownership has a positive impact on the change in employment status from unemployed to employed. On the other hand, ownership of a computer by a household and computer literacy do not increase the likelihood of getting employed. The average probability of becoming employed increases from 54.2% when no one among unemployed adults has a mobile phone to 57.4% when all of them have a mobile phone, which is an increase of 5.9%.

Key Words: *Mobile phones; Employment; NIDS; South Africa*

JEL Classification: L13, L50, L96

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1 Introduction

The deployment and adoption of mobile phones and Internet services have broad implications for the economies of developing countries. This includes improved market efficiency (see Jensen (2007); Aker and Mbiti (2010)), increased employment (Hjort and Poulsen (2019)) and reduced household poverty levels (see Bahia et al. (2020); Bahia et al. (2021)). In this paper, we provide further evidence on the impact of mobile phones on employment in the case of South Africa, where unemployment rates have been persistently high and increasing from 22.5% in 2008 to 33.5% in 2022.[1]

One of the key problems of the labour market in South Africa is the spatial distribution of supply and demand for labour. Due to spatial laws implemented during Apartheid, many people live in rural areas which are far away from towns and cities where jobs are located (Bhorat, 2012). Moreover, search costs and limited access to information make it difficult for people living in rural areas to find jobs. As suggested by Festus et al. (2016), based on Quarterly Labour Force Survey conducted in South Africa in 2015, seeking assistance from family or friends and enquiring at workplaces were the most popular channels for unemployed individuals to search for work. Mobile phones and Internet access can help people to find jobs by improving access to information and reducing search costs. They can search for jobs online and call potential employers instead of personal inquiries, and they can be called back when opportunities arise.[2]

In this paper, we study whether change in employment status over time can be attributed to some extent to ownership of mobile phones. We use five waves of panel data from the National Income Dynamic Survey (NIDS), which was conducted in South Africa from 2008 to 2017. In the estimation, we control for a set of individual and household characteristics such as race, age, gender, physical health, educational attainment, ownership of a computer by a household, place of living, and other. The panel data structure allows us to account

[1] Source: Statistics South Africa (Stats SA), QLFS Trends 2008-2022Q4. We derived annual rates by averaging the quarterly unemployment rates reported by Stats SA.

[2] When examining the job search strategies of employed individuals, Posel, Casale and Vermaak (2014) find that 44% of South Africans rely on social networks (friends and relatives in a different household), while finding work through newspapers/Internet only accounted for 18%.

for unobserved heterogeneity amongst individuals. During the period covered by our data, Internet usage among South Africans increased from 8.4% in 2008 to 56.2% of the population in 2017.[3] Mobile devices are the most popular means of accessing the Internet with 69.4% of South African households using mobile broadband in 2021 (up from 56.9% in 2017) as compared to 10.4% with fixed Internet access at home.[4][5] Our estimation results suggest that mobile phone ownership has a positive impact on the change in employment status from unemployed to employed. On the other hand, ownership of a computer by a household and computer literacy do not increase the likelihood of getting employed. We also find that having a mobile phone and ownership of a computer by a household reduces the likelihood of becoming unemployed. However, after accounting for a potential endogeneity of owning a mobile phone its impact on becoming unemployed becomes insignificant. The average probability of becoming employed increases from 54.2% when no one among unemployed adults has a mobile phone to 57.4% when all of them have a mobile phone, which is an increase of 5.9%. Thus, the impact of mobile phones on changing employment status is not large, which suggests that other factors play a role.

The paper is organized as follows. In the next section, we provide an overview of the relevant literature. Section 3 describes our data. Section 4 discusses the econometric methodology followed by Section 5 which discusses estimation results. Finally, Section 6 concludes.

2 Literature review

There is a growing body of research on the economic impact of mobile phones and Internet access on the wellbeing of people in developing countries. In an earlier paper, Jensen (2007) uses a micro-level survey data to show that the adoption of mobile phones by fisherman and wholesalers in Kerala led to a reduction in price dispersion. He finds that the use of mobile phones led to complete elimination of waste and near adherence to the Law of One Price, which

[3]Source: World Bank 2021. World Development Indicators.

[4]Source: General Household Survey 2017 and General Household Survey 2021. Statistics South Africa (Stats SA).

[5]Using mobile devices to access the Internet includes access on mobile phones or mobile access devices such as 3G cards.

increased both consumer and producer welfare. In a related paper, Aker and Mbiti (2010) study how the introduction of mobile phones between 2001 and 2006 affected grain prices in Niger. These papers emphasize the importance of rolling out mobile network infrastructure for improving economic efficiency of markets.

One of the channels is through the functioning of the labour markets. In general, the Internet made labour markets more efficient as information about job openings can now reach a much broader audience while reducing search costs (Autor, 2001). But at the same time, empirical evidence suggests that access to the Internet and digitization benefits educated and skilled workers more than those who are unskilled (Atasoy, 2013).

In an earlier paper, Kuhn and Skuterud (2004) use the Current Population Survey data in the U.S. coupled with data on Internet job search to investigate the impact of Internet usage on unemployment duration. Surprisingly, they do not find that using the Internet to search for work results in shorter unemployment periods as compared to non-Internet users. In their estimation they account for observable characteristics of the unemployed and postulate that this result could be due to Internet job searchers being negatively selected on unobservable characteristics. This result is similar to Kroft and Pope (2014) who find that the expansion of Craigslist, a U.S. website that provides a platform for people to advertise jobs and apartment rentals among other things, did not have any effect on employment. These results are also confirmed by Kuhn and Mansour (2014) when using the same dataset as Kuhn and Skuterud (2004). But when using the National Longitudinal Survey of Youth (NLSY97), which was conducted in years 2008-2009, they find that using the Internet for job search decreased unemployment duration by 25%. One of the reasons given for these contradictory findings is that the two surveys were conducted almost a decade apart allowing for job search sites and Internet penetration to improve.

In another paper, Atasoy (2013) uses U.S. county level panel data that spans from 1999 to 2007 and finds that increased broadband penetration led to a 1.8 percentage point increase in employment. He also suggests that broadband adoption complements skilled labour as counties with a greater proportion of college educated individuals had higher employment rates. In addition, broadband access increases employment in industries that have a greater share of college educated individuals but had the opposite effect in some lower skilled industries. On the other hand, Ivus and Boland (2015) studied the deployment of fixed broadband in Canada over the period 1997-2011 and found that broadband deployment promotes employment in rural areas and not in urban areas. These results are contrary to the findings of Kandilov and Renkow (2010), who analysed the United States Department of Agriculture's (USDA) Pilot Broadband Loan Program and Broadband Loan Program and found that neither one promoted employment in rural areas. These programs were launched to develop telecommunications infrastructure in rural America. In a paper for Germany, Czernich (2014) finds that broadband availability among households does not lead to a reduction in unemployment. The author notes that there is no effect observed because broadband Internet may increase employment for those who are unemployed but not registered, and it may improve the efficiency of job searches for currently employed individuals.

Dettling (2017) uses data from U.S. Census current Population Survey from 2000 to 2009 and finds that married women with access to high speed Internet are more likely to join the labour force relative to men and single women. In particular, the impact is greater for married women who are college educated, which provides further evidence that broadband benefits skilled labour. Akerman et al. (2015) use rich Norwegian firm-level data and estimate production functions, where firms can change their production technology by adopting broadband Internet. They conclude that broadband Internet complements skilled workers in executing non-routine abstract tasks, and substitutes for unskilled workers in performing routine tasks. Finally, by exploiting the gradual arrival of submarine Internet cables on the coast of Africa, Hjort and Poulsen (2019) show that Internet coverage increases employment. Similar to developed countries, there is also a bias towards higher-skilled occupations.

The labour market papers discussed above focus on the deployment of fixed broadband in developed economies, with the exception of Hjort and Poulsen (2019). There are however fewer studies which focus on the impact of mobile coverage on labour markets in developing countries, where fixed broadband coverage is small or non-existent. One exception is an earlier unpublished paper by Klonner and Nolen (2010), who finds that the roll-out of mobile networks in rural areas in South Africa has a positive impact on employment. In localities which moved from no coverage to full coverage, employment increased by 15 percentage points, with a greater impact on women employment. In another recent paper by Bahia et al. (2020) for Nigeria, the authors combine survey and coverage data for years 2010-2016 and show that greater mobile broadband coverage increases household consumption and reduces poverty. They attribute these results to increased labour force participation and wage-based employment.

Our paper contributes to the literature by studying the impact of having a mobile phone on the change in employment status. We use a unique household panel dataset that tracks individuals over time which consists of five waves and covers the period between 2008 and 2017. In each period we observe whether people are employed or unemployed and thus whether they changed their employment status. By using a dataset that follows individuals overtime we are able to account for the unobserved heterogeneity amongst individuals, which could not be considered in other papers. Unlike Klonner and Nolen (2010), Bahia et al. (2020) and Bahia et al. (2021) who focus on mobile coverage, we are able to analyse the direct impact of mobile ownership on employment. Furthermore, the employment dynamics of individuals could not be analysed in previous studies due to the unavailability of panel data.

3 Data

Our analysis is based on the National Income Dynamics Survey (NIDS), which is the first nationwide panel survey data in South Africa collected by the Southern Africa Labour and Development Research Unit (SALDRU) at the University of Cape Town (UCT). This survey was conducted in five waves in years: 2008, 2010-2011, 2012, 2014-2015 and 2017. The data includes information on a representative sample of households and their members living across the country.[6]

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

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

the care-giver). In this analysis we only consider questionnaires from adult household members and from proxies. A proxy is a knowledgeable household member who is interviewed when it is not possible to interview the relevant individual (aged 15+) in person.

Each questionnaire consists of several modules with questions related to household expenditure and consumption, demographics, education, personal asset ownership and debt, various income sources and intra-household decision-making, among others.

The first two columns in Table 1 show the number of households and adults interviewed in all five waves. The first wave of the survey completed in December 2008 includes successful interviews of 7,296 households and 17,217 adults. The second wave was completed approximately two years later between May 2010 and September 2011 including 6,781 households and 18,725 adults. The third wave was completed in 2012, the fourth wave ran from October 2014 to August 2015 and finally in 2017 NIDS conducted its fifth wave. The remaining columns in Table 1 show the classification of people with respect to employment status based on their responses in the survey. See the Appendix for the definition of these categories based on survey responses.

Table 1: The number of successfully interviewed households and adults across all five waves and their declarations about employment

	Households	Adults	Not Active	Employed	Unempl.strict	Unempl.disc.	Refused
Wave 1	7,296	17,217	7,191	6,774	2,277	975	0
Wave 2	6,781	18,725	10,185	5,542	1,932	868	198
Wave 3	8,031	21,399	10,210	7,246	3,694	157	92
Wave 4	9,615	24,334	11,581	9,269	3,076	308	100
Wave 5	10,842	25,813	12,465	9,888	3,055	312	93

Note: Successful proxy interviews are included in the adults column

Employment status: Our main variable of interest is employment status, y_{it}, which in the data takes four values: (i) not economically active; (ii) discouraged unemployment; (iii) strict unemployment; and (iv) employed. We exclude individuals who are not economically active as they do not actively look for work. Unemployed individuals, $y_{it} = 0$, belong to two categories: (ii) discouraged unemployed and (iii) strict unemployed. Employed individuals, $y_{it} = 1$, belong to the last category. We discuss the rationale for such definition of unemployment in Section 3.1.

We create two dependent variables for change in employment status. Our first variable is a change from unemployed to employed between two consecutive waves, Y_{it}, which takes the value zero when individuals who were unemployed in wave t remained unemployed in wave $t+1$ ($y_{it} = 0$ and $y_{it+1} = 0$), and value one when they change status to employed ($y_{it} = 0$ and $y_{it+1} = 1$). As shown in Table 2, in Wave 2 there were 1,332 individuals who were classified as unemployed in Wave 1. Among them, 681 remained unemployed, and 651 became employed in Wave 2. Our estimation sample has repeated information on individuals who remain unemployed in two or more consecutive waves. When they change status to employed, then they are dropped from the data in the next wave.

Our second dependent variable takes the value zero when individuals who were employed in wave t remained employed in wave $t+1$ ($y_{it} = 1$ and $y_{it+1} = 1$), and value one when they change status to unemployed ($y_{it} = 1$ and $y_{it+1} = 0$). Table 2 shows that there were 3,403 individuals classified as employed in Wave 1. Among them, 2,878 remained employed, while 525 became unemployed in Wave 2. In this case, our estimation sample has repeated information on individuals who remain employed in two or more consecutive waves. When they change status to unemployed then they are dropped from the data in the next wave.

If owning a mobile phone lowers the search costs associated with finding employment, thereby increasing the likelihood of securing a job, it should also facilitate job transitions. Unfortunately, our dataset lacks the necessary detailed information on workplaces and job responsibilities to conduct such an analysis.

Table 1 shows the total amount of adults that were successfully interviewed in each wave, while Table 2 displays the number of adults who move between unemployment and employment and the other way around in two consecutive waves. The remaining people are: economically inactive; move from employment or unemployment into inactivity; or do not appear in the database in two consecutive waves. The data loss due to missing observations on employment status is minimal; however, there is a non-negligible attrition rate between waves. For instance, there were 17,217 individuals with recorded employment status in wave 1, of whom only 13,011 reappeared in wave 2, accounting for 75.6%. Out of 18,725 individuals in wave 2, 15,153 were present in wave 3, which is 80.1%. From 21,399 participants in wave 3, 17,055 continued to wave 4, representing 79.7%, and out of 24,334 in wave 4, 18,928 were tracked in wave 5, equating to 77.8%. The attrition rates for individuals who were employed or unemployed are comparable.[7]

Table 2: The number of people changing employment status by wave

	Remain unempl.	Become empl.	Total	Remain empl.	Become unempl.	Total
Wave 2	692	659	1,351	2,956	526	3,482
Wave 3	721	752	1,473	3,217	524	3,741
Wave 4	807	1,167	1,974	4,363	522	4,885
Wave 5	696	949	1,645	5,280	681	5,961
Total	2,916	3,527	6,443	15,816	2,253	18,069

Mobile phones: Our main explanatory variable is ownership of a mobile phone by an individual, which is a binary variable. Mobile phone adoption increased over the period covered by the NIDS data. The overall penetration changed from 57.0% in the first wave to 59.8% in the second wave, 77.4% in the third wave, 76.2% in the fourth wave and 79.8% in the fifth wave. Unfortunately, we are not able to analyse how Internet connectivity impacts change in employment status because questions about Internet access were not asked in the survey. We also do not know whether mobile phones are smartphones, which could approximate Internet access. But as mentioned above, the growth of internet users in South Africa has increased from 8.4% in 2008 to 56.2% of the population in 2017 with mobile devices being the most popular means for households to access the internet (56.9% in 2017). We therefore account for the increase in the number of smartphone owners and Internet users by interacting the mobile phone variable with a set of wave dummy variables.

Other variables: In the estimation we include a set of individual and household characteristics which may determine employment such as: gender, race, age, educational attainment, physical health, computer ownership within a household, place of living and others. We drop

[7] There are three categories of attrition. "Refusals" refer to individuals who were not interviewed across the panel due to an individual or household refusal. "Not Contacted" consists of respondents who were not tracked, could not be located, or moved outside of South Africa. Finally, "Deceased" includes those respondents who passed away between waves. More details on the survey's design and sampling methodology can be found in the "National Income Dynamics Study Panel User Manual," SALDRU, 2018.

from the sample individuals who are outside the working age, younger than 15 years and older than 65 years. Table (4) shows the summary statistics of the variables used in our estimation, split by change in employment status as defined above. The data shows that there are more individuals with a mobile phone who changed their employment status than those who did not. There are also significant differences between both groups with respect to gender, race, geographical location and physical health. Figure (1) shows how the change in employment status varies between individuals with mobile phones and without. A greater proportion of individuals that own a mobile phone switched from being unemployed to employed across the different waves, relative to individuals that do not own a mobile phone. The difference between the two groups is more pronounced in waves 2 and 4. Furthermore, Table (5) shows that a greater share of individuals who lost employment do not own a mobile phone, which can be also seen on Figure (2).

3.1 Definition of Unemployment

A broad definition of unemployment including discouraged unemployed in the context of South Africa has been a topic of debate for many years (see Kingdon and Knight (2000); Kingdon and Knight (2006); Lloyd and Leibbrandt (2014) and Posel et al. (2014)). The contention is centered on why individuals who want employment are not actively seeking employment and whether that justifies their inclusion or exclusion from the labor force. By excluding the non-searchers, we are ignoring a large segment of the labor force that employers consider when setting wages (Kingdon and Knight, 1999).

From the labour supply side, we find the inclusion of the non-searching unemployed is relevant for the following reasons. Kingdon and Knight (2000) show that individuals are less likely to search for work if they are situated in more remote areas as it increases the cost of looking for work. Additionally, Dinkelman and Pirouz (2002) find that having a migrant member in a household increases the probability of being part of the non-searching unemployed. They postulate that migrants provide a low-cost method of job search. This is relevant to our study, as mobile phones can help in connecting migrants to their households and thus reduce search costs.

Second, Posel et al. (2014) showed that non-searching unemployed individuals are not less likely to find work relative to the searching unemployed, and that human capital is a stronger predictor of employment. They also showed that social networks are the most common job finding strategy among the employed, with around 44% mentioning that "a friend/relative (in a different household) told me" about the job. Given that this information is from individuals outside the household, communication devices such as mobile phones may play a role in the dissemination of employment opportunities.

Moreover, the non-searching unemployed are a distinct group from the not economically active (NEA) population. By measuring the subjective well-being of these two groups, Lloyd and Leibbrandt (2014) showed that the non-searching group is significantly worse off than the NEA group, and that the non-precautionary costs are also greater for the non-searching unemployed. Given that this state provides less life satisfaction suggests that their choice to not search is not voluntary, and we should not confound their search choice with their willingness to work.

The findings from Posel et al. (2014) on how employed individuals find work, waiting for someone from their social network to contact them, suggest that mobile phones are likely to encourage passive forms of job search. It is for this reason, in addition to the ones mentioned above, that we use the broad definition of unemployment.

4 Econometric model

We estimate a probit model with a binary dependent variable where the probability of a change in employment status, Y_{it}, is explained by a vector of individual and household characteristics. In another specification, we also allow for unobservable heterogeneity by means of individual random effects. The probability that an individual i takes up employment in wave $t = 1, ..., T_i$ can be written as:

(1) $$Pr(Y_{it} = 1 | X_{it}, \xi_i) = \Phi(X_{it}\beta + \xi_i)$$

where X_{it} denotes a vector of individual and household characteristics, ξ_i are unobserved individual-specific effects assumed to be normally distributed and $\Phi(.)$ is the standard normal cumulated distribution function of the error term ϵ_{it}. Note that the panel data is unbalanced because we lose some individuals over time and new ones join the sample. Also, when individuals become employed they are dropped from the sample, but would be included again if they become unemployed in subsequent waves.

The probability of a particular pattern of employment status for an individual i over the whole period when she/he is present in our data can be written as:

$$(2) \quad l_i\left(\beta|X_{it},\xi_i\right) = \prod_{t=1}^{T_i} \Phi(X_{it}\beta+\xi_i)^{Y_{it}}(1-\Phi(X_{it}\beta+\xi_i))^{1-Y_{it}}$$

In a model with unobserved heterogeneity, ξ_i, we need to integrate the conditional probability $l_i\left(\beta|X_{it},\xi_i\right)$ over the normal distribution of $\xi_i \sim N(\mu_\xi, \sigma_\xi)$:

$$(3) \quad P_i = \int_\xi l_i\left(\beta|X_{it},\xi_i\right) f(\xi) d\xi,$$

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

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

The vector of all parameters which are estimated is denoted by θ, which includes β and the parameters of the distribution of random effects $\xi_i \sim N(\mu_\xi, \sigma_\xi)$. The maximum likelihood estimator is the value of the parameter vector θ that maximizes the likelihood function $\mathcal{L}$ given by equation (4).

4.1 Endogeneity

There is a potential issue of endogeneity if mobile phone ownership is correlated with the error term. We select people who are unemployed in period t and estimate whether those who have a mobile phone are more likely to become employed in period $t+1$. By construction of the survey the impact of having a mobile phone is measured 1-2 years later. Having a mobile phone could be endogenous in our setup if people get it in anticipation of becoming employed 1-2 years later. Moreover, unemployed people with mobile phones may be different from those without mobile phones, where unobserved characteristics such as being more entrepreneurial or better connected impact chances of becoming employed.

In the second set of regressions, we select people who are employed in period t and estimate whether those who have a mobile phone are less likely to become unemployed in period $t+1$. In this case, people may get a mobile phone in anticipation of continuing employment in 1-2 years. The endogeneity problem in these regressions may be more severe because people should have a better idea as to whether they will be able to keep their job than as to whether they will be able to find employment in 1-2 years. The second set of regressions should therefore be interpreted with caution. There may be again unobserved individual characteristics correlated with having a mobile phone and staying employed for which we can control to some extent.

In the estimation we include a rich set of observed characteristics such as gender, race, education, region of residence and others. In addition, we estimate a model with individual random effects. We also estimate a recursive bivariate probit model, in which we use access to electricity as an instrumental variable for owning a mobile phone. The deployment of electricity networks should be correlated with mobile network coverage and growing adoption of mobile phones among poor and rural households. In the second wave of our data 24.4% of households did not have access to electricity, as compared to 13% in the fifth wave. Individuals not having a mobile phone during these periods were 40% and 22.1%, respectively. At the same time, access to electricity does not have significant impact on change in employment status, as shown in Table 9.

As an additional test for endogeneity of owning a mobile phone we estimate regressions where becoming employed between period t and $t+1$ explains having a mobile phone in period t, which are shown in the first two columns in Table 6. The coefficient on change of employment status should be positive and significant if there are unobserved factors, which impact both change in employment status and having a mobile phone. The coefficient is positive but insignificant, which supports exogeneity of owning a mobile phone in these regressions. In the second set of regressions shown in columns (3) and (4), becoming unemployed between period t and $t+1$ is used to explain having a mobile phone in period t. The coefficient on change of employment status is significant and negative. This indicates that there may be endogeneity problems in that people who become unemployed are less likely to have a mobile phone. These additional regressions shown in Table 6 suggest that our estimation results for the negative impact of mobile phones on becoming unemployed shown in Table 8 be interpreted with caution.

5 Estimation results

First, we estimate a simple probit model to show how a change in employment status depends on individual and household characteristics. Second, we estimate a probit model with individual random effects, which accounts for unobserved heterogeneity. Each of these models is estimated in three specifications. The first one includes a binary variable for the possession of a mobile phone (Model I). The second specification in addition includes binary variables for the possession of a computer by the household and for individual computer literacy (Model II). The third specification includes interaction terms between mobile phone ownership and survey wave dummy variables to approximate the growing adoption of smartphones and Internet usage (Model III).

The estimation results for becoming employed are shown in Table (7), where the dependent variable takes a value of one if an individual was unemployed in period t and becomes employed in period $t+1$, and zero if she/he stays unemployed. Models I to III are probit models and Models IV to VI are probit models with random effects. The models for becoming unemployed are shown in Table (8). Now the dependent variable takes a value of one when an individual who was employed in period t becomes unemployed in period $t+1$ and zero when she/he stays employed. Based on the log-likelihood values the preferred specifications are models with individual random effects.

In all model specifications in Table (7), we find that having a mobile phone has a positive impact on the employment status. This can be seen on Figure (1), which shows that a greater proportion of people who have a mobile phone in wave t find employment in wave $t+1$, relative to those who do not own a mobile phone. Moreover, using Model VI the average probability of becoming employed increases from 54.2% when no one among unemployed adults has a mobile phone to 57.4% when all of them have a mobile phone, which is an increase of 5.9%. Thus, the impact of mobile phones on changing employment status is not large, which suggests that other factors play a role.

Having a computer in the household and being computer-literate are both statistically insignificant. This may be surprising as Table (4) shows that relatively more people who change employment have a computer in the household and are computer literate. However, having access to a computer or declaring computer literacy does not necessarily mean that individuals have computer skills which are desired by the market. In particular, individuals with more education should be better positioned to take advantage of computer literacy and get a job. In our data, 22% of individuals with tertiary education who changed employment status had a computer at home, as compared to 14% of individuals with secondary and 6% with primary education. There is therefore a correlation between education and computer variables. When education dummy variables are dropped from the model, having a computer and computer literacy become significant.

In general, individuals who declared having a computer in their household and being computer literate are under 50 years old. They also tend to have secondary and tertiary education and live in urban areas. Moreover, as shown in Table (3), having a computer in the household increases the share of young people under the age of 25 and between 25-35 years old who become employed. In the case of mobile phones the impact on becoming employed seems to be stronger for older people.

Individual characteristics have a significant impact on the change in employment status. Females are less likely to become employed relative to men. Older individuals have a greater chance of becoming employed as compared to individuals who are younger than 25 years old, which may be due to work experience. There are no differences between race groups in the probability of becoming employed. Individuals with secondary and tertiary education are

Table 3: Share of people becoming employed between periods t and $t+1$ by age group and device ownership

Age	Computer		Computer literacy		Mobile phone	
	No	Yes	No	Yes	No	Yes
Below 25	50%	65%	47%	57%	47%	53%
25-35	54%	65%	52%	62%	49%	57%
35-50	60%	61%	59%	67%	61%	59%
50-65	67%	47%	65%	63%	60%	67%
Total	54%	64%	53%	60%	52%	56%

more likely to become employed relative to those with less than primary education. Individuals with excellent health conditions are more likely to become employed as well as people living in urban areas. Over time, chances of become employed increase and are greater in waves 4 and 5 than in waves 3 and 2. There are significant differences in the likelihood of becoming employed for people living in different geographic regions across the country, with individuals from the Western Cape having the highest chances of becoming employed, compared to other provinces. The interaction terms between mobile phone possession and the wave dummy variables are significant and negative for wave 3 but insignificant for waves 4 and 5, which suggests that the impact of having a mobile phone on change in employment status increases over time. We interpret this result as the effect of an increase in the adoption of smartphones and Internet usage.

In the regressions in Table (8), we find that owning a mobile phone and having a computer at home decreases the probability of becoming unemployed. This corroborates the pattern in Figure (2), which shows that a larger proportion of individuals who own a mobile phone remain employed over time relative to those without a mobile phone. In terms of impact, using Model VI the average probability of becoming unemployed when people do not have a mobile phone is 11.6%, as compared to 8.1% when everyone has a mobile phone, which is a decrease of 30.1%. In comparison, the average probability of becoming unemployed when people do not have a computer is 9.0%, as compared to 6.4% when everyone has a computer, which is a decrease of 28.9%. Thus, the relative impact of ownership of a mobile phone and a computer on maintaining employment is comparable. However, as discussed in Section (4.1), mobile phone as well as computer ownership may be endogenous and the impact of having a mobile phone on remaining employed may be overestimated. For example, people may expect keeping their job in the future which allows them to take up a long-term mobile subscription and purchase a computer.

Furthermore, living in an urban area, being older, having a tertiary or secondary education and being in good health are all contributing factors in decreasing the probability of losing one's job. In terms of gender and race, the results show that women are more likely to become unemployed relative to men, while African and Coloured adults are more likely to become unemployed relative to White adults.

In addition to the models discussed above, we estimate a recursive bivariate probit model with two dependent binary variables, change in employment status and phone ownership, where phone ownership also appears on the right-hand side of the equation for change in employment status, but not the other way around. As discussed in Section 4.1, we include one additional variable to explain phone ownership which is having electricity connection at the household. In the regressions for becoming employed in Table 9, phone ownership is positive and significant. In the regressions for loss of employment in Table 10, phone ownership is insignificant with a negative sign. This suggests that phone ownership may be endogenous among employed individuals, which is consistent with our findings reported in Table 6 and discussed in Section 4.1. We are therefore cautious with interpreting the role of owning a mobile phone in retaining employment.

6 Conclusion

In this paper, we study whether the change in employment status over time can be attributed to mobile phone ownership. We use five waves of panel data from the National Income Dynamic Survey (NIDS), which was conducted in South Africa from 2008 to 2017. During the period covered by our data, Internet usage among South Africans increased from 8.4% in 2008 to 56.2% of the population in 2017, which is driven by the adoption of smartphones and use of mobile broadband.

Our estimation results suggest that mobile phone ownership has a positive impact on changing status from unemployed to employed. The impact is greater in the last waves of the survey. On the other hand, ownership of a computer by a household and computer literacy do not have a significant impact on becoming employed. The average probability of becoming employed increases from 54.2% when no one among unemployed adults has a mobile phone to 57.4% when all of them have a mobile phone, which is an increase of 5.9%. Thus, the impact of mobile phones on changing employment status is not large, which suggests that other factors play a role.

We also find that having a mobile phone and ownership of a computer by a household reduce the likelihood of becoming unemployed. However, the impact of having a mobile phone on retaining employment may be overestimated due to endogeneity of mobile phone ownership. We are therefore cautious with interpreting these results.

In our estimation, we control for a set of individual and household characteristics such as race, age, gender, physical health, educational attainment, computer ownership within a household, place of living and others. The panel data allows us to account for unobserved heterogeneity amongst individuals.

Our paper contributes to the growing body of research on the impact of mobile phones and Internet on the labour market. This is particularly important in developing countries where search costs for jobs are high due to the lack of physical infrastructure among others. It is therefore critically important to develop policies which stimulate the adoption of mobile phones. The key factors for this are expanding network coverage, affordable prices of smartphones and mobile devices, and low prices of mobile data services. In this paper we focused on the impact of mobile phones on employment. But as shown by some of the earlier research, there are other channels through which mobile phones impact the economy including increased market efficiency, access to financial services and overall reduction in poverty.

Our analysis is based on a specific definition of unemployment, where another large group are individuals who are identified as being not economically active. We observe that many individuals move from being not economically active into employment and vice versa. Furthermore, it appears that inactive individuals with access to mobile phones are more likely to become employed, while employed individuals with mobile phones are less likely to become inactive. These findings suggest that a more comprehensive analysis of the role of communication technologies in economic activity is warranted. However, such an analysis is beyond the scope of this paper and could be another research project.

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Appendix A: Definition of Unemployment

An employed person must have positively answered at least one of the following questions:

- Are you currently being paid a regular wage/salary, part-time/full-time?
- Do you have a secondary occupation?
- Are you self-employed?
- Have you had paid casual employment in the last 30 days?
- Have you assisted others with business activities in the last 30 days?

Not economically active person is classified as unemployed based on the questions above and gave a negative answer to the following question:

- Have you desired to work in the last 4 weeks?

A discouraged unemployed person is someone who is unemployed, economically active, and has answered 'nothing' to the following question:

- Have you done ... to search for work or start a business?

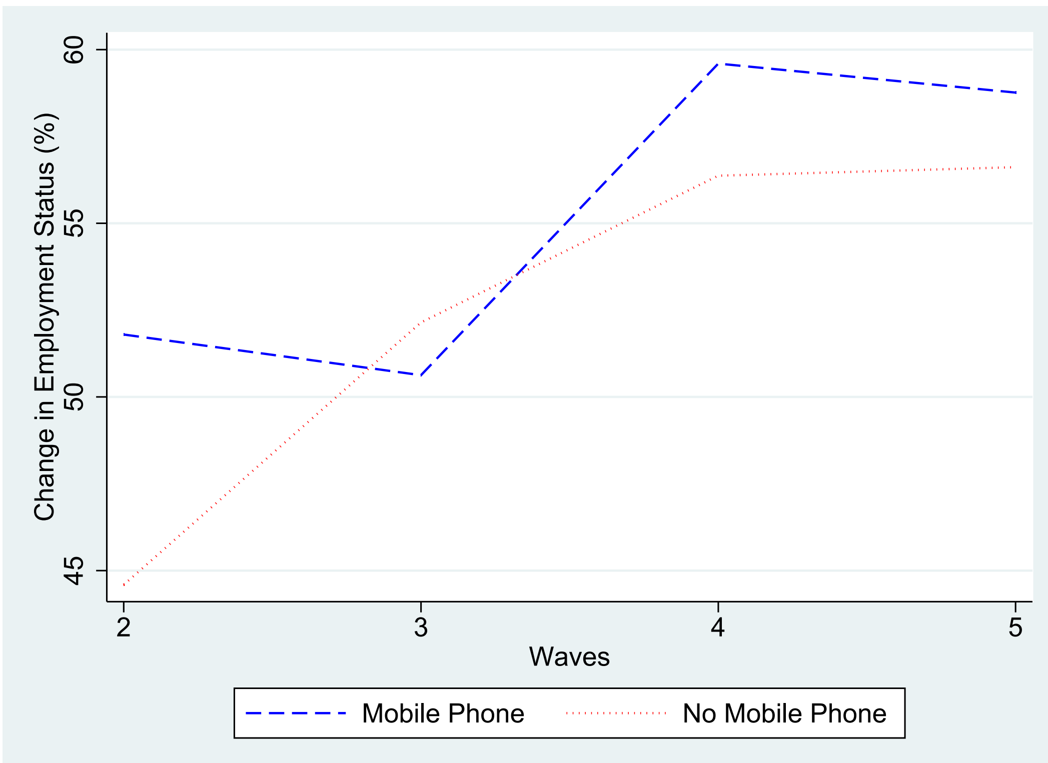
A strict unemployed person is someone who is unemployed, not discouraged, and has declared one of the following actions in search for employment:

- Registered at an employment agency
- Enquired at workplaces, farms, factories, or called other possible employers
- Placed advertisement(s)
- Answered advertisements
- Searched through job advertisement(s) on the internet
- Sought assistance from relatives or friends

- Looked for land, building, equipment, or applied for a permit to start their own business or farming
- Waited at the side of the road
- Sought financial assistance to start a business
- Other (specify)

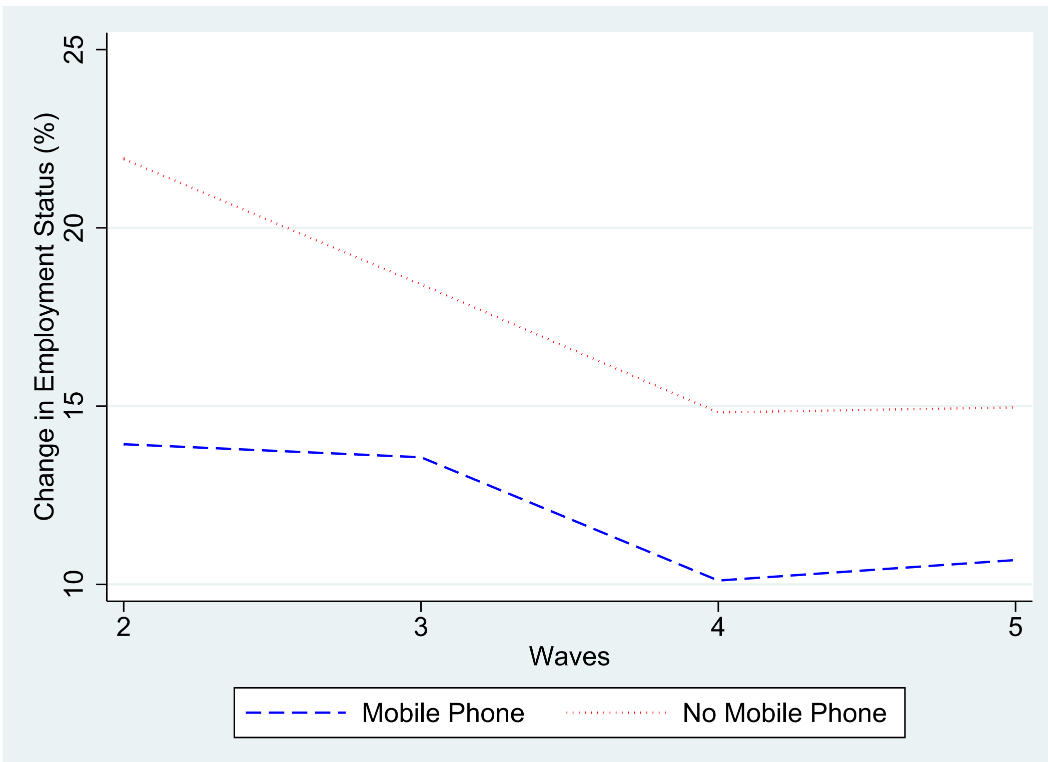
Appendix B: Tables

Figure 1: Proportion of adults who became employed over time by mobile phone ownership



Note: Change in employment status represents a binary variable with the base category being adults who remained unemployed and the alternative being adults who became employed, across adjacent waves. The above graph compares the change in employment status across adjacent waves between adults with and without mobile phones.

Figure 2: Proportion of adults who became unemployed over time by mobile phone ownership



Note: Change in employment status represents a binary variable with the base category being adults who remained employed, and the alternative being adults who became unemployed, across adjacent waves. The above graph compares the change in employment status across adjacent waves between adults with and without mobile phones.

Table 4: Summary statistics of adults who remained unemployed and those who became employed.

Variables	Remain unemployed		Become employed	
	Mean	Std	Mean	Std
Mobile Phone	0.714	0.452	0.753	0.431
Female	0.646	0.478	0.538	0.499
Age	29.3	9.1	30.9	9.7
Race				
African	0.890	0.313	0.853	0.354
White	0.004	0.060	0.007	0.083
Coloured	0.100	0.300	0.134	0.340
Asian/Indian	0.006	0.080	0.006	0.079
Education				
<Primary	0.111	0.314	0.112	0.316
Primary	0.619	0.486	0.547	0.498
Secondary	0.205	0.403	0.226	0.418
Tertiary	0.065	0.247	0.115	0.319
Health				
Poor-fair	0.077	0.267	0.064	0.244
Good-Very Good	0.547	0.498	0.545	0.498
Excellent	0.376	0.484	0.391	0.488
Household Computer	0.065	0.247	0.094	0.292
Computer Literate	0.288	0.453	0.351	0.477
Geographic Location				
Urban	0.457	0.498	0.534	0.499
Non-Urban	0.543	0.498	0.466	0.499
Province				
Western Cape	0.060	0.237	0.103	0.304
Eastern Cape	0.137	0.344	0.111	0.314
Northern Cape	0.081	0.273	0.084	0.278
Free State	0.063	0.243	0.073	0.260
KwaZulu Natal	0.290	0.454	0.246	0.431
North West	0.087	0.282	0.067	0.251
Gauteng	0.109	0.312	0.135	0.342
Mpumalanga	0.081	0.273	0.085	0.279
Limpopo	0.092	0.289	0.095	0.293
Observations	2,474		3,013	

Note: Columns 2 and 3 ("Remain unemployed") represents the mean and standard deviation (Std) of adults who remained unemployed across adjacent waves while columns 3 and 4 ("Become employed") represents the descriptive statistics of adults who became employed across adjacent waves. The sample used in the table represents the adults who have available data on all the variables shown above.

Table 5: Summary statistics of adults who remained employed and those who became unemployed.

Variables	Remain employed		Become unemployed	
	Mean	Std	Mean	Std
Mobile Phone	0.851	0.356	0.777	0.416
Female	0.482	0.500	0.528	0.499
Age	37.6	10.7	32.7	10.2
Race				
African	0.746	0.435	0.819	0.385
White	0.045	0.207	0.008	0.092
Coloured	0.195	0.397	0.164	0.371
Asian/Indian	0.014	0.117	0.008	0.089
Education				
<Primary	0.144	0.352	0.134	0.341
Primary	0.446	0.497	0.577	0.494
Secondary	0.191	0.393	0.191	0.393
Tertiary	0.219	0.413	0.098	0.298
Health				
Poor-fair	0.080	0.271	0.096	0.294
Good-Very Good	0.571	0.495	0.539	0.499
Excellent	0.349	0.477	0.365	0.482
Household Computer	0.205	0.404	0.096	0.294
Computer Literate	0.438	0.496	0.333	0.471
Geographic Location				
Urban	0.649	0.477	0.562	0.496
Non-Urban	0.351	0.477	0.438	0.496
Province				
Western Cape	0.175	0.380	0.134	0.341
Eastern Cape	0.085	0.279	0.112	0.315
Northern Cape	0.082	0.275	0.081	0.273
Free State	0.070	0.256	0.066	0.248
KwaZulu Natal	0.208	0.406	0.260	0.439
North West	0.060	0.238	0.060	0.237
Gauteng	0.169	0.374	0.125	0.331
Mpumalanga	0.083	0.276	0.087	0.282
Limpopo	0.067	0.250	0.075	0.263
Observations	13,855		2,003	

Note: Columns 2 and 3 ("Remain employed") represents the mean and standard deviation (Std) of adults who remained employed across adjacent waves while columns 3 and 4 ("Become unemployed") represents the descriptive statistics of adults who became unemployed across adjacent waves. The sample used in the table represents the adults who have available data on all the variables shown above.

Table 6: Estimation results for owning a mobile phone

	Becoming employed		Becoming unemployed	
	Probit	RE Probit	Probit	RE Probit
Employment change	0.058	0.061	-0.202***	-0.239***
	(-0.039)	(-0.044)	(-0.036)	(-0.046)
Female	0.244***	0.275***	0.135***	0.175***
	(-0.039)	(-0.046)	(-0.026)	(-0.036)
Urban	0.121**	0.137**	0.183***	0.204***
Age categories				
	(-0.05)	(-0.058)	(-0.038)	(-0.049)
25-35	0.230***	0.262***	0.239***	0.279***
	(-0.046)	(-0.053)	(-0.037)	(-0.051)
35-50	0.186***	0.219***	0.152***	0.183***
	(-0.053)	(-0.061)	(-0.047)	(-0.064)
50-6 5	0.276***	0.312***	-0.256***	-0.363***
	(-0.102)	(-0.118)	(-0.091)	(-0.126)
Race				
African	0.012	0.015	-0.713***	-0.950***
	(-0.286)	(-0.327)	(-0.093)	(-0.131)
Coloured	-0.485*	-0.535	-0.171	-0.245
	(-0.288)	(-0.33)	(-0.153)	(-0.212)
Asian/Indian	0.378	0.422	0.454***	0.585***
	(-0.384)	(-0.44)	(-0.035)	(-0.051)
Education				
Primary	0.408***	0.468***	0.795***	1.025***
	(-0.06)	(-0.071)	(-0.046)	(-0.067)
Secondary	0.786***	0.904***	0.971***	1.218***
	(-0.072)	(-0.09)	(-0.048)	(-0.071)
Tertiary	0.864***	0.979***	-0.006	-0.032
	(-0.093)	(-0.112)	(-0.046)	(-0.059)
Health				
Very good / good	-0.107	-0.129	0.099**	0.088
	(-0.077)	(-0.088)	(-0.049)	(-0.063)
Excellent	-0.071	-0.085	0.131***	0.171***
	(-0.08)	(-0.091)	(-0.031)	(-0.043)
Waves				
Wave 3	0.061	0.073	0.169***	0.234***
	(-0.054)	(-0.06)	(-0.038)	(-0.046)
Wave 4	0.668***	0.760***	0.496***	0.637***
	(-0.056)	(-0.068)	(-0.038)	(-0.048)
Wave 5	0.454***	0.516***	0.277***	0.370***
	(-0.054)	(-0.064)	(-0.034)	(-0.043)
Constant	-0.463	-0.534	0.248**	0.383**
	(-0.306)	(-0.35)	(-0.115)	(-0.158)
Observations	5,549	5,549	16,105	16,105
Log likelihood	-2874	-2866	-6376	-6240

Note: The dependent variable is a binary variable, taking on a value of one when an individual owns a mobile phone. The employment change is also binary taking a value of one when an individual moves from being unemployed to being employed across adjacent waves in the first two columns, or from being employed to unemployed in the last two columns. Other variables include gender (base category = males), age groups (base category = 15-25 years), race (base category = White), education (base category less than primary education), health (base category = poor-fair), urban (base category = non-urban), waves (base category = wave 2), Provinces. Standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1

Table 7: Estimation results for being unemployed and becoming employed

	Probit Model			Probit Model with R.E.		
Variables	Model I	Model II	Model III	Model IV	Model V	Model VI
Mobile phone	0.070*	0.077*	0.164**	0.070	0.078*	0.164*
	(0.041)	(0.042)	(0.077)	(0.046)	(0.046)	(0.085)
Home computer		0.062	0.061		0.072	0.071
		(0.069)	(0.069)		(0.077)	(0.077)
Computer literate		0.019	0.023		0.024	0.028
		(0.044)	(0.044)		(0.049)	(0.049)
Female	-0.330***	-0.328***	-0.330***	-0.364***	-0.363***	-0.366***
	(0.036)	(0.036)	(0.036)	(0.042)	(0.042)	(0.042)
Urban	0.087**	0.086*	0.085*	0.097*	0.096*	0.095*
	(0.044)	(0.045)	(0.045)	(0.050)	(0.051)	(0.051)
Age categories						
25-35	0.149***	0.147***	0.148***	0.180***	0.181***	0.182***
	(0.041)	(0.041)	(0.041)	(0.046)	(0.047)	(0.047)
35-50	0.320***	0.326***	0.328***	0.380***	0.390***	0.392***
	(0.048)	(0.049)	(0.049)	(0.056)	(0.058)	(0.058)
50-65	0.415***	0.406***	0.411***	0.476***	0.468***	0.474***
	(0.093)	(0.097)	(0.097)	(0.106)	(0.110)	(0.111)
Race						
African	-0.171	-0.132	-0.134	-0.232	-0.190	-0.193
	(0.244)	(0.247)	(0.247)	(0.280)	(0.285)	(0.286)
Coloured	-0.074	-0.035	-0.040	-0.122	-0.079	-0.085
	(0.248)	(0.251)	(0.251)	(0.284)	(0.290)	(0.290)
Asian/Indian	-0.208	-0.194	-0.184	-0.234	-0.220	-0.207
	(0.326)	(0.327)	(0.327)	(0.373)	(0.377)	(0.378)
Education						
Primary	-0.044	-0.037	-0.041	-0.052	-0.044	-0.049
	(0.058)	(0.060)	(0.060)	(0.066)	(0.068)	(0.068)
Secondary	0.147**	0.143**	0.140**	0.161**	0.158**	0.154*
	(0.067)	(0.070)	(0.070)	(0.076)	(0.080)	(0.080)
Tertiary	0.397***	0.381***	0.375***	0.440***	0.423***	0.417***
	(0.081)	(0.088)	(0.088)	(0.093)	(0.100)	(0.100)
Health						
Good / Very good	0.109	0.106	0.105	0.115	0.111	0.110
	(0.070)	(0.071)	(0.071)	(0.078)	(0.079)	(0.079)
Excellent	0.149**	0.146**	0.146**	0.161**	0.157*	0.157*
	(0.073)	(0.074)	(0.074)	(0.080)	(0.082)	(0.082)
Survey waves						
Wave 3	0.011	0.002	0.131	0.052	0.044	0.186*
	(0.052)	(0.053)	(0.087)	(0.057)	(0.059)	(0.097)
Wave 4	0.207***	0.201***	0.231**	0.264***	0.257***	0.273**
	(0.050)	(0.050)	(0.100)	(0.057)	(0.057)	(0.111)
Wave 5	0.183***	0.175***	0.226**	0.255***	0.249***	0.294***
	(0.050)	(0.051)	(0.094)	(0.059)	(0.060)	(0.105)
Mobile phone x Waves 3			-0.203*			-0.222*
			(0.109)			(0.121)
Mobile phone x Waves 4			-0.058			-0.042
			(0.115)			(0.128)
Mobile phone x Waves 5			-0.083			-0.075
			(0.111)			(0.123)
Constant	0.266	0.215	0.170	0.333	0.278	0.236
	(0.265)	(0.268)	(0.271)	(0.303)	(0.308)	(0.312)
Provinces	yes	yes	yes	yes	yes	yes
Observations	5,549	5,487	5,487	5,549	5,487	5,487
Log likelihood	-3670	-3626	-3625	-3660	-3616	-3614

Note: The dependent variable is a binary variable which takes a value of one when an individual moves from being unemployed to being employed across adjacent waves. The mobile phone variable is also binary, taking on a value of one when an individual owns a mobile phone. Other variables include gender (base category = males), age groups (base category = 15-25 years), race (base category = White), education (base category less than primary education), health (base category = poor-fair), urban (base category = non-urban), waves (base category = wave 2), Provinces. Standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1

Table 8: Estimation results for being employed and becoming unemployed

	Probit Model			Probit Model with R.E.		
Variables	Model I	Model II	Model III	Model IV	Model V	Model VI
Mobile phone	-0.196***	-0.185***	-0.229***	-0.239***	-0.226***	-0.265***
	(0.035)	(0.035)	(0.064)	(0.046)	(0.046)	(0.083)
Home computer		-0.160***	-0.161***		-0.198***	-0.199***
		(0.044)	(0.044)		(0.058)	(0.058)
Computer literate		-0.055	-0.055		-0.072	-0.072
		(0.034)	(0.034)		(0.045)	(0.045)
Female	0.181***	0.181***	0.181***	0.252***	0.252***	0.252***
	(0.027)	(0.027)	(0.027)	(0.039)	(0.039)	(0.039)
Urban	-0.068**	-0.060*	-0.059*	-0.108**	-0.097**	-0.096**
	(0.032)	(0.032)	(0.032)	(0.045)	(0.046)	(0.046)
Age categories						
25-35	-0.296***	-0.300***	-0.299***	-0.360***	-0.364***	-0.364***
	(0.036)	(0.036)	(0.036)	(0.048)	(0.048)	(0.048)
35-50	-0.629***	-0.634***	-0.634***	-0.788***	-0.795***	-0.795***
	(0.037)	(0.038)	(0.038)	(0.054)	(0.055)	(0.055)
50-65	-0.822***	-0.844***	-0.844***	-1.057***	-1.084***	-1.084***
	(0.054)	(0.056)	(0.056)	(0.078)	(0.080)	(0.080)
Race						
African	0.533***	0.431***	0.429***	0.743***	0.612***	0.610***
	(0.113)	(0.116)	(0.116)	(0.157)	(0.159)	(0.159)
Coloured	0.355***	0.273**	0.270**	0.508***	0.403**	0.401**
	(0.116)	(0.118)	(0.118)	(0.160)	(0.162)	(0.162)
Asian/Indian	0.271	0.245	0.243	0.386	0.356	0.354
	(0.175)	(0.175)	(0.175)	(0.242)	(0.242)	(0.242)
Education						
Primary	0.074*	0.086**	0.087**	0.097*	0.119**	0.120**
	(0.041)	(0.043)	(0.043)	(0.059)	(0.060)	(0.060)
Secondary	-0.130***	-0.091*	-0.089*	-0.195***	-0.136*	-0.134*
	(0.050)	(0.053)	(0.053)	(0.071)	(0.074)	(0.074)
Tertiary	-0.423***	-0.343***	-0.341***	-0.574***	-0.465***	-0.464***
	(0.054)	(0.060)	(0.060)	(0.077)	(0.084)	(0.084)
Health						
Good / Very good	-0.191***	-0.198***	-0.197***	-0.227***	-0.238***	-0.237***
	(0.049)	(0.049)	(0.049)	(0.063)	(0.064)	(0.064)
Excellent	-0.158***	-0.163***	-0.162***	-0.181***	-0.190***	-0.189***
	(0.051)	(0.052)	(0.052)	(0.067)	(0.067)	(0.067)
Survey waves						
Wave 3	-0.035	-0.026	-0.097	0.017	0.023	-0.042
	(0.041)	(0.042)	(0.086)	(0.051)	(0.052)	(0.109)
Wave 4	-0.222***	-0.212***	-0.235***	-0.233***	-0.225***	-0.249**
	(0.040)	(0.040)	(0.090)	(0.050)	(0.050)	(0.115)
Wave 5	-0.198***	-0.179***	-0.219***	-0.221***	-0.197***	-0.233**
	(0.037)	(0.038)	(0.077)	(0.047)	(0.048)	(0.099)
Mobile phone x Waves 3			0.093			0.085
			(0.098)			(0.124)
Mobile phone x Waves 4			0.034			0.034
			(0.100)			(0.128)
Mobile phone x Waves 5			0.054			0.048
			(0.088)			(0.113)
Constant	-0.813***	-0.717***	-0.686***	-1.121***	-0.999***	-0.970***
	(0.137)	(0.139)	(0.144)	(0.191)	(0.193)	(0.199)
Provinces	yes	yes	yes	yes	yes	yes
Observations	16,105	15,858	15,858	16,105	15,858	15,858
Log likelihood	-5,671	-5,570	-5,570	-5,612	-5,514	-5,514

Note: The dependent variable is a binary variable which takes a value of one when an individual moves from being employed to being unemployed across adjacent waves. The mobile phone variable is also binary, taking on a value of one when an individual owns a mobile phone. Other variables include gender (base category = males), age groups (base category = 15-25 years), race (base category = White), education (base category less than primary education), health (base category = poor-fair), urban (base category = non-urban), waves (base category = wave 2), Provinces. Standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1

Table 9: Estimation results for owning a mobile phone and becoming employed in a recursive bivariate probit model

	RBP Model I		RBP Model II		Probit: becoming employed	
Variables	Employed	Mobile phone	Employed	Mobile phone	Model I	Model II
Mobile phone	0.822***		0.892***		0.069*	0.076*
	(-0.266)		(-0.253)		(-0.041)	(-0.042)
Home computer			0.064			0.06
			(-0.065)			(-0.069)
Computer literate			0.018			0.018
			(-0.041)			(-0.044)
Female	-0.365***	0.245***	-0.362***	0.238***	-0.329***	-0.327***
	(-0.036)	(-0.039)	(-0.035)	(-0.039)	(-0.036)	(-0.036)
Urban	0.056	0.101**	0.053	0.097*	0.083*	0.082*
	(-0.045)	(-0.05)	(-0.046)	(-0.05)	(-0.045)	(-0.045)
Age						
25-35	0.090*	0.233***	0.083*	0.232***	0.149***	0.147***
	(-0.047)	(-0.045)	(-0.047)	(-0.046)	(-0.041)	(-0.041)
35-50	0.257***	0.188***	0.257***	0.180***	0.319***	0.324***
	(-0.055)	(-0.052)	(-0.056)	(-0.053)	(-0.048)	(-0.049)
50-65	0.325***	0.291***	0.308***	0.282***	0.415***	0.405***
	(-0.101)	(-0.102)	(-0.102)	(-0.104)	(-0.094)	(-0.097)
Race						
African	-0.169	0.016	-0.128	0.013	-0.171	-0.134
	(-0.24)	(-0.28)	(-0.242)	(-0.28)	(-0.244)	(-0.247)
Coloured	0.055	-0.490*	0.107	-0.496*	-0.074	-0.036
	(-0.248)	(-0.282)	(-0.25)	(-0.282)	(-0.248)	(-0.251)
Asian/Indian	-0.288	0.383	-0.28	0.386	-0.218	-0.205
	(-0.322)	(-0.383)	(-0.321)	(-0.383)	(-0.327)	(-0.327)
Education						
Primary	-0.151**	0.393***	-0.157**	0.408***	-0.048	-0.041
	(-0.068)	(-0.06)	(-0.069)	(-0.062)	(-0.058)	(-0.06)
Secondary	-0.051	0.770***	-0.075	0.786***	0.141**	0.138**
	(-0.099)	(-0.072)	(-0.099)	(-0.074)	(-0.068)	(-0.07)
Tertiary	0.184	0.865***	0.145	0.882***	0.391***	0.376***
	(-0.115)	(-0.093)	(-0.117)	(-0.094)	(-0.082)	(-0.088)
Health						
Very good / good	0.125*	-0.099	0.124*	-0.105	0.11	0.106
	(-0.069)	(-0.077)	(-0.069)	(-0.078)	(-0.07)	(-0.071)
Excellent	0.157**	-0.068	0.155**	-0.075	0.149**	0.146**
	(-0.072)	(-0.08)	(-0.072)	(-0.08)	(-0.073)	(-0.074)
Waves						
Wave 3	-0.006	0.072	-0.016	0.067	0.012	0.002
	(-0.051)	(-0.054)	(-0.052)	(-0.055)	(-0.052)	(-0.053)
Wave 4	0.047	0.661***	0.025	0.660***	0.205***	0.198***
	(-0.079)	(-0.055)	(-0.077)	(-0.055)	(-0.05)	(-0.05)
Wave 5	0.062	0.447***	0.042	0.449***	0.180***	0.172***
	(-0.069)	(-0.054)	(-0.068)	(-0.054)	(-0.051)	-0.051
Electricity		0.124***		0.119**	0.035	(0.037)
		(-0.047)		(-0.047)	(-0.046)	-0.046
Constant	-0.041	-0.515*	-0.12	-0.506*	0.244	(0.193)
	(-0.283)	(-0.3)	(-0.283)	(-0.301)	(-0.266)	-0.269
Provinces	yes	yes	yes	yes	yes	yes
Observations	5,549	5,549	5,487	5,487	5,549	5,487
Log-likelihood	-6,540	-6,540	-6,456	-6,456	-3,669	-3,626

Note: The dependent variable is a binary variable which takes a value of one when an individual moves from being unemployed to being employed across adjacent waves. The mobile phone variable is also binary, taking on a value of one when an individual owns a mobile phone. Other variables include gender (base category = males), age groups (base category = 15-25 years), race (base category = White), education (base category less than primary education), health (base category = poor-fair), urban (base category = non-urban), waves (base category = wave 2), Provinces. Standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1

Table 10: Estimation results for owning a mobile phone and becoming unemployed in a recursive bivariate probit model

	RBP Model I		RBP Model II		Probit: becoming unemployed	
Variables	Employed	Mobile phone	Employed	Mobile phone	Model I	Model II
Mobile phone	-0.112		-0.152)		-0.193***	-0.183***
	(-0.273)		(-0.28		(-0.035)	(-0.035)
Home computer			-0.160***			-0.159***
			(-0.044)			(-0.044)
Computer literate			-0.055			-0.053
			(-0.034)			(-0.034)
Female	0.178***	0.129***	0.180***	0.127***	0.181***	0.181***
	(-0.028)	(-0.026)	(-0.029)	(-0.026)	(-0.027)	(-0.027)
Urban	-0.071**	0.109***	-0.061*	0.105***	-0.063**	-0.055*
	(-0.033)	(-0.031)	(-0.034)	(-0.031)	(-0.032)	(-0.033)
Age						
25-35	-0.299***	0.197***	-0.301***	0.203***	-0.295***	-0.299***
	(-0.038)	(-0.038)	(-0.038)	(-0.038)	(-0.036)	(-0.036)
35-50	-0.634***	0.263***	-0.637***	0.258***	-0.628***	-0.633***
	(-0.041)	(-0.037)	(-0.042)	(-0.037)	(-0.037)	(-0.038)
50-65	-0.826***	0.175***	-0.846***	0.192***	-0.819***	-0.841***
	(-0.055)	(-0.047)	(-0.057)	(-0.048)	(-0.054)	(-0.056)
Race						
African	0.537***	-0.251***	0.432***	-0.249***	0.530***	0.429***
	(-0.113)	(-0.091)	(-0.116)	(-0.091)	(-0.113)	(-0.116)
Coloured (	0.370***	-0.707***	0.278**	-0.701***	0.354***	0.272**
	(-0.125)	(-0.093)	(-0.127)	(-0.093)	(-0.116)	(-0.118)
Asian/Indian	0.273	-0.195	0.246	-0.207	0.274	0.249
	(-0.175)	(-0.153)	(-0.175)	(-0.153)	(-0.174)	(-0.175)
Education						
Primary	0.062	0.427***	0.081	0.406***	0.079*	0.090**
	(-0.057)	(-0.035)	(-0.056)	(-0.036)	(-0.042)	(-0.043)
Secondary	-0.149*	0.766***	-0.098	0.748***	-0.124**	-0.085
	(-0.078)	(-0.046)	(-0.079)	(-0.047)	(-0.05)	(-0.053)
Tertiary	-0.443***	0.948***	-0.351***	0.927***	-0.416***	-0.337***
	(-0.085)	(-0.049)	(-0.088)	(-0.049)	(-0.054)	(-0.06)
Health						
Very good / good	-0.191***	0	-0.198***	-0.004	-0.190***	-0.197***
	(-0.049)	(-0.046)	(-0.049)	(-0.046)	(-0.049)	(-0.049)
Excellent	-0.160***	0.104**	-0.163***	0.101**	-0.157***	-0.162***
	(-0.052)	(-0.049)	(-0.052)	(-0.05)	(-0.051)	(-0.052)
Waves						
Wave 3	-0.039	0.168***	-0.028	0.198***	-0.034	-0.025
	(-0.043)	(-0.038)	(-0.045)	(-0.039)	(-0.041)	(-0.042)
Wave 4	-0.232***	0.496***	-0.216***	0.496***	-0.220***	-0.210***
	(-0.052)	(-0.038)	(-0.053)	(-0.038)	(-0.04)	(-0.04)
Wave 5	-0.205***	0.268***	-0.182***	0.270***	-0.195***	-0.176***
	(-0.043)	(-0.035)	(-0.044)	(-0.035)	(-0.037)	(-0.038)
Electricity		0.230***		0.228***	-0.043	-0.047
		(-0.034)		(-0.035)	(-0.037)	(-0.038)
Constant	-0.861***	0.026	-0.736***	0.044	-0.784***	-0.686***
	(-0.205)	(-0.117)	(-0.213)	(-0.118)	(-0.139)	(-0.141)
Provinces	yes	yes	yes	yes	yes	yes
Observations	16,105	16,105	15,858	15,858	16,105	15,858
Log likelihood	-12,041	-12,041	-11,785	-11,785	-5670	-5,569

Note: The dependent variable is a binary variable which takes a value of one when an individual moves from being employed to being unemployed across adjacent waves. The mobile phone variable is also binary, taking on a value of one when an individual owns a mobile phone. Other variables include gender (base category = males), age groups (base category = 15-25 years), race (base category = White), education (base category less than primary education), health (base category = poor-fair), urban (base category = non-urban), waves (base category = wave 2), Provinces. Standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1

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