Computer literacy, employment and earnings: A cross-sectional study on South Africa using the National Income Dynamics Study 2008

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Abstract

In this study I explore the extent of computer literacy in South Africa, the correlates of computer literacy, and the relationship between computer literacy and labour market outcomes, namely the probability of employment and earnings among working-age South Africans. I use data from the first wave of the National Income Dynamics Panel survey of 2008, the first national household survey to collect information on computer skills. This study focuses on computer literacy as it has become an integral skill in today's world of fast technological change. Understanding the unequal distribution of this form of human capital and the benefits it affords those in the labour market, is important particularly in South Africa, where there is a growing gap between the rich and the poor. I find that the distribution of computer skills in South Africa tends to mirror existing inequalities; females, Africans, those with low levels of schooling and those living outside of formal urban areas, for instance, are less likely to be computer literate. Further, I find that there is a positive association between computer literacy and the probability of employment among working-age adults, and a positive relationship between computer literacy and earnings among the employed in South Africa. These associations hold after controlling for a variety of demographic, human capital, family background, and in the case of the earnings regressions, job characteristics. The results also suggest that, as would be expected, those who are highly computer literate do better than those who have basic use skills. I also consider the limitations of my methods and the data I use, and the implications of the results for education and skills development policy in South Africa.

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List of Acronyms

UNDP: United Nations Development Program

OECD: Organisation for Economic Co-operation and Development

ASGISA: The Accelerated and Shared Growth Initiative for South Africa

NIDS: National Income Dynamics Study

SALDRU: Southern Africa Labour and Development Research Unit

PSUs: Primary Sampling Units

OLS: Ordinary Least Squares

Dedication

To my parents, Samuel and Bupsie, thank you for appreciating education and making extreme sacrifices to provide me with this learning experience. Thank you for giving me the opportunity you never had. This dissertation is dedicated to you.

Chapter 1: Introduction

1.1 Introduction

It is by now well-documented that the vast majority of the unemployed in South Africa are poorly educated and have limited skills, while firms increasingly demand high skilled workers **(**Pauw, Oosthuizen, and Van Der Westhuizen, 2006:1**)**. This study focuses on computer literacy as an integral skill in today's world of fast technological change. Understanding the unequal distribution of this form of human capital and the benefits it affords those in the labour market, is important particularly in South Africa, where there is a growing gap between the rich and the poor. The core objective of this study is to analyse who is computer literate in South Africa, and to determine whether or not computer literacy is associated with economic success (i.e. a greater chance of employment and higher earnings) in the labour market. This chapter provides the background and rationale of the study, and highlights the main objectives and research questions that are asked in this study.

1.2 Background and Rationale of the study

The impact of technology, and the accompanying change in skills, occupies a key role in proposed explanations of both economic growth and the changing distribution of wages in many developing countries, where there has been an increased demand and competition for individuals with higher skill levels (Gush et al, 2004 and Borghans, Green and Mayhew, 2001). Seo, Lee and Oh (2009) support this view by suggesting that there is a strong positive correlation between Information and Communication Technology (ICT) investment in particular and economic growth. Raising the skills of national workforces through education and training has therefore become a core objective of economic polies aimed at developing national competitiveness.

While no empirical work has explored the benefits of computer literacy in South Africa at the national level due to a previous lack of data, empirical studies in America, Britain and Canada show that individuals with higher levels of computer literacy are more likely to be employed, hold higher positions, and generally experience higher incomes (Olsen et al, 2011; Peng and Eunni, 2011; Dolton and Makepeace, 2004; Morissette and Drolet, 1998). Economists postulate that the higher earnings of these workers are related to greater skill and productivity in the broader context of technological change which results in an increasing demand for this type of skilled worker (Tyler, 2004). A work force that is highly skilled and more productive is likely to be more competitive in the global market. Even within developed countries, there are concerns about educational and income divides along racial and gender lines. Rao (2005) posits that the digital divide is in fact an amplifier of economic and social divides that that exist universally across regions.

According to Chinn and Fairlie (2007), there were approximately 2.5 personal computers per 100 people worldwide in 1990, and by 2001 it had climbed to nearly 9 per 100 people. Internet use in the world grew from almost zero in the 1990s to about 8.1% of the world's population in 2001 (Chinn and Fairlie, 2007). These crude statistics conceal the large differences between different regions of the world. In North America for example, in 2001 there were approximately 61.1 computers per 100 people, whereas Europe and central Asia had 18.1 computers per 100 people. Compared to these figures, the numbers in Sub-Saharan Africa and South Asia are strikingly low, where approximately 1 and 0.5 personal computers per 100 people existed in 2001 respectively (Chinn and Fairlie, 2007). The 2002 estimates from the United Nations Development Program (UNDP) show that there were 1.3 million internet users in Africa, of which 750 000 users were South Africans. In the same year it was estimated that in Africa there was one internet user for every 150 in comparison to the world average of one user for every 15 people. These internet penetration rates are extremely low in comparison to North America and Europe who boast one user for every 2 people (Polikanov and Abramova, 2003). With this in mind Africa accounts for only 1 per cent of the global internet population.

The belief in the importance of proficiency in computer use has been strong enough to prompt numerous countries to develop national computer plans to aid national economic development. Many of these national strategies make specific reference to the association between the promotion of computing and economic growth (Gattiker, 1995). Taiwan's 1981 computer policy is an example of the above, ". . . government has become aware that in order to assure national survival and development, the country must enhance competitiveness by resorting to the promotion of new information technology, enhancement of the government's efficiency and the increase of industrial productivity. . . so as to promote the application of computers, expand the domestic computer market, and assist the development of the local information industry." (Kraemer, Gurbaxani, King, 1992:147). Similarly in Canada, the government's strategy to reduce skills obsolescence among semi-skilled workers was to increase their skills with certain computer related training such as knowledge of word processing (Gattiker, 1995). Gattiker (1995) argues that government policies and sponsorship of computer skills among Canadian semi-skilled workers yielded positive returns as these workers did not become obsolescent in light of technological change but rather continued to participate in the labour force. These two examples support the view that governments' contribution to increasing the skills of their populations through computers can have a significantly positive effect on economic growth, and national and international competitiveness.

Rapid technological change has increased the risk of skill obsolescence for workers, and the increase in educational levels of the population overall has made finding employment more difficult for semi-skilled workers (Gattiker, 1995). Skills development has therefore taken centre-stage in many of government's recent policy initiatives. One important example has been the South African government's mandate for 2013, which stipulates that no child will leave a public school in South Africa without basic computer literacy (Kasonde, 2007). This mandate suggests that computer skills are a vital tool in making the transition to higher education institutions and/or the job market. The South African National Research Foundation supports this view by promoting information and communication technology, and computer skills, as a catalyst for socioeconomic development in the country (Herselman, 2003).

This skills premium has important implications for inequality in South Africa, where the gap between the privileged and underprivileged in the context of opportunities is ever increasing (Thinyane, Slay, Terzoli and Clayton, 2006). Differences in the ability to access, contribute to and participate with technology, and in particular computer skills, can widen this gap (Thinyane, Slay, Terzoli and Clayton, 2006). The "digital divide" was a term created in the 1990s referring to the broadening gap between those who have access to ICT and those who have limited or no access to such facilities due to their age, ethnicity, gender, social, economic, and/or geographic (urban/ rural) status (Rao, 2005). Hawkins and Paris (1997) predict that in the social and economic setting of America individuals who are computer illiterate will become economically marginalised and have no chance of sustaining a career, accruing wealth, or controlling capital. A bold prediction like this is of particular concern in a country like South Africa where unemployment rates are already very high (Woolard, 2000; Kingdon and Knight, 2005).

South Africa is one of the African countries in which the importance of ICT is growing fast especially in the area of education. According to the School Register of Needs Survey 2001 there have been substantial improvements in the provision of basic facilities at schools since their first survey in 1996. The increase in the roll-out of computers for teaching and learning was among the improvements mentioned. According to this survey, computer availability in South African schools increased from 8.7% in 1996 to 12.3% in 2000. Lundall and Howell (2000, as cited in Bovee et al, 2007) stated that in 2000, approximately 13% of all South African schools at primary and secondary levels use computers. Technological advancement in the areas of mining, agriculture, manufacturing, and service provision and other sectors in South Africa have opened the door for many employment possibilities. These opportunities however are only accessible to those with sufficient ICT knowledge and skills. With this growing demand for ICT Skills in South Africa, entry and/or success in the labour market for people lacking such skills is likely to become increasingly difficult as there is a large gap between a small group of people who have access to ICT skills and a large group of people who do not.

Within South Africa, there is likely to be inequality in ICT access and computer literacy based on race given the effects of apartheid on education and skills access and household incomes. It has been established by past literature that there exists a strong correlation between education and computer literacy (Ying Chu Ng, 2006); therefore the wide differentials in schooling infrastructure and resources as well as the quality of education in South Africa can also perpetuate this form of inequality.

South Africa's plan to combat the inequality in ICT use is to increase the capacity of the workforce by improving infrastructure for internet access and educational tools in schools and colleges. These ambitions all form part of the e- Education policy developed by the state. The concept of e- Education in South Africa is defined as the use of ICT's to accelerate the achievement of national education goals by connecting learners and teachers to professional support services, and providing platforms for learning (White paper on e-education, 2004). This concept views ICT's as a resource for reorganising schooling to assist with holistic schooling development from administration to creating an environment that advances productivity, creativity and communication among teachers and learners. The e-Education policy goal is therefore to ensure that "every South African manager, teacher and learner in the general and further education and training bands will be ICT capable (that is, use ICT's confidently and creatively to help develop the skills and knowledge they need as lifelong learners to achieve personal goals and to be full participants in the global community) by 2013" (White paper on e-education, 2004). To achieve this objective government focuses on access to ICT infrastructure and capacity building, providing electronic learning resources that are translated into indigenous languages, and creating a national learning portal whereby teachers and learners can access various learning and teaching materials.

In light of the above, skills development, and in particular development of skills in the area of computer literacy, is likely to be crucial for strengthening the economy and reducing inequality internationally and nationally. Previous work done on computer skills development in South Africa, all of which has involved small-scale case study work (such as the "Hole in the Wall", "Digital Doorway", and "iEarn" initiatives) suggests important benefits (Thinyane et al, 2006). These programs aimed to introduce computers and other forms of technology in marginalised and semi- marginalised communities in South Africa. This qualitative research has shown that such interventions help individuals in these communities to seek employment via the internet, enhance their C.V's, learn basic computer skills such as word processing and emailing, as well as learn about the world around them. The success of these small-scale interventions calls for research at a national level to assess the need for computer training for all economically active South Africans. In a South African study of computer attitudes of primary and secondary school learners Bovee et al (2007) found that those from upper and middle class schools had a more positive computer attitude and less stereotypical views about women in computing than the students from township schools. More surprisingly those in township schools who had limited computer access and computer experience found a computer-related career attractive. Perhaps for these students a computer-related career is seen as an opportunity to enhance their social status. (Bovee et al, 2007).

It is in this context that this study tries to make a contribution to the literature. It uses nationally representative survey data from the National Income Dynamics Study conducted in 2008 to explore the extent of computer literacy in South Africa, the characteristics of the computer literate, and the links between computer literacy and success in the labour market. This survey is the first to collect information on computer literacy among adults at the national level in conjunction with a wide range of other socio-economic and demographic variables.

1.3 Research problems and objectives: Key questions asked

There are two key aims of this study:

1) To estimate the extent of computer literacy among adults in South Africa using nationally representative data and to describe the characteristics of South Africans that are computer literate; and
2) To estimate the benefits of computer literacy in the labour market by determining if there is (i) a positive relationship between computer literacy and the probability of employment, and (ii) a positive relationship between computer literacy and earnings among the employed.

The key questions are:

i. What proportion of the adult population is computer literate?

ii. Which individuals are more likely to be computer literate, i.e. what characteristics are related to being computer literate among adults?
    - Age
    - Race
    - Gender
    - Educational level
    - Income
    - Employment status
    - Other demographic and socioeconomic characteristics

iii. Is there a statistically significant relationship between computer literacy and the probability of employment, controlling for key socioeconomic variables?

iv. Is there a significant earnings premium to being computer literate in South Africa among the employed, controlling for key socio-economic variables?

1.4 Organisation of dissertation

This dissertation is divided into 6 main chapters. Chapter One provided an introduction and background for the study. It highlighted the importance of computer literacy and ICT's in bridging the gap between those who are favoured and those who are marginalised in society, and argued that computer literacy may be an important tool for entry into and success in the workplace. The key objectives of the study and the main research questions were outlined. Chapter Two explains how computer literacy has been traditionally defined, and contextualises the definition of computer literacy used in this study. It introduces the Human Capital Theory as the theoretical framework on which this study is based. This chapter also summarises the work of previous international studies that identify who is more likely to be computer literate in a population, and whether there is an earnings premium for being computer literate. In Chapter Three, the data and analytical methods used are described. This chapter introduces the NIDS data and describes the key questions used from the NIDS questionnaire for this study. Furthermore is describes the econometric techniques employed in the analysis and some of the limitations thereof. Chapters Four and Five are results chapters. Chapter Four provides descriptive statistics on who is computer literate in South Africa. This chapter cross-tabulates overall computer literacy and degrees of computer literacy by a host of demographic and socio-economic characteristics. Chapter Five reports on the regression analysis of the relationship between computer literacy and employment, and computer literacy and earnings. Finally Chapter Six concludes by discussing the main findings of this paper.

Chapter 2: Literature review

2.1 Introduction

Computers are changing the way in which we live and work and through their many processes have increased office efficiency dramatically due to the implementation of electronic mail and internet services in order to reach new markets and gain information more effectively (Dolton and Makepeace, 2002). Academics studying the links between computer use and economic growth postulate that computer literacy will be as important for economic growth in the 21st century as reading, writing, and mathematics were in the previous century (Hawkins and Paris, 1997). It is believed that inequalities in access to computer based technology in the so called “Information Age” will further marginalise the economically disadvantaged in society.

This chapter first draws from existing literature to provide an understanding of how computer literacy is generally defined. It then establishes the operational definition of computer literacy that compliments the context of this particular research. This chapter also introduces human capital theory and further explains how human capital relates to computer literacy in a technologically-advancing era. Based on a review of previous research, the chapter then describes empirical work that interrogates the relationship between computer literacy (as a form of human capital) and earnings and employment, and socioeconomic and demographic characteristics. The human capital theory is the theoretical lens through which I focus my study and the findings thereof.

2.2 Defining computer literacy

Based on the literature in this area, the notion of computer literacy appears to be fluid in nature and varies across groups of people and time (Claro et al, 2012). The term computer literacy was coined and used to create awareness of the issue that writing and reading were not enough to be a productive citizen in the information society. This emerged from evidence that suggests that labour markets value higher order cognitive skills and abilities (Claro et al, 2012). The existing body of literature puts forward that there are many definitions of computer literacy which vary according to the context in which it has **been** studied. Bork (1985: 33) broadly defined computer literacy as the “minimum knowledge, know how, capabilities and abilities about computers”. Although computer literacy varies across people and time, it essentially encompasses all an individual needs to work on and know about computers (Cole and Kelsey, 2004). This implies that computer literacy is influenced by the context in which it is used and refers to the skills required to retrieve and use information relating to routine tasks on a computer for the individual (Cole and Kelsey, 2004). De la Fuente and Ciccone (2002: 9) concur by adding that computer literacy focuses on the basic skill needed to access information through technology in an "understandable and organised manner, process information using a computer, combine it with other resources, and find solutions to practical problems in the workplace or in everyday life". Norman (1984) augments this definition by suggesting that computer literacy can be understood by four main themes namely; understanding the general principles and concepts of a computer, understanding how to use computers, knowing how to program computers, and understanding the science of computation.

In a human development context one can use a broader interpretation of computer literacy and define it as a tool used within the context of every day problem solving where one has the technical ability to utilise computers to process information, search and evaluate information, and exchange and develop ideas in a digital environment (Claro et al, 2012). In other words, computer literacy is the general use of computers outside the realm of specialist computer science work (Cole and Kelsey, 2004). It is through these definitions that I adopt a broad operating definition of computer literacy. For the purpose of this chapter and in keeping with Claro et al (2012), Cole and Kelsey (2004), and De le Fuente and Ciccone (2002), I define computer literacy as the minimum knowledge and skill required to operate a computer to carry out routine tasks and functions in the workplace or in everyday life. In the next chapter, I will describe how the survey data I use collects information on computer skills/literacy.

2.3 The human capital framework

Although several theories from the economics perspective emerged to explain wage differentials in light of the relationship between skills and earnings, the human capital theory is the most widely used among them. The human capital theory broadly postulates that earnings are a payoff to human capital, and that education and work experience are the two major determinants of wage differences among workers (Mincer, 1974 as cited in Desjardins). Desjardins (2001) contributes further to the theory by suggesting that people need to learn for the purpose of constantly adapting to and coping with their surroundings. Not only is being able to adapt necessary for survival but also to improve well-being in all spheres of life which include the personal, social, and economic spheres. In Desjardins' work, human capital is interpreted more broadly as "[t]he knowledge, skills, competencies and attributes embodied in individuals that facilitate the creation of personal, social, and economic well-being" (Desjardins, 2001:223). It refers to an individual's traits, both cognitive and non-cognitive. Cognitive traits are defined as mind processes, education, ability, personality, and the like, whereas non-cognitive traits make up the socio-demographic characteristics of the individual (Hartog, 2001).This reformulated version of human capital theory indicates that individuals' cognitive and non-cognitive traits influence his/ her employability and earnings and are therefore relevant for economic success (Hartog, 2001).

The theory adds that an individual's decision to invest in acquiring new skills and improving their existing skills for the job is weighed against the net present value of the costs and rewards of such an investment. Morissette and Drolet (1998) state that the adoption of new technologies increases the skills requirements of workers and this increase in skills requirements is associated with an increase in training cost and human capital cost. Black and Lynch (1996) argue that individuals invest in training during an initial period and perceive that their investment will pay off in the form of higher wages in the future. The wages of individuals are said to increase over an individual's life span due to investments in human capital, particularly in on-the-job training (Mincer, 1974). Individuals are assumed to invest in training during initial periods and reap the rewards in the future, in some instances even opting for lower wages where there is training provided. The general premise behind this is that training makes workers more productive, and these workers collect higher returns from their investment in later periods by producing more (by being more effective and efficient on the job) and therefore earning more (Mincer, 1964 and Black and Lynch, 1996).

Using the National Longitudinal Survey of Youth in America between 1986 and 1996, studying a sample of 10000 men who were between the ages of 14 and 22 in 1979 and re-interviewed annually from 1979 to 1994, Veum (1999) found that training received on the job is positively associated with wage growth. More importantly he finds that general training can be transferred to other jobs, and therefore the skills premium still exists if the employee changes their job (Veum, 1999). A study by Blundell et al (1999) has shown that even workers with low levels of schooling or qualifications who received training on the job also increase their productivity significantly and received higher wage returns. Gattiker (1995) points out that government programs aimed at helping small firms train semi-skilled employees is important in keeping these workers relevant and employable in the workplace.

Highly educated workers have a comparative edge in adjusting to new technologies and implementing them, therefore the diffusion of these technologies is likely to increase the demand for high human capital workers (Helpman and Rangel, 1999), and if the demand for such workers outstrips the supply; the return to schooling increases (Di Pietro, 2002). Machin and Van Reenen (1998) found a strong correlation between the level of computer investment and the demand for workers with high human capital in Denmark, France, Germany, Japan, Sweden, and the UK. Human capital is therefore a prerequisite for the implementation of new technologies. The general consensus among researchers in this field is that the rise in the schooling wage premium and the rise in wage inequality are driven by technological change. Most research has centred on human capital gained from formal schooling mainly because it is the easiest dimension of human capital to measure (De la Fuente and Ciccone, 2002).

Raising the quality of education is therefore a key component in increasing the human capital of the population. Ensuring that quality education is more accessible strengthens the human capital of those entering the workforce, which in turn allows them to maintain their employability in a technologically changing labour market (De la Fuente and Ciccone, **2003**). By focusing on early education, improvement can be made in the depth and variety of skills attained, especially by those from disadvantaged backgrounds. Countries like Australia have developed policies that focus on the promotion of digital literacy through increasing the population's educational attainment beyond primary and secondary school and promote life-long learning that is relevant to labour market needs (De la Fuente and Ciccone, **2003**). Similarly Sylwester (2002) argues that increasing human capital through public education is one possible mechanism to lower the rate of income inequality and proposes that governments that spend more resources on education as a percentage of their GDP lower income inequality in forthcoming years, however he acknowledges that the process is slow to be achieved.

As described above much economic research hypothesises that there is a positive relationship between formal education and training and economic well-being, however the true causal effect is debatable. Many argue that the effect of education and training is overstated and state that education is rather an indicator of those with greater innate ability or other unobservable characteristics (Desjardins, 2001). The relationship between education and earnings is explained by the human capital theory in a linear fashion where acquiring more knowledge and skills leads to increases in productivity, and this increase in productivity results in higher earnings. Labour economists often differentiate between human capital during three phases of life namely: early human capital; which is acquired at home, human capital gained through formal education, and human capital gained from work experience. Desjardins (2001) claims that initial education, that is education in one's formative years, plays a significant role in influencing economic well-being by creating the opportunity to gain access in the labour market in the future, especially in jobs that require high skill levels. This kind of human capital is often unobservable in survey data.

Despite this concern about causality, human capital theory has become the cornerstone in recent economic growth and employment research, where studies find significant returns to education and training. The European Investment Bank found that university students have lower unemployment rates than workers with less education in almost all European countries (Heinrich and Hildebrand, 2001). In Ireland for example, the unemployment rate for men with basic education was five times the unemployment rate of male graduates. Similarly in Finland male workers with basic education were twice as likely to be unemployed as those with upper- secondary education (Heinrich and Hildebrand, 2001). Studies by Bassanini and Scarpetta (2002) substantiate this claim and find that one additional year of schooling can raise per capita output of at least 6 per cent in OECD (Organisation for Economic Co-operation and Development) countries. De la Fuente and Ciccone (2002) also maintain that school attainment is an essential component of human capital and plays a crucial role in economic growth especially in the context of rapid technological change, and is also vital for enhancing social cohesion. Their studies have shown that an additional year of schooling increases wages at an individual level by approximately 6.5 per cent in developed countries and up to 9 per cent in less developed countries where the labour markets are less regulated. In a study investigating the link between human resource development produced by formal schooling and economic growth, and between investment in physical capital and growth in Africa from 47 African nations, Oketch (2006) found that investments in human and physical capital are important determinants of growth and development in Africa. He highlighted that human resource development through the medium of formal schooling is a major role player in implementing reforms for economic growth. This is in line with the vast microeconomic literature in this area (some of which was described above), where studies document the link between human capital and individual wages, and suggest that the link becomes even more significant during times of technological change. There is thus substantial empirical evidence at a macroeconomic and microeconomic level that illustrates the enhancing effects of education on productivity.

2.4 Understanding Computer Literacy as a Form of Human Capital

As Information and Communication Technology (ICT) has become more prevalent, computer literacy has become a more vital component of human capital that affects economic success and/or growth. Many empirical studies acknowledge computer literacy as a form of human capital. One such study conducted in the US manufacturing industry suggests that the widespread introduction of computers and related technologies has increased the demand for more educated and therefore more skilled workers (Bernard and Jensen, 1997). This study together with a host of other empirical work, has established that there is a positive association between computer literacy and earnings, however the strength of this association varies by country. Ono and Zavodny (2005) postulate that not having computer skills in today's job market could lead to social exclusion and economic penalties. Technological change has increased the risk of skill obsolescence for workers, and the improved educational levels of the overall population has made finding formal employment even more difficult for semi-skilled and low-skilled workers (Gattiker, 1995). The prevalence of this risk is evident in computer skills such as word processing becoming a prerequisite for many jobs, creating a barrier for these individuals' entry into the labour market. More and more job advertisements list such skills as required or desired for available positions and those who lack these skills may experience difficulty in finding jobs (Gattiker, 1995). Understanding the relationship between computer literacy and employment/earnings is therefore important in order to identify, monitor and intervene in the ICT divide for those who are at risk of being excluded from job opportunities due to their limited access to ICT and computer usage.

This gap between the skills required and available in the workforce is evident in the South African context where the nature and severity of unemployment can be attributed to the poor education many South Africans receive. This results in a workforce with limited skill, while firms continue to demand a higher skilled work force (Pauw, Oosthuizen, and Van Der Westhuizen, 2006). The pressure on the economy to become more technologically advanced with the hope of increasing productivity in order to stay competitive in the global market has further increased the demand for high skilled workers at the expense of lower skilled workers. As a result there is a severe shortage of workers with technologically compatible skills due to the fact that the supply cannot meet the demand. The Accelerated and Shared Growth Initiative for South Africa (ASGISA) reiterated this view by identifying skills shortages as one of the greatest obstacles to growth in South Africa. Indeed the high level of poverty that is prevalent in South Africa is closely linked to the problem of unemployment. The reality that many households are not directly linked to the formal economy via the labour market, as well as poor employment growth over the past years, have been matters of great concern for policy makers in South Africa.

It is in this setting that computer literacy is increasingly seen to represent one of the most important basic skills necessary for an individual to work and grow in an advanced industrial economy. Krussel et al (2000) submit that skill-biased technological change is the main factor responsible for the skills premium and that the relationship between human capital and skills is vital for understanding wage inequality. Many believe that the demand for high skilled workers will become an even more serious problem because the pace of change is accelerating and jobs are becoming more high tech, service oriented, and reorganised to involve greater employee participation in the workplace (Handel, 2003). As more computers are introduced in the labour market due to the decreasing cost of technology, they become widely used to do more routine tasks. If firms are adopting computers to do routine tasks then those who are economically active will be required to use computers, and if they cannot they will be excluded from the labour market. Therefore the need for computer literate people increases with the diffusion of technologies (Peng and Eunni, 2011).

De la Fuente and Ciccone (2002) explain that skilled workers are expected to be more productive than unskilled workers for any given production process, and therefore should be able to operate more complex technologies than their unskilled counterparts allowing them to yield greater economic returns. It must be noted that although computer diffusion is a highly common explanation for inequality in earnings, it is empirically difficult to link the adoption of computers with wage differentials (Zohgi and Pabilonia, 2007). However many studies show that industries with greater growth in employee computer usage or with more computers per worker have more effectively upgraded the skills of their workforce (Helpman and Rangel, 1999), thus creating the opportunity for their workers to be more productive and subsequently earn more.

It is noted that human capital is a broad and multifaceted concept incorporating many different types of investment in people. For instance health and nutrition are important aspects of such an investment, especially in developing countries where deficiencies in these respects may greatly hinder the ability of entire populations to engage in productive activities (De la Fuente and Ciccone, 2002). For the purpose of this study, I focus on one dimension of human capital which suggests that knowledge and skills are gained through formal schooling, training, and work experience. It is in this light that I view computer literacy as a form of human capital which is regarded as useful in the production of goods, services, and further knowledge, with the assumption (supported by previous studies) that increases in human capital is associated with higher levels of earnings in the future. The use of human capital theory in this work is not to imply that the variation in wages and employment in South Africa can only be explained by the rewards to human capital. There may be other factors that are at play (such as social/cultural capital or discrimination for instance). However, human capital theory is a useful way of conceptualising the impact of computer literacy on earnings. Using the human capital theory as my theoretical framework, I will investigate whether computer literacy is indeed an important form of human capital in the South African context, by exploring whether it increases the likelihood of finding work and the ability to earn higher wages on the job.

2.5 Linking Computer Literacy to Employment and Earnings: Empirical Evidence

As described above, human capital theory provides a strong case for the positive relationship between computer literacy and earnings, especially given the pace of technological change in many industries. The basis for acquiring computer skills is motivated by the perception that one would be compensated sufficiently for that particular skill, and only if the payoff for such an investment is an increase in future earnings would individuals be motivated to acquire computer skills (Peng and Eunni, 2011). We therefore can assume that in order for individuals to invest in computer skills they expect to be adequately rewarded by means of an increase in future earnings for that particular skill set (Peng and Eunni, 2011). It is suggested that in the context where the supply of such skills cannot meet the demand, the returns to computer skills tend to increase (Levina and Xin, 2007). While the positive returns to computer use are well established in developed countries, limited evidence is available about the same relationship in developing economies (Ng, 2006).

The issue of wage differentials among workers with different skill sets, especially in the area of computer use, has intrigued researchers since Krueger (1993). Krueger who was one of the first researchers to investigate this relationship found that there was an economic premium for being computer literate in America. Utilising data from the American Current Population Survey in 1984 and 1989, Krueger (1993) found that employees who use computers on the job earn a skills premium of between 10 and 15 per cent. He argued that more educated workers were more likely to use computers on the job, and that the rise in computer use accounted for between one third and one half of the increase in the rate of return to education between 1984 and 1989. It is Krueger's early work that lays the foundation for all subsequent research investigating the complex relationship between computer use and earnings.

Work by Hawke (1998) on Australia describes how the 1980s and 1990s were periods of significant change in the types of jobs in which computer skills were required. Government eager to capitalise on the technological advances available to them dramatically increased their expenditure on computer technology and educational institutions, and understanding the importance of computer skills for future employment, encouraged all students to enrol in courses which would enhance their computer skills. Hawke (1998) using the 1993 Survey of Education and Experience conducted by the Australian Bureau of Statistics found that the effect of computer use on wages differs according to the type of usage. The magnitude of the wage effect ranged from 2- 6.2 per cent for word processing and data base experience. This study found that it is not merely computer use that has the wage premium but rather the type of usage (Hawke, 1998).

Oosterbeek (1997) studied the returns to computer use in the Netherlands using longitudinal data of a birth cohort who were 12 years old in 1952 and who were re- interviewed in 1983 and 1993 respectively. Unlike Hawke, he found that the returns to computer use did not vary with the intensity of computer use. The study showed that while workers who used computers on the job earned between 10 per cent and 20 per cent more than workers who did not, the intensity of computer use and the frequency was not statistically significant. Merely having access to and using a computer appeared to be enough to earn a substantial wage premium (Oosterbeek, 1997).

In the UK, Dolton and Makepeace (2002) find evidence that the rate of return to computer use lies between 10 and 15 per cent. Entorf, Gollac, and Kramarz (1998) using labour force panel data from France show a modest 4 per cent total return to computer use in France compared to the 15- 20 per cent yielded in America by Krueger (1993) and Di Nardo and Pishke (1997) in Germany. The computer skills earning premium in Italy was 4.3 per cent (Di Pietro, 2007).

Zoghi and Pabilonia (2007) using the Canadian Workplace and Employee Survey suggest that the returns to computer use are even higher for managers and professionals, highly educated workers, and workers who had more computer experience. Their results show strong evidence that highly skilled workers do experience immediate and large returns to computer adoption even after controlling for the demographic characteristics of workers and wages prior to adoption. The study also noted that the wage premium differs across occupational groups, for instance managers and professionals who adopt the use of computers earn a 9 per cent premium over all other occupation groups in Canada (Zoghi and Pabilonia, 2007).

Morissette and Drolet (1998) introduce a slightly different angle and explore whether those who use computers receive higher wages than their counterparts because they have different unobserved characteristics. Using data from the 1994 General Social Survey in Canada they found that computer use is associated with a wage premium of approximately 14 per cent, even after controlling for observable worker attributes, and conclude that those who use computers earn more than others mainly because they have more unobserved skills. In a similar study using the Canadian Workplace and Employee Survey, Zoghi and Pabilonia (2007) use a fixed effects analysis, which tries to account for unobservable characteristics. They find that within a year of adopting a computer, the average worker earned a 3.6 per cent higher wage than a worker who did not use a computer.

Some studies have also explored whether the earnings premium to computer use is different for certain groups. Dolton et al (2007) find gender differences in the premium and show that after for controlling for type of work the computer is used for, there is an 8 per cent premium for women and a 12 per cent premium for men. Morissette and Drolet (1998) show similar findings in Canada where men who use computers earn a 14 per cent premium whereas women earn an 11 per cent premium.

The increased diffusion of computer use in the 1990's coincided with a rise in the black-white wage gap among young workers in America. Using panel data from the High School and Beyond Survey between 1980 and 1986, Hamilton (1997) finds that Blacks with computer skills earn more than their white counterparts. In contrast, among workers without computer skills, Blacks earn significantly less. The study also found that individuals investing in computer skills earn 4 per cent to 18 per cent more than the unskilled among all races in America. Indeed the lack of investment in computer skills among Blacks may play a role in explaining the trend toward increased racial earnings inequality (Hamilton 1997).

It must be noted that the vast majority of the existing literature provides evidence of a computer literacy earnings premium for developed countries. Not much work in this field has been done in developing countries, in Africa in particular, and to my knowledge, there has been no empirical work done in South Africa based on nationally representative data. Furthermore the existing body of literature draws attention to the relationship between computer literacy and earnings but very few studies provide empirical evidence for the effect of computer literacy on employment. Entorf, Gollac, and Kramarz (1998) revealed that computer users are protected from losing their jobs (unemployment) in the short run for as long as business conditions are "stable". A study by Gattiker (1995) on Canada on the returns to employees and employers of computer training among semi-skilled workers, points out that computer skills add to an individual's already existing skills base, thus creating better employment prospects. The reason that the relationship between computer literacy and employment probabilities is not commonly studied, might have to do with the fact that the countries for which data are available do not suffer from a very large unemployment problem, unlike South African. In this study I therefore aim to try and fill these gaps in the existing body of knowledge by examining the links between computer literacy and the probability of employment, and computer literacy and earnings in South Africa.

2.6 The Socioeconomic and Demographic Determinants of Computer Use

So far in this chapter, I have discussed how computer literacy or computer skills form an integral part of human capital, whereby attaining such skills may lead to a significant increase in earnings. This section interrogates some of the socioeconomic and demographic determinants of computer literacy, as another of my key objectives in this study is to describe the correlates of computer literacy in South Africa with a view to understanding inequality in the distribution of this skill.

As mentioned earlier, school attainment and education is a core component of the stock of human capital in an individual. More notably, education is seen to have a positive impact on the probability of computer use. Chiswick and Miller (2007) using Australian national data found that an extra year of schooling increases the probability of computer use by 7-8 percentage points. In studying the determinants of computer use and internet penetration, Chinn and Fairly (2004) find that a one year increase in schooling results in a one percentage point increase in computer use. Similarly Arabsheibani and colleagues (2004) found that schooling increases the propensity of using computers. Possible explanations for this are that those with higher educational attainment learn how to adopt computers more efficiently, and also spend less on computer training in order to become computer proficient (Zoghi and Pabilonia, 2007).

Luu and Freeman (2011) find that having access to a computer at home, family education, and family income is strongly related to positive attitudes towards computers and the use thereof. The ownership and use of a personal computer is an indication of a student's cultural possessions and home educational resources. Here it is noted that parents with higher educational levels and income may view computer literacy as an educational and economic advantage (Luu and Freeman, 2011). The use of computers at home appears to be a highly profitable investment with respect to labour market earnings (Chinn and Fairlie, 2004 and Chiswick and Miller, 2007).

Various studies also show gender differences in computer usage. Arabsheibani et al (2004) argue that being female is associated an increased likelihood of using a computer. In their work using data from the UK they suggest that women who are formally employed in the manufacturing industry tend to work in clerical positions, thus increasing their propensity of computer use compared to men who work in the same industry. Dolton and Makepeace (2002) support the view that women are more likely than men to use computers due to the pattern of computer use in secretarial and clerical posts, however they find that the return to computer use is lower for women than for men. Ono and Zavodny (2005) in their study on gender differences in ICT usage among workers in Japan and America find that gender inequality in the labour market and human capital development flows over to gender differences in ICT use (Ono and Zavodny, 2005).

Hawkins and Paris (1997) argue that there exists a digital divide among Black and White college students in America. They support the notion that race is a key element of social stratification, where socially privileged students have greater access to highly valued benefits compared to less advantaged students, even when both groups function in the same environment (Hawkins and Paris, 1997). In the case of South Africa this is undoubtedly true. The effects of the isolation of the majority of Black South Africans from quality education and training during the apartheid era persist, and access, opportunity, and support structures at a community and national level still hinder the fight to bridge the gap in education and training. There is also evidence to suggest that computer usage declines with a decrease in English proficiency. Language barriers often prevent non-English speakers from using computers due to the increased cost of training (Chinn and Fairlie, 2007, and Ono and Zavodny, 2008).

Although researchers find differences in computer use and earnings across a variety of socioeconomic and demographic characteristics it is argued that the digital divide is simply a mirror of the existing disparities in a particular region (Chinn and Fairlie, 2007). Morissette and Drolet (1998) support this view and suggest that the propensity to use computers is associated with the perpetuation of inequalities in the labour market that already exist. Morissette and Drolet (1998) note that existing income and education disparities are the largest contributors to the ICT divide in Canada.

2.7 Conclusion

In this chapter I have drawn on the existing body of literature to describe and understand both the correlates of computer literacy, and its consequences in the labour market in terms of employment and earnings. For the purpose of this particular study computer literacy can be defined as the minimum knowledge and skill required to operate a computer to carry out routine tasks and functions in the workplace or in everyday life. There is a general consensus among researchers working in this field that computer literacy is an important aspect of human capital, especially in areas of widespread technological diffusion. The empirical literature in this area provides sound evidence that computer literacy is a vital component of human capital and various studies show that there is an economic premium for computer skills, even at the most basic level.

It has also been suggested that other demographic and socioeconomic characteristics of individuals determine computer use and the skills premium thereof. These included education, gender, race and family background. Importantly, differences in computer use and differences in the earnings premium seem to largely mirror inequalities that already exist in a region. The differences in computer use and the earnings benefit associated with it are likely in part to be a spill over of pre-existing inequalities in education and in the labour market.

In the following chapters a description of who is computer literate in South Africa is presented, as is regression analysis investigating whether there is a positive relationship between computer literacy and employment, and computer literacy and earnings in South Africa, as has been found elsewhere.

Chapter 3: Methodology

3.1. Introduction

The core objective of this study is to determine if there is a positive association between computer literacy and employment, and computer literacy and earnings in South Africa using the NIDS 2008. This chapter outlines the methods employed to understand the relationship between computer literacy and employment, and computer literacy and earnings. The first section (3.2) of this chapter describes the household survey dataset used for this study. Section 3.3 provides a description of the sample and the weights used. Section 3.4 describes the econometric techniques utilised to study the relationship between computer literacy, employment and earnings and outlines the equations in the regression analysis. Section 3.5 identifies and explains which variables from the NIDS data were used and how they were derived.

3.2. The National Income Dynamics Study

This study uses data from the National Income Dynamics Study (NIDS) of 2008 to describe the characteristics of the computer literate, and particularly to investigate the relationship between computer literacy and employment and earnings in South Africa. NIDS is the first national panel study to follow a sample of households and their members in South Africa. The main focus of NIDS is to track changes that occur among individuals in households with a particular interest in income, expenditure, assets, access to services, education, health, and other dimensions of well-being (Leibbrandt, Woolard and de Villiers, 2009).

The baseline wave of NIDS, which I use for this study, was conducted by the Southern Africa Labour and Development Research Unit (SALDRU) based at the University of Cape Town (UCT). The first wave took place in February 2008 and the data was released in July 2009. NIDS is comprised of 3 questionnaires, namely, a household, adult, and child questionnaire. In the first wave of the survey, NIDS enumerated 7 305 unique households, with a total of 28 255 household residents.

3.3. Sample and weights

For my study I merged the household, adult, and individual-level data collected in NIDS.[1] The sample consists of approximately 17 000 observations for the working age population (officially, those aged between 15- 65). In the descriptive and econometric analysis presented in Chapters 4 and 5, I restrict the sample to those who are aged between 18 and 65 years, given that many of those under the age of 18 would still be in education. This resulted in a sample of 14 949 observations. In the empirical work for the dissertation, I utilise the post stratified population weights assigned by SALDRU as these were designed to match the age, sex, and race structure of the South African population and were based on the mid-year population estimates for 2008 (Leibbrandt, Woolard and de Villiers, 2009).

3.4. Analysis Techniques

Using the cross-sectional data from the first wave of NIDS (2008), the study first presents what proportion of South Africans of working-age (defined as 18-65 years) are computer literate, and describes the characteristics (socio-demographic and economic) of individuals who are computer literate. This analysis provides some insight into who is more likely to be computer literate, and therefore how these key skills are distributed across different groups in South Africa.

In Chapter 5, regression techniques are used to establish whether there is a positive relationship between computer literacy and employment, as well as computer literacy and earnings in South Africa. In these regressions, in addition to including a variable for whether the individual is computer literate or not (and disaggregated by the level of literacy achieved, i.e. basic or high), I control for a number of other socio-economic factors typically included in employment probability and wage equations in South Africa. This includes age, education, race, gender, urban or rural residence and province of residence, among others. Furthermore, added to the models are variables not previously available in earlier surveys in South Africa, such as language proficiency and family socio-economic background to reduce omitted variable bias. In both analyses, I progressively add controls to the regressions to explore how the association between computer literacy and the outcome variables, changes. In model one for example, only the relationship between computer literacy and employment/earnings is measured. Subsequent models include demographic variables, other forms of human capital,

[1] I used the statistical software package, STATA, for the data work and analysis.

and family background. In the earnings regressions job characteristics, such as occupation, industry, and years of tenure are also added to the model. The choice of explanatory variables used will be developed further below.

3.4.1. Probit regression

Probit regressions are used to determine the association between computer literacy and the probability of employment. This technique is utilised when the dependent variable is a binary variable such that it is equal to 1 if the event occurs or 0 if it does not. In this context the dependent variable is whether the individual was employed or not, where 1 represents being employed and 0 represents not being employed. 'Not being employed' here includes both the unemployed (the searching and non-searching) and the inactive, although I also test as part of some robustness checks described in Chapter 5, whether the results hold when I exclude the inactive from the zeroes of the dependent variable. The probit model takes the following form:

$Pr(y_i = 1) = \Phi\ (C_i; X_i)$

Where,

y_i is a binary categorical variable which takes the value one if the individual is employed and zero if otherwise. C_i is a dummy variable representing computer literacy (1 representing if the individuals is computer literate and 0 if not) for individual i. X_i is a vector of observed characteristics for individual i which includes gender, race, age, geographic type, province, education, English language proficiency, and perceived relative family background. Φ is the standard cumulative normal distribution.

3.4.2. Ordinary Least Squares regression

Ordinary Least Squares regression analysis is used to determine the association between computer literacy and earnings. This technique is used when the dependent variable is a continuous variable, as in this case where the dependent variable is the log of hourly wages. The regression sample here is limited to the group of working-age individuals (18-65 years) who are employed in regular work, as certain information on the characteristics of the job are only collected for regular workers. The equation for the OLS regression is:

$\ln(Wi) = \alpha + \gamma Ci + \beta Xi + \varepsilon i$

The dependent variable, W_i is the log of hourly earnings of respondent i. C_i represents an indicator equal to 1 if the respondent is computer literate and 0 if they are not. X_i is a vector of observable characteristics which include gender, race, age, geographic type, province, education, English language proficiency, perceived relative family background, industry, occupation, and years of tenure. E_i is the error term. To compare the returns to being highly computer literate to having basic computer skills only, in further regressions dummy variables indicating whether an individual is highly computer literate or not or has basic use skills or not, are included.

3.5. Description of variables

3.5.1. Dependent variables

There are two dependent variables in this study, namely employment and earnings. Section E of the NIDS adult questionnaire consists of many questions that ask about the work activities of the respondent.

3.5.1a Employment

Question E1 asks "Are you currently being paid a wage or salary to work on a regular basis for an employer (that is not yourself) whether part time or full time?" (Response options were yes/no). In subsequent questions in this section respondents are asked about whether they had engaged in any casual work, self-employment, subsistence activities or unpaid family labour. Both primary and secondary job information is collected. Using this information and further questions on **the** desire to work, and non-employment related activity, variables on employment status were derived by SALDRU. Individuals are classified as "not economically active", "unemployed- discouraged/non-searching", "unemployed-strict/searching" and "employed". Not economically active is defined as those who are not willing or are unable to work due either to age (being too young or old to work), disability that permanently prevents the individual to work, being in school or tertiary education, or in home care (housewives). The 'discouraged' unemployed are individuals who are of working-age who express the desire to work but had not actively sought employment in the four weeks prior to enumeration, while the 'strict' unemployed are those who had actively sought work over that period. Using this derived variable from SALDRU the binary variable employed was created where as described above 1 represents being employed and 0 represents being either inactive or unemployed (searching and non-searching).

3.5.1b Earnings

An earnings variable was created using various questions from section E in the adult questionnaire of NIDS. NIDS asked in question E8: How much did you earn last month at your main job before any deductions for tax, medical aid or pension? This question gives an indication of gross earnings from an individual's primary occupation. Question E9 asks: How much was your take-home pay? If the respondent refused to answer questions on earnings, a show card with net income earnings categories was provided for the respondent to choose which earning category he/she fell into. The NIDS dataset has derived variables that include the gross and net income of adults in the dataset. Using the net income variable the log of hourly earnings was calculated. The log of hourly earnings was created for those who had regular work, individuals in self- employment, and casual workers for the descriptive analysis (I exclude subsistence workers and unpaid family workers from the analysis). However, as mentioned above, in the earnings regression analysis I restrict the sample to those in regular employment.

3.5.2. Independent Variables

3.5.2a Computer literacy

Computer literacy is the main independent variable in this study and is based on a self-assessment question. Question H34 in NIDS asks: "Are you computer literate?" and provides the following response options "Yes, highly literate"; "Yes, basic use"; and "No". This categorical variable was used in the descriptive statistics where cross tabulations are run for various demographic and socio-economic characteristics by computer literacy and levels of computer literacy. For the regression analysis three main computer literacy variables were created. The first variable was complit. This variable is a dummy variable that captures all those who are computer literate versus all those who are not computer literate. In other words those who are highly computer literate and those who have basic computer use are coded as 1 and those who are not computer literate are coded as 0. Secondly, a binary variable for highly computer literate (highcomp) was created, where 1 is highly computer literate and 0 is other, and thirdly, the same was done for basic computer use (basiccomp), where 1 is basic computer use and 0 is other. Evaluating the effect of being highly computer literate versus having basic computer use on the likelihood of employment and wage returns is useful in this study as it helps us to understand if the level of skill is important in determining labour market outcomes.

3.5.2b Other forms of human capital (education and English language proficiency)
De la Fuente amd Ciccone (2002) argue that formal education is used to measure human capital due to a lack of better measures of capital stock. In most of the studies investigating the relationship between computer literacy and earnings, formal education was controlled for. Section H of the NIDS questionnaire asks a variety of questions relating to the respondents educational history. Question H1 for example asked, “What is the highest grade in school that you have successfully completed?” Question H7 asked, “Have you successfully completed any diplomas, certificates or degrees outside of school?”

If the respondent stated that they have completed some higher education they were asked question H8 which stated, “If yes, what is the highest level of education you have successfully completed?” Using these questions among others in the education section NIDS derives a variable which consists of approximately 25 response options ranging from no schooling to higher degree. Using this variable, the 25 response options were collapsed into 6 education categories namely: 1= no schooling; 2= primary education; 3= incomplete secondary education; 4= matric; 5= diploma; and 6= degree. Each category was then created into a binary variable for the regression analysis. As mentioned in the literature review, researchers studying the relationship between computer literacy and earnings consider education to be highly correlated with computer literacy. Therefore controlling for education in the regression analysis would be expected to reduce the bias association between computer literacy and employment/earnings.

English language proficiency is also included in the regression analysis as a measure of human capital in South Africa. Question H38 of NIDS asks “How well can you read in English?” and provides the following response options: Very well, Fair, Not well, and Not at all. Similarly question H39 asks “How well can you write in English?” (the same response options are provided). Using these two questions a dummy variable called English proficiency was created, where those who responded that they could read and write “very well” were given a value of 1 (the rest were set to 0).

There is a large international literature and some South African literature which suggests that, as with computer literacy, dominant language proficiency is a measure of human capital which raises productivity in the labour market (Chiswick and Miller, 2007; Casale and Posel, 2011; Posel and Casale, 2011). Even though there are 11 official languages in South Africa, English is the language of business and to a large extent schooling (Casale and Posel, 2011). In their study investigating the association between English language proficiency and earnings in South Africa, Casale and Posel, 2011 find high returns for being proficient in English (that is being able to read and write very well). This study controls for English proficiency as a measure of human capital in examining the association between computer literacy and employment/ earnings, because English proficiency is likely to be highly correlated with computer literacy as well as employment/earnings, given the finding in the international literature that people who are proficient in English acquire computer skills more easily. Again, we would expect the coefficient on computer literacy to be reduced when English proficiency is controlled for.

3.5.2c Socio-demographic characteristics (age, gender, population group, geographic type, province)

Included in the NIDS questionnaire are various demographic questions. Using information on age in the survey, a categorical age variable was created where 1= 18-27 years; 2= 28-37 years; 3= 38-47 years; 4= 48-57 years; and 5= 58-65 years. Each of these categories was then transformed into a set of binary variables for the regression analysis.

A binary categorical variable for gender was created, where
1= male; and 0= female.

Population group (race) continues to be a vital indicator of the inequalities that exists in South African society. Therefore a set of binary variables were also included in the analysis to represent the African, Coloured, Indian, and White population groups.

The geographic type of the respondents was recorded in the survey as follows: 1 = rural formal; 2 = tribal authority areas; 3 = urban formal; and 4 = urban informal. Binary variables for each geographic type were created. Similarly indicators for the 9 provinces of South Africa were included in the analysis (i.e. Western Cape, North West Province, Eastern Cape, Gauteng, Northern Cape, Mpumalanga, Free State, Limpopo, and KwaZulu-Natal. NIDS cautions against making inferences at a provincial level due to not sampling enough Primary Sampling Units (PSUs). Nevertheless this study uses the provincial data in the descriptive results to provide an estimate of computer literacy rates by province, and also in the regressions as controls.

3.5.2d Family background (perceived relative economic standing)

Section M of the adult questionnaire of NIDS seeks to uncover information about the respondent's social interactions with those living in their surroundings as well as their perception of life in the past compared to now. This study uses one question from this section which can give insight into family background. Question M3 states, "Please imagine a six step ladder where the poorest people in South Africa stand on the bottom (the first step) and the richest people in South Africa stand on the highest step (the sixth step). M3.1 asks, "On which step was your household when you were 15?" I use this question to control to some extent for the family background of the respondent. We want to control for family background because we are trying to mitigate for the effects of certain 'unobservable' confounding characteristics. This question on perceived relative economic standing allows us to control to some degree for the socioeconomic status of the individual's family in their childhood as we might expect that individuals from better off families would be more likely to become computer literate, and more likely to gain employment (or higher earnings) in adulthood, because of social networks and better job opportunities.

3.5.2e Job Characteristics (occupation type, industry, tenure, and job type)

The above sets of explanatory variables are included in both the employment and earnings regressions. In this section I describe some of the job characteristics that are included in the earnings equations only, estimated on the sample of regular workers. Section E of NIDS asks a wealth of questions relating to the characteristics of the respondent's job, for regular workers in particular. In addition to information on the job type (i.e. regular, casual, self-employment), derived variables for industry and occupation were created by NIDS. Using the derived occupation variables, occupation dummies were created for those whose main job was regular work for the categories legislators, professionals, technicians, clerks, sales, agricultural workers, craft and related trade, machine operators and assemblers, and those working in elementary occupations. Similarly, industry dummy variables were created for regular workers, namely, agriculture, mining, manufacturing, electrical, construction, trade, transport, finance, community service, and private households (mainly domestic workers). In the descriptive analysis cross-tabulating occupation type and industry by computer literacy shows which industries and occupations have the highest rates of computer literacy and the levels thereof. This information can help us establish which industries and occupations favour computer skills.

Question E2 in NIDS asks of regular workers “When did you start this job?” A variable called tenure was created which captures the number of years an individual had been working in their primary job. The years of tenure were collapsed into 5 categories where 1= less than 1 year, 2=2-5 years, 3= 6-10 years, 4 = 11-20 years, 5= 21+ years in the current job. Some outliers were reset to missing, i.e. those observations that had years of tenure greater than 56 years. These categories were also transformed into a set of dummy variables for the regression analysis.

3.6. Limitations

One of the major limitations of this study is that the measure of computer literacy in NIDS is based on self-assessment. It is noted that self-reported data can result in individuals overestimating their skills due to social desirability (Bunz, Curry, and Voon, 2007), resulting in an upward bias in one’s results on the extent of computer literacy and a likely downward bias in the relationship between computer literacy and earnings or employment (Dolton and Makepeace, 2004; Bozionelos, 2004). This bias is noted and following Casale and Posel (2011), I will attempt to account for this problem as much as possible by also disaggregating the analysis into a strict definition of computer literacy (requiring individuals to be ‘Highly literate’) and a weaker definition (that is ‘Basic use’).

Another limitation of the work is that there may be unobserved heterogeneity which could also bias the results upwards (Casale and Posel, 2011). In other words, there could be unobserved or unmeasurable individual factors, such as innate ability or motivation, which could result in individuals being more likely to acquire computer skills and do well in the labour market. The techniques required to control for this, i.e. instrumental variable analysis, rely on the availability of suitable data that could be used as identifying variables (i.e. instruments). These are not available in the 2008 dataset and, in any case, these techniques are beyond the scope of this Masters dissertation. Nonetheless this study acknowledges the possible upward bias in the results.

A further limitation of my study is that I am unable to ascertain when an individual acquired their computer skills. It may be the case that the acquisition of computer skills for some respondents post-dates their employment i.e. computer skills may be acquired on the job. I want to test whether computer skills allow people to gain access to employment, and access to higher earnings; but it is also possible that access to employment allows a person to acquire computer skills on the job. In this case computer skills may be an outcome of employment; and of a particular type of employment. One way to attenuate this endogeneity concern in the absence of instruments is to restrict my sample size to young labour force participants (those who are 18- 25 years old for example) who are unlikely to have had much previous work experience or would have only been employed for a short period of time. These results are also discussed in Chapter 5.

Lastly, I need to mention the issue of sample selection, particularly a concern in the earnings equations which are restricted to those who had regular employment. Those in regular employment may not be a random sample of those in employment. Consequently those in employment may not be a random sample of labour force participants, who in turn may not be a random sample of the working-age population. This multi-stage selection problem is again very difficult to solve without suitable instruments at each stage. In any case, the Heckman selection model is beyond the scope of this dissertation. Nonetheless, it is important to recognise these possible biases.

3.7 Conclusion

This study uses quantitative analysis to study the association between computer literacy and employment and earnings in South Africa using the first wave of NIDS data from 2008. This chapter described the variety of variables from this survey that are used in the analysis. Before presenting the regression results, Chapter Four presents descriptive statistics on computer literacy rates by the above mentioned human capital, demographic and socioeconomic, and job characteristics, to determine who is computer literate in South Africa. In Chapter Five, probit and OLS regression analysis is used to determine if computer literacy increases the likelihood of employment and leads to higher earnings, after controlling for variables that that are commonly included in employment and earnings regressions in South Africa. Moreover the analysis also includes variables that have not been captured before in national datasets such as English language proficiency and perceived relative economic standing at age 15.

Chapter 4: Descriptive results

4.1. Introduction

A large previous literature has studied the relationship between computer literacy and earnings and, to a lesser extent, computer literacy and employment with the view that computer literacy forms an integral part of human capital in today's labour market. There is concern among researchers in this field that the increased use of computers and technological change may exclude some groups of society, especially those already marginalised from participating in the labour market (Dolton and Makepeace, 2002, and Krussel et al, 2000). Therefore, understanding who is computer literate and who is not is important in gaining insight into the relationship between human capital and labour market inequality. Using the NIDS 2008 data, this chapter provides a descriptive picture of the distribution of those who are computer literate in South Africa by various demographic and socio-economic characteristics. The literature review highlighted a gap in knowledge in this area, particularly that no such study has been conducted in South Africa using nationally representative data. These results also contribute to the literature by exploring the degree of computer literacy among those who are computer literate. The tables below illustrates the proportion of those who are computer literate as well as the degree of computer literacy, i.e. basic use versus highly literate, among those who are computer literate, by each characteristic.

4.2. Computer literacy by gender

Table 4.1 suggests that 30.42% of all working-age males and females (defined here as those aged 18-65 years) in the sample are computer literate. This compared to computer literacy rates in North America and the UK is relatively low where 1 in every 2 people in these regions is an internet user for example (Polikanov and Abramova, 2003). Of all males and females who are computer literate, 41.86% reported that they are highly computer literate while 58.14% reported that they have basic computer use skills. There are a greater **percentage** of males who are computer literate compared to that of females (32.81% and 28.58% respectively). Among all working-age males who are computer literate, 41.81% are highly computer literate whereas 58.19% have basic computer use. This pattern is similar among females (41.91% and 58.09%).

Table 4.1: Computer literacy by gender (%)

	Computer literate	Highly computer literate	Basic computer use	Total
		A +	B =	100
Male **N= 4978**	32.81 (1.10)	41.81 (2.19)	58.19 (2.19)	100
Female **N=7487**	28.58 (0.89)	41.91 (1.95)	58.09 (1.95)	100
Total N= 12465	30.42 (0.70)	41.86 (1.46)	58.14 (1.46)	100

Source: NIDS, 2008
Note: Data are weighted, standard errors in parentheses
Sample is of working-age individuals (18-65)

The results suggest that although a slightly greater proportion of males are computer literate compared to females, the distribution across highly computer literate and basic use is almost the same. Arabsheibani et al (2004) and Dolton and Makepeace (2002) proposed that women are more likely to use computers in the UK due to the fact that they more often work in clerical positions compared to men. Thus the results obtained in this study differ from their findings in this regard.

4.3. Computer literacy by race

Table 4.2 shows computer literacy for the different race groups in South Africa. The results indicate that White working-age South Africans have the highest percentage of computer literate individuals compared to all other race groups (82.87%), while Africans have the lowest percentage of computer literate individuals (21.94%). Among working-age Africans who are computer literate, 62.64% have basic computer use and only 37.36% report that they are highly computer literate. The proportion of those who are computer literate among Coloureds is almost twice that of Africans. Although Coloureds have a higher proportion of those who are computer literate compared to Africans, the pattern of levels of computer literacy among Africans and Coloureds are similar, where approximately one third of those who are computer literate are highly computer literate while two thirds report having basic computer use. Within South Africa, this pattern of racial inequality in computer literacy is expected given the effects of apartheid on education, skills access and household incomes.

Table 4.2: Computer literacy by race (%)

	Computer literate	Highly computer literate		Basic computer Use		Total
		A	+	B	=	100
African **N= 9704**	21.94 (0.63)	37.36 (1.61)		62.64 (1.61)		100
Coloured **N= 1855**	41.48 (2.43)	33.43 (4.29)		66.57 (4.29)		100
Indian **N= 183**	50.92 (6.05)	52.06 (9.03)		47.94 (9.03)		100
White **N= 723**	82.87 (2.11)	53.32 (3.32)		46.86 (3.32)		100
Total N=12465	30.42 (0.70)	41.86 (1.46)		58.14 (1.46)		100

Source: NIDS, 2008
Note: Data are weighted, standard errors in parentheses
Sample is of working-age individuals (18-65)

4.4. Computer literacy by province

The analysis in Table 4.3 presents the percentages of those who are computer literate by province. The results suggest that the Western Cape has the highest percentage of computer literate working-age adults compared to all the other provinces (48.78%). The Eastern Cape has the lowest percentage of computer literate adults (17.74%). Interestingly, only 41.18% of adults living in Gauteng report that they are computer literate. This is surprising as Gauteng is deemed the economic hub of South Africa, but may reflect the kinds of occupations (mining, for instance) people are involved in compared to the Western Cape for example. Less than 20% of working-age adults living in KwaZulu-Natal are computer literate. Similarly, the vast majority of working-age individuals living in the other provinces are not computer literate, where computer literacy rates are less than 35%.

The Western Cape also has the highest percentage of highly computer literate working-age adults (46.86%). Overall, the majority of individuals in all provinces reported that they had basic use of computers rather than being highly computer literate. The North West province has the highest disparity in skill level between those who are highly computer literate and those who have basic computer use. In this province 34.32% of working-age adults report they are highly computer literate whereas 65.68% report having basic computer use.

Table 4.3: Computer literacy by province (%)

	Computer literate	Highly computer literate	Basic computer use	Total
		A +	B =	100
Western Cape **N= 1637**	48.78 (2.20)	46.86 (3.53)	53.14 (3.53)	100
Eastern cape **N= 1536**	17.74 (1.58)	44.14 (5.04)	55.86 (5.04)	100
Northern Cape **N= 910**	28.35 (2.07)	43.21 (4.56)	56.79 (4.56)	100
Free State **N= 782**	32.46 (2.82)	42.15 (6.15)	57.85 (6.51)	100
KwaZulu-Natal **N= 3077**	19.45 (1.61)	35.64 (5.05)	64.36 (5.05)	100
North West **N= 1121**	30.95 (2.42)	34.32 (4.69)	65.68 (4.69)	100
Gauteng **N= 1376**	41.18 (1.70)	42.16 (2.65)	57.84 (2.65)	100
Mpumalanga **N= 868**	34.28 (2.29)	44.80 (4.20)	55.20 (4.20)	100
Limpopo **N= 1158**	18.52 (1.37)	41.30 (3.99)	58.70 (3.99)	100
Total N=12465	30.42 (0.70)	41.86 (1.46)	58.14 (1.46)	100

Source: NIDS, 2008
Note: Data are weighted, standard errors in parentheses
Sample is of working-age individuals (18-65)

4.5. Computer literacy by geographic type

Results in Table 4.4 show that working-age adults living in rural and tribal areas have the lowest rates of computer literacy (11.06% and 11.34% respectively), whereas urban formal areas have the highest percentage of individuals who are computer literate (46.58%). This is expected, as infrastructure to support the use of computers is scarce in the former areas in South Africa. Only 17.90% of working-age adults living in urban informal areas are computer literate. Even though these individuals are perceived to have greater opportunities and access to education and the formal economy compared to those living in rural areas, their access to and use of computers is relatively low and likely to be due in part to the living conditions in these areas. Urban formal areas according to Table 4.4 have the highest proportion of working-age adults that are highly computer literate. There is the greatest gap in levels of computer literacy among working-age adults in urban informal areas compared to all other geographic types, where of those who are computer literate, only 18.79% are highly computer literate and 81.21% have basic computer use.

Table 4.4: Computer literacy by geographic type (%)

	Computer literate	**Highly computer literate**	**Basic computer Use**	**Total**
		A +	**B =**	**100**
Rural **N= 1392**	11.06 (1.39)	38.98 (7.04)	61.02 (7.04)	100
Tribal **N= 4721**	11.34 (0.59)	32.86 (2.56)	67.14 (2.56)	100
Urban Formal **N= 5489**	46.58 (1.07)	45.10 (1.72)	54.90 (1.72)	100
Urban Informal **N= 863**	17.90 (1.75)	18.79 (3.79)	81.21 (3.79)	100
Total N=12465	30.42 (0.70)	41.86 (1.46)	58.14 (1.46)	100

Source: NIDS, 2008
Note: Data are weighted, standard errors in parentheses
Sample is of working-age individuals (18-65)

4.6. Computer literacy by age categories

Table 4.5 illustrates the percentage of working-age adults who are computer literate by age categories. The results in Table 4.5 highlight that those who are entering the job market are most likely to be computer literate. Individuals between 18 and 27 are most likely to be computer literate compared to all other age groups (35.79%). It is evident that rates of computer literacy decrease with age, with those who are exiting the job market (aged between 58 and 65 years) having the lowest rate of computer literacy (17.30%) compared to all other age groups. One explanation for such a pattern could be due to the fact that when the oldest age group entered the job market computer penetration would have been low in almost all industries. Computer users during this time used computers for specialised and non-routine tasks. Therefore computer skills were not a requirement for entering the job market. Type-writing, language proficiency, and basic mathematics skills were desired traits for those searching for jobs between 30 and 40 years ago. In contrast, in today's job market computers form a part of almost every office operation including menial administrative tasks. Therefore those entering the job market may be attaining such skills to give themselves an advantage in gaining access into the job market. Furthermore, the internet and computers are becoming increasingly integrated into the daily lifestyle of many South Africans, where students in schools are taught how to use computers and the internet, and where computers are used as a tool for learning other subjects outside the realm of specialist computer courses. This could explain why individuals at younger ages are more likely to be computer literate.

Table 4.5: Computer literacy by age categories (%)

	Computer literate	**Highly computer literate**	**Basic computer use**	**Total**
		A +	**B** =	**100**
18-27 years **N= 4062**	35.79 (1.14)	39.25 (2.08)	60.75 (2.08)	100
28-37 years **N= 2783**	33.60 (1.46)	44.26 (2.78)	55.74 (2.78)	100
38-47 years **N= 2507**	27.39 (1.55)	49.81 (3.53)	50.19 (3.53)	100
48-57 years **N= 2023**	22.63 (1.89)	39.90 (5.18)	60.10 (5.18)	100
58-65 years **N= 1090**	17.30 (2.47)	22.39 (8.19)	77.61 (8.19)	100
Total N= 12465	30.42 (0.70)	41.86 (1.46)	58.14 (1.46)	100

Source: NIDS, 2008. Note: Data are weighted, standard errors in parentheses . Individuals (18-65)

Almost 78% of computer literate working-age adults between 58-65 years old have basic computer use while the remaining 22% are highly computer literate. There is approximately an even split between individuals who are highly computer literate and individuals who have basic computer use in the age category 38-47 years. One possible reason for this could be that individuals in this age category may be settled in their careers and have honed their computer skills to undertake particular tasks for their respective jobs (an issue which, as described in the previous chapter, complicates the identification of causality in regression analysis).

4.7. Computer literacy by education

Table 4.6 shows the percentage of working-age adults who are computer literate by their level of completed education. It indicates that, as we might expect, as the level of schooling increases so does the proportion of individuals who are computer literate.

Less than 1% of working-age adults with no schooling are computer literate and just under 3% of individuals who have primary education are computer literate. The proportion of those who are computer literate drastically increases for those who have some secondary schooling. Almost 19% of working-age adults who have incomplete secondary schooling are computer literate. This is more than six times the proportion of individuals with primary schooling who are computer literate. Just over one in every two working-age adults who have a matric are computer literate (53.04%).

The pattern continues where those with post-secondary education are even more likely to be computer literate. About 75% of individuals with diplomas and 93.54% of those with degrees are computer literate. Among those who have no schooling and are computer literate, 96.02% report having basic use while 3.98% are highly computer literate. This pattern is similar among those who have completed primary school and some secondary school, where the vast majority of individuals within these education levels report having basic computer use compared to being highly computer literate. The inverse is true for those who have diplomas and degrees. About 52% and 69% of working-age individuals in these respective categories who are computer literate, report that they are highly computer literate. Among those who are computer literate and have a matric, 43.01% are highly computer literate while 56.99% have basic computer use. It has been established by past literature that there exists a strong correlation between education and computer literacy (Ying Chu Ng, 2006); the wide differentials in schooling and post-schooling infrastructure and resources as well as the quality of education in South Africa **are** likely to contribute to this form of inequality.

Table 4.6: Computer literacy by education category (%)

	Computer literate	Highly computer literate	Basic computer use	Total
		A +	B =	100
No schooling **N= 1429**	0.61 (0.31)	3.98 (4.30)	96.02 (4.30)	100
Primary School **N= 2994**	2.85 (0.45)	6.23 (3.36)	93.77 (3.36)	100
Incomplete secondary School **N= 4614**	18.94 (0.92)	18.66 (1.98)	81.34 (1.98)	100
Matric **N= 2110**	53.04 (1.60)	43.01 (2.34)	56.99 (2.34)	100
Diploma **N= 1005**	75.01 (1.99)	52.20 (2.78)	47.80 (2.78)	100
Degree **N= 288**	93.54 (1.72)	69.25 (4.71)	30.75 (4.71)	100
Total N= 12443	30.31 (0.69)	41.99 (1.46)	58.01 (1.46)	100

Source: NIDS, 2008
Note: Data are weighted, standard errors in parentheses
Sample is of working-age individuals (18-65)

4.8. Computer literacy by employment status

Table 4.7 provides a broad representation of who is computer literate in South Africa by labour market status. The table shows that 20.47% of working-age adults who are not economically active are computer literate. Approximately 17% of the non-searching unemployed report that they are computer literate. Among those who are unemployed but searching for a job, 26.61% are computer literate. This difference among the unemployed likely reflects that the searching unemployed are more educated than the non-searching (Posel, Casale and Vermaak, *forthcoming*). More surprising is that 23.79% and 28.89% of the non-searching and searching unemployed respectively who are computer literate, are highly computer literate. This suggests that being computer literate does not guarantee the attainment of a job, even if it increases one's chances of gaining employment (as I discuss further in the next chapter on employment probabilities). One possible explanation for this could be that these unemployed individuals who are computer literate could be fresh out of school or further education and lack work experience, which could explain why they are unemployed.

Table 4.7: Computer literacy by employment status (%)

	Computer literate	Highly computer literate	Basic computer use	Total
		A +	B =	100
Not economically active **N= 3962**	20.47 (1.11)	35.38 (3.22)	64.62 (3.22)	100
Unemployed non-searching **N= 910**	17.23 (2.10)	23.79 (5.45)	76.21 (5.45)	100
Unemployed searching **N= 1788**	26.61 (1.68)	28.89 (3.40)	71.11 (3.40)	100
Employed **N= 5305**	39.01 (1.06)	47.24 (1.87)	52.76 (1.87)	100
Regular work N= 3778	44.25 (1.32)	50.29 (2.12)	49.71 (2.12)	100
Self- employed N= 830	34.67 (3.28)	44.70 (6.49)	55.30 (6.49)	100
Casual work N= 697	23.63 (3.36)	24.44 (8.32)	75.56 (8.32)	100
Total **N= 11965**	30.41 (0.70)	41.59 (1.46)	58.41 (1.46)	100

Source: NIDS, 2008
Note: Data are weighted, standard errors in parentheses
Sample is of working-age individuals (18-65)

The results also show that among those who are employed, 39.01% are computer literate. Less than half of the individuals who are employed in regular work are computer literate (44.25%). There are smaller percentages of the self-employed and casual workers who are computer literate compared to regular workers (34.67% and 23.63% respectively). Of those who are employed and computer literate, 52.76% report having basic computer use while the remaining 47.24% report that they are highly computer literate. Among those who are employed, casual workers have the largest discrepancy between having basic computer use and being highly computer literate (75.56% compared to 24.44%).

4.9. Computer literacy by industry

Table 4.8 illustrates the percentage of those who are computer literate by industry for those who are employed in regular work only. Individuals who work in the community, social and personal services industry have the highest percentage who are computer literate (66.52%) compared to all other industries, with 47.76% of those reporting being highly literate. Those working in private households have the lowest percentage of computer literate individuals (5.71%), likely to be explained by the fact that this industry comprises mostly domestic workers. Interestingly, only 56.67% of those working in the financial intermediation and insurance industry are computer literate, however nearly 80% of these individuals are highly literate. One might have expected a much higher proportion of workers in this industry to be computer literate as this is a service-related industry. In all other industries shown in Table 4.8, those who are computer literate could possibly be office workers working either in administration or management posts for example. Individuals who are not computer literate could be engaged in more manual types of work.

Industries such as agriculture, mining, manufacturing, and construction are all labour intensive and in many instances workers do not require computer skills to perform their duties. Theorists suggest that in the near future even workers in such industries will be required to have some computer skills to adapt to technological change and computer diffusion which could make production and output more efficient and effective (Tyler, 2004). In the agricultural industry of those who are computer literate, 18.48% are highly computer literate whereas the remaining 81.52% have basic computer use. In contrast, of the computer literate individuals who work in the mining and quarrying industry, 74.33% are highly computer literate and 25.67% have basic use of computers. This pattern is similar for the electricity, gas and water supply; construction; transport, storage and communication; and financial intermediation and insurance industries, in which the majority of those who are computer literate are highly computer literate (67.13%, 52.36%, 54.38%, and 79.65% respectively). It would seem that these industries favour individuals who are highly computer literate to perform specialist tasks for that particular industry. Individuals working in these industries may have been given training on the job to perform their functions or they may have gained the skills due to their own personal investment in computer training to meet the requirements for that particular job.

Table 4.8: Computer literacy by industry (%)

	Computer literate	**Highly computer literate**	**Basic computer use**	**Total**
		A +	**B =**	**100**
Agriculture, hunting, forestry and fishing **N= 504**	7.79 (1.94)	18.48 (7.24)	81.52 (7.24)	100
Mining and quarrying **N= 154**	40.96 (6.23)	74.33 (9.34)	25.67 (9.34)	100
Manufacturing **N= 476**	38.80 (3.46)	34.80 (5.62)	65.20 (5.62)	100
Electricity, gas and water supply **N= 25**	56.90 (12.75)	67.13 (18.46)	32.87 (18.46)	100
Construction **N= 163**	29.92 (5.41)	52.36 (10.93)	47.64 (10.93)	100
Wholesale and retail trade **N= 444**	46.54 (3.51)	47.38 (5.31)	52.62 (5.31)	100
Transport, storage and communication **N= 119**	43.29 (6.45)	54.38 (10.03)	45.62 (10.03)	100
Financial intermediation insurance **N= 225**	56.67 (4.58)	79.65 (4.39)	20.35 (4.39)	100

Community, social and personal services **N= 765**	66.52 (2.40)	47.76 (3.51)	52.24 (3.51)	100
Private households, exterritorial organisations **N= 373**	5.71 (1.46)	6.66 (4.94)	93.34 (4.94)	100
Total N= **3248**	43.15 (1.36)	51.70 (2.20)	48.30 (2.20)	100

Source: NIDS, 2008
Note: Data are weighted, standard errors in parentheses
Sample is of working-age individuals (18-65) who are employed in regular work

Based on Table 4.8 it would seem that industries such as agriculture, hunting, forestry and fishing; manufacturing; wholesale and retail trade; and community, social and personal services, favour computer literate individuals who have broad and more basic computer skills (81.52%, 65.20%, 52.62%, 52.24%).

4.10. Computer literacy by occupation type

Table 4.9 illustrates the percentage of individuals who are computer literate by occupation type for those who are employed in regular work only. Legislators, senior officials and managers are the most likely to be computer literate (85.87%) compared to individuals in all the other occupational types. Professionals, technicians and associate professionals, and those working in clerical posts are also highly likely to be computer literate. These occupations are service-focused rather than involving physical labour, which likely explains why the majority of people working in these occupations are computer literate. As mentioned earlier, many of these occupations require people with computer skills to perform routine, as well as specialist tasks. Being computer literate is therefore a likely requirement for those working in such fields. Individuals in occupations such as skilled agriculture and fishery, craft and related trade, plant and machinery and assembly workers, and those working in elementary occupations are all significantly less likely to be computer literate. These occupations mostly involve physical labour and generally would not require soft skills such as computer literacy.

Of the legislators, senior officials, and managers who are computer literate, 68.65% are highly computer literate whilst 31.35% have basic computer use. Although more than half of those who are computer literate among professionals, technicians, and clerks are highly computer literate (55.47%, 58.98%, and 59.09% respectively), the difference between those who are highly computer literate and those who have basic computer use is marginal. One possible reason for this could be that employers seek both highly computer skilled and broad computer skilled workers.

Table 4.9: Computer literacy by occupation type (%)

	Computer literate	**Highly computer literate**	**Basic computer use**	**Total**
		A **+**	**B** **=**	**100**
Legislators, senior officials and managers **N= 139**	85.87 (3.62)	68.65 (5.88)	31.35 (5.88)	100
Professionals **N= 452**	75.20 (2.86)	55.47 (4.21)	44.53 (4.21)	100
Technicians and associate professionals **N= 145**	76.83 (4.55)	58.98 (7.64)	41.02 (7.64)	100
Clerks **N= 317**	84.42 (2.90)	59.09 (4.41)	40.91 (4.41)	100
Service workers and shop and market sales **N= 442**	39.29 (3.51)	36.58 (5.66)	63.42 (5.66)	100
Skilled agricultural and fishery workers **N= 371**	6.52 (2.24)	23.18 (15.98)	76.82 (15.98)	100
Craft and related trade workers **N= 466**	34.38 (3.52)	36.94 (6.22)	63.06 (6.22)	100
Plant and machinery operators and assembly workers **N= 334**	19.98 (3.33)	32.44 (8.35)	67.56 (8.35)	100
Elementary occupations	11.84 (1.65)	25.37 (6.44)	74.63 (6.44)	100

N= 916				
Total **N= 3457**	43.97 (1.33)	50.49 (2.14)	49.51 (2.14)	100

Source: NIDS, 2008
Note: Data are weighted, standard errors in parentheses
Sample is of working-age individuals (18-65) who are employed in regular work

Those who are highly computer literate may use computers to undertake tasks using specific or specialised software, while those with basic computer skills are required to perform more routine tasks. In all other occupations in Table 4.9 (service workers and shop and market sales; agriculture and fishery; craft and trade; plant and machinery operators and assembly workers; and elementary occupations), employees mostly report that they have basic computer use.

4.11. Average hourly income among regular, self- employed and casual workers by computer literacy.

Finally, given that the next chapter examines the association between computer literacy and earnings in the multivariate context, it is useful to show simple average earnings estimates by the various categories of employment and computer literacy. Table 4.10 presents the average hourly earnings of employed individuals who are computer literate compared to those not computer literate, and by degree of computer skill.

Table 4.10: Average hourly income of computer literate versus non computer literate by type of employment (Rands)

	Hourly income			
	Not computer Literate	**Computer literate**	**Highly computer literate**	**Basic computer use**
Regular work **N= 3778**	17.98 (3.67)	44.07 (2.43)	57.10 (4.11)	30.96 (2.09)
Self-employed **N= 830**	16.77 (2.42)	74.12 (16.80)	94.52 (26.30)	59.11 (19.50)
Casual worker **N= 697**	29.82 (3.61)	58.76 (13.19)	54.00 (12.03)	60.29 (17.08)
Average earnings of all employed	21.52	58.98	68.54	50.12

Source: NIDS, 2008
Note: Data are weighted, standard errors in parenthesis
Sample is of working-age individuals (18-65) who are employed, excluding subsistence workers and unpaid workers.

The results suggest that workers who are computer literate earn on average substantially more than workers who are not computer literate. Regular workers who are computer literate earn on average more than twice than that of their counterparts who are not computer literate (R44.07 compared to R17.98). Similarly, casual workers in the sample who are computer literate earn on average almost twice as much per hour as individuals who are not computer literate (R58.76 compared to R29.82). Self-employed workers who are computer literate earn the highest hourly rate compared to all other employed individuals in the sample. They earn on average four times more than their counterparts who are not computer literate (R74.12 compared to R16.77). For regular work and self-employment, individuals who are highly computer literate earn significantly more on average than individuals who have basic skills, whereas among casual workers, there is not much difference. Self- employed workers who are highly computer literate earn the highest hourly rate (R94.52). Upon further inspection it was found that approximately 17% of self-employed workers work either as legislators and government officials, professionals, technicians, or service workers. About 54% of self-employed workers work in elementary occupations. It could be that the high values earned by skilled workers in this type of employment result in the high average earnings among those with computer skills. For all three types of employment, individuals who have basic computer use earn on average more per hour than those who are not computer literate.

4.12. Conclusion

This chapter shed light on who is computer literate in South Africa. Using the NIDS 2008 data the results generally find that differences in computer literacy spill over from inequalities that already exist in South Africa. The results broadly show that individuals who are/were marginalised in society are less likely to be computer literate than individuals who live in better socio-economic conditions. The descriptive results highlighted that among those who are least likely to be computer literate are Africans; those living in rural, tribal and urban informal areas; those living in the poorest provinces; individuals who have no schooling or only primary schooling, the unemployed, individuals who work in private households (mostly domestic workers), and those in elementary occupations. In addition, the oldest cohorts have the lowest levels of computer literacy, as would be expected given changing technology.

All else equal (i.e. if the factors described above were controlled for), the disparities in computer skills are also likely to reflect the quality of schooling and post-schooling obtained, information on which is not available in the NIDS data. Part of the disparity might also be due to some individuals with the means and motivation acquiring further skills through computer training courses after schooling. In addition, computer skills are likely to be acquired on the job, and many of the correlations described above reflect the skills needed for particular types of jobs that people hold – this was evident in the description of computer skills by occupation and industry type. These factors will be discussed further in the next chapter, in which the associations between computer literacy and the probability of finding work and earning high wages are studied in the multivariate context.

Chapter 5: Regression Analysis

5.1. Introduction

According to human capital theory, the acquisition of computer skills requires significant investment. The motivation for investing in such skills is due to the perceived benefits it has on future earnings. While positive returns to computer literacy are well documented in developed countries, little evidence is available about the same relationship in a developing country context. This chapter presents the findings of the regression analysis on the relationship between computer literacy (as a form of human capital) and labour market outcomes in South Africa; namely the probability of finding employment, and among those employed in regular work, their earnings. A review of the South African labour market literature suggests that there have been no studies investigating the relationship between computer literacy and employment and/or earnings using nationally representative data for South Africa.

Using NIDS 2008 data, probit regression analysis is undertaken to examine the relationship between computer literacy and employment, and Ordinary Least Squares (OLS) regression analysis is used to estimate the association between computer literacy and earnings. In both regression models a range of variables are controlled for, namely, demographic characteristics, family socio-economic background, schooling, English proficiency, and in the earnings regressions, industry, occupation type, and years of tenure. The main variable of interest is the dummy variable capturing computer literacy, and in some of the specifications this is disaggregated further into having basic computer skills and being highly literate.

5.2. Probit regression analysis on the association between computer literacy and the probability of getting employment among working-age adults

Table 5.1 presents the results on the relationship between computer literacy and employment among working-age adults in the sample. As described in the methods chapter, the dependent variable is equal to one if the individual was employed in any type of work, i.e. regular, self-employment or casual, and equal to zero if the individual was either unemployed or inactive. In this regression analysis five models are used to test how the association between computer literacy and the likelihood of employment changes as additional possible covariates are included, i.e. demographic characteristics (gender, race, age, area type and province), human capital variables (level of education completed and proficiency in English); and family socio-economic background (captured in perceived relative economic standing at age 15).

Table 5.1: Probit regression analysis of the probability of being employed among working-age adults (coefficients displayed)

	Model 1	Model 2	Model 3	Model 4	Model 5
Computer Literacy					
Computer literacy	0.501*** (0.042)	0.453*** (0.048)	0.229*** (0.055)	0.225*** (0.055)	
High computer literacy					0.388*** (0.081)
Basic computer use					0.160*** (0.060)
Demographic Characteristics					
Female		-0.584*** (0.038)	-0.590*** (0.039)	-0.589*** (0.039)	-0.590*** (0.039)
African		-0.080 (0.092)	0.019 (0.097)	0.016 (0.097)	0.035 (0.097)
Indian		0.145 (0.173)	0.226 (0.181)	0.238 (0.177)	0.243 (0.179)
Coloured		-0.016 (0.111)	0.112 (0.118)	0.111 (0.118)	0.135 (0.119)
Urban		0.119*** (0.043)	0.066 (0.044)	0.066 (0.045)	0.069 (0.044)
Aged 18-27		-0.042 (0.077)	-0.082 (0.085)	-0.080 (0.086)	-0.098 (0.086)
Aged 28-37		0.704*** (0.078)	0.615*** (0.085)	0.616*** (0.085)	0.602*** (0.085)
Aged 38-47		0.831*** (0.080)	0.785*** (0.085)	0.787*** (0.085)	0.772*** (0.085)

Aged 48-57		0.675*** (0.081)	0.644*** (0.085)	0.646*** (0.085)	0.637*** (0.085)
Province controls	No	Yes	Yes	Yes	Yes
Human Capital					
Primary School			0.145** (0.065)	0.145** (0.065)	0.150** (0.065)
Incomplete secondary School			0.088 (0.071)	0.085 (0.071)	0.102 (0.071)
Matric			0.421*** (0.084)	0.419*** (0.084)	0.421*** (0.084)
Diploma			0.698*** (0.103)	0.700*** (0.103)	0.682*** (0.103)
Degree			0.772*** (0.207)	0.771*** (0.210)	0.709*** (0.209)
English proficiency			-0.029 (0.048)	-0.028 (0.048)	-0.037 (0.049)
Family socioeconomic background (relative economic standing)					
Rung 2				0.072* (0.044)	0.071 (0.044)
Rung 3				-0.005 (0.053)	-0.012 (0.053)
Rung 4				0.084 (0.091)	0.068 (0.091)
Rung 5				-0.025 (0.165)	-0.028 (0.164)
Rung 6				-0.140 (0.291)	-0.145 (0.298)
Constant	-0.185***	-0.175	-0.340***	-0.367***	-0.385***

	(0.019)	(0.119)	(0.126)	(0.129)	(0.128)
F	145.19	48.05	37.57	31.26	30.12
Prob>F	0.000	0.000	0.000	0.000	0.000
N	**12465**	**12465**	**12413**	**12411**	**12411**

Source: NIDS, 2008
Note: Data are weighted, standard errors in parentheses
Sample is of working-age individuals (18-65)
*** p< 0.01, **p<0.05 , *p< 0.1
Omitted variables: Male, White, Rural, Western Cape, Age 58- 65, No schooling, Not proficient in English, Rung 1.

Model one presents the association between computer literacy and the likelihood of being employed without controlling for any other variables. The result shows that there is a statistically significant and positive association between computer literacy and employment (a coefficient of 0.50). In Model two, demographic variables such as gender, race, area type, age, and province are included. When these variables are included, the likelihood of gaining employment still remains positively correlated with computer literacy, although the coefficient drops from 0.50 in Model one to 0.45 in model two. Females have a lower chance of gaining employment than males. Surprisingly the effect of race on the employment likelihood is not significant, suggesting no statistical difference in gaining employment based on one's race, if computer literacy, gender, area type, age, and province are fixed. Living in an urban area is positively correlated with employment, compared to living in a rural area. Individuals in the age groups 28-37, 38-47, and 48-57 are more likely to be employed compared to their counterparts aged between 58-65. In this Model province is also controlled for. Although not shown in the table, all province coefficients with the exception of Eastern Cape and Limpopo are not statistically significant, where the omitted category is the Western Cape.

Model three includes other measures of human capital, i.e. completed levels of schooling and proficiency in English, as well as the demographic characteristics described above. As mentioned in the methodology chapter, this study defines English proficiency as being able to read and write very well. In a South African context English proficiency has perceived benefits in the labour market. Casale and Posel (2011) in a study investigating the returns to English proficiency in South Africa find very high returns for being proficient in English. This study therefore controls for English proficiency on the premise that it forms part of human capital, and because studies elsewhere suggest that those who are English proficient are more likely to assimilate computer skills more easily. Again the likelihood of gaining employment for the computer literate is positive and remains statistically significant. However, given the expected correlation between computer literacy and formal education and English proficiency, the coefficient on computer literacy falls quite substantially now, from 0.453 in Model 2 to 0.229 in Model 3.

When educational attainment is added into the regression, area type becomes statistically insignificant, but the other correlations stay much the same. The results for education reveal that those with a primary level of schooling are more likely to be employed compared to individuals with no schooling. The results suggest that there is no statistical difference between the likelihood of gaining employment for individuals who have an incomplete secondary education compared to those who have no education. Having a matric is positively correlated with being employed compared to those with no schooling, where the coefficient on matric is around 0.42. Individuals who have diplomas and degrees are also more likely to have employment compared to those with no schooling, with the highest coefficients of 0.70 and 0.77 respectively. Although English proficiency has no significant impact on finding employment in general proficiency in English is likely to be correlated with the type of job one obtains (which is beyond the scope of this study to explore further).

In Model four a subjective measure of relative economic standing is used to control for family socioeconomic background in addition to the above-mentioned independent variables. This self-perception question asked where respondents thought their household fitted on a scale from poorest to richest in South Africa when they were 15 years old, with rung 1 being the poorest and rung 6 being the richest. This is included in the regression as one of the key confounding factors in the analysis is likely to be socioeconomic status; i.e. individuals from better off families would be more likely to become computer literate and more likely to gain employment in adulthood. When this scale is included in the model, the results indicate that the positive and significant association between computer literacy and employment remains. The coefficient only falls slightly from the previous model to 0.225. The effects of the other demographic characteristics also do not change. On the relative standing ladder, only rung 2 is positive and statistically different from rung 1, the omitted category.

In Model 5, the association between computer literacy and employment is split into highly computer literate and basic computer use. This regression includes the same variables as Model four (demographic characteristics, human capital characteristics, and family background). The results suggest that after controlling for this host of variables, being highly computer literate and having basic skills are both correlated with the probability of gaining employment, compared to not being computer literate. However, basic computer use has a coefficient of 0.16 while the coefficient on highly computer literate is more than twice the size at 0.388.

After controlling for a variety of characteristics, the results suggest that there is a significant positive correlation between computer literacy and the probability of employment in South Africa among working-age adults. Those who are highly computer literate have the greatest chance of employment compared to those who are not computer literate, and even those with basic computer use have an increased chance of employment compared to those who are not computer literate.

As mentioned in the Methods chapter, it is not possible to say unequivocally that the direction of causality is from computer literacy to employment probability. It is likely that a large part of an individual's computer skills are developed at school and post-secondary schooling for the younger cohorts. Computer skills might also be developed/honed after schooling through additional specific training or through self-learning. However, especially among the older cohorts, computer skills are also likely to be learnt on the job, or earning an income might provide individuals the resources necessary to invest in their computer skills. If this is the case, then the causality could run in the opposite direction. To try and attenuate this concern, the regressions are run for a very young cohort of individuals, aged 18-25, who are likely entering the job market for the first time and who will have had less time to acquire computer skills on the job. The results of the probit regressions are shown in Table 5.2. Model one regresses employment on computer literacy without controlling for any other variables. The results suggest a positive and statistically significant correlation between computer literacy and the probability of finding employment among the youth of South Africa.

Table 5.2: Probit regression analysis on the probability of employment among working-age youth, 18 – 25 years (coefficients displayed)

	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**
Computer Literacy					
Computer literacy	0.307*** (0.073)	0.088 (0.080)	-0.024 (0.088)	-0.010 (0.089)	
High computer literacy					0.113 (0.132)
Basic computer use					-0.057 (0.097)
Demographic Characteristics					
Female		-0.464*** (0.070)	-0.484*** (0.071)	-0.481*** (0.071)	-0.485*** (0.071)
African		-0.716*** (0.207)	-0.676*** (0.212)	-0.709*** (0.209)	-0.665*** (0.213)
Indian		-0.106 (0.385)	-0.062 (0.388)	-0.062 (0.379)	-0.013 (0.384)
Coloured		-0.372 (0.236)	-0.332 (0.237)	-0.367 (0.234)	-0.329 (0.235)
Urban		0.071 (0.078)	0.035 (0.080)	0.045 (0.080)	0.051 (0.080)
Province controls	No	Yes	Yes	Yes	Yes
Human Capital					
Primary school			0.037 (0.323)	0.021 (0.311)	0.022 (0.311)
Incomplete secondary school			-0.110 (0.311)	-0.116 (0.300)	-0.110 (0.299)
Matric			0.295 (0.319)	0.282 (0.308)	0.280 (0.307)
Diploma			0.475 (0.341)	0.476 (0.332)	0.444 (0.332)
Degree			0.704 (0.487)	0.684 (0.477)	0.643 (0.470)
English proficiency			-0.155** (0.078)	-0.151* (0.078)	-0.161** (0.078)
Family socioeconomic background (relative economic standing)					
Rung_2				-0.037 (0.083)	-0.039 (0.083)
Rung_3				-0.132 (0.100)	-0.146 (0.100)
Rung_4				0.009 (0.148)	-0.007 (0.148)
Rung_5				-0.189 (0.311)	-0.217 (0.315)
Rung_6				0.194 (0.431)	0.181 (0.431)
Constant	-0.659*** (0.041)	0.438* (0.237)	0.524 (0.380)	0.599 (0.372)	0.571 (0.372)
F	**17.97**	**13.27**	**10.52**	**8.59**	**8.43**
Prob>F	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**

N	3437	3437	3429	3428	3428

Source: NIDS, 2008
Note: Data are weighted, standard errors in parentheses
Sample is of working-age individuals (18-25)
*** p< 0.01, **p<0.05 , *p< 0.1
Omitted variables: Male, White, Rural, Western Cape, No schooling, Not proficient in English, Rung 1.

Model two includes demographic characteristics such as gender, race, area type, and province in the regression. The coefficient on computer literacy becomes statistically insignificant in this model as well as in subsequent models where variables measuring human capital and family socioeconomic background were included. Although the effect of being computer literate is not statistically different from not being computer literate in these models, it is noted that female youth have lower chances of gaining employment compared to their male counterparts, and young African's have lower chances of being employed compared to white youth. These results are consistent throughout models two to five.

Education and family background have no statistically significant effect on gaining employment among youth (although the coefficients on matric, degree and diploma are positive and display the expected increasing pattern). A surprising result is that being English language proficient reduces the probability of finding work among the youth compared to being unemployed or inactive. These findings might be related to the fact that some youth (and possibly the better off and more able ones) could still be studying in tertiary institutions to increase their human capital in order to gain access to the job market in the future – these are captured in the zeroes in the dependent variable which includes the inactive.

Therefore I ran a similar regression restricting the sample to youth, but where youth who were not economically active were excluded from the sample (see Appendix 1). Table 1 in Appendix 1 shows that now computer literacy is positive across all the models, although in models 2 to 4 the significance level is not strong. However there is a positive and strongly significant effect of being highly literate in particular on the probability of employment among the youth. The coefficients on the educational and English proficiency variables are not statistically significant.

Given that the youth are more likely to be computer literate (as shown in the descriptive results, where about a third of this age group is computer literate) compared to those who are older, due to increasing computer diffusion in schools and colleges, it may be that a high level of computer skill is necessary to be desirable in the job market. Also, other features such as previous work experience (unmeasured in the NIDS survey for the employed before they got their current jobs) may be more important for getting into the job market among this youth cohort than education. Alternatively, it may be that important computer skills are often acquired on the job and that this group of individuals has not yet been in employment long enough to have acquired them, accounting for the somewhat lower correlation between computer literacy and the probability of employment compared to the full sample. [2] In the next section, this problem is attenuated to a certain degree, as the relationship between computer literacy and earnings is examined among those who are in employment.

5.3. Ordinary Least Squares Regression Analysis on the association between computer literacy and the log of hourly earnings for working-age adults who are in regular work

Table 5.3 presents ordinary least squares regression analysis on the association between computer literacy and earnings in South Africa. The dependent variable is the log of hourly earnings for individuals who are employed in regular work.

Table 5.3: Ordinary Least Squares regression analysis of the log of hourly earnings for regular workers

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Computer Literacy						
Computer literacy	1.133*** (0.058)	0.902*** (0.061)	0.378*** (0.067)	0.361*** (0.067)	0.263*** (0.068)	
High computer literacy						0.470*** (0.084)
Basic computer use						0.160** (0.070)
Demographic Characteristics						
Female		-0.267*** (0.051)	-0.304*** (0.047)	-0.312*** (0.047)	-0.219*** (0.051)	-0.219*** (0.051)
African		-0.506*** (0.088)	-0.340*** (0.076)	-0.323*** (0.077)	-0.275*** (0.080)	-0.255*** (0.078)
Indian		0.245 (0.203)	0.303 (0.214)	0.304 (0.210)	0.358** (0.180)	0.327* (0.180)
Coloured		-0.547*** (0.109)	-0.333*** (0.096)	-0.307*** (0.100)	-0.274*** (0.106)	-0.234** (0.105)
Urban		0.415*** (0.063)	0.229*** (0.059)	0.227*** (0.058)	0.185*** (0.061)	0.180*** (0.061)

[2] For the sake of comparability, Table 2 in Appendix 1 also presents results for the full sample, i.e. for all age cohorts pooled, but excluding the not economically active from the zeroes of the dependent variable. The results on computer literacy show strong positive significant results in all models.

Aged 18 – 27		-0.187* (0.111)	-0.428*** (0.115)	-0.433*** (0.116)	-0.203* (0.119)	-0.241** (0.118)
Aged 28 – 37		0.277** (0.108)	-0.023 (0.112)	-0.030 (0.113)	0.135 (0.106)	0.098 (0.106)
Aged 38 – 47		0.412*** (0.110)	0.191* (0.111)	0.189* (0.111)	0.217** (0.102)	0.188* (0.102)
Aged 48 – 57		0.426*** (0.114)	0.266** (0.112)	0.286** (0.113)	0.250** (0.100)	0.213** (0.100)
Province controls	No	Yes	Yes	Yes	Yes	Yes
Human Capital						
Primary school			0.145 (0.096)	0.149 (0.095)	0.039 (0.092)	0.045 (0.092)
Incomplete secondary school			0.354*** (0.101)	0.355*** (0.099)	0.214** (0.097)	0.238** (0.097)
Matric			0.653*** (0.122)	0.658*** (0.120)	0.461*** (0.118)	0.457*** (0.118)
Diploma			0.976*** (0.134)	0.978*** (0.134)	0.599*** (0.128)	0.576*** (0.127)
Degree			1.550*** (0.141)	1.580*** (0.143)	1.066*** (0.148)	1.027*** (0.149)
English proficiency			0.275*** (0.065)	0.266*** (0.065)	0.189*** (0.065)	0.182*** (0.065)
Family socioeconomic background (relative economic standing)						
Rung_2				0.028 (0.057)	-0.018 (0.056)	-0.032 (0.055)
Rung_3				0.119* (0.064)	0.054 (0.064)	0.035 (0.064)
Rung_4				0.168 (0.120)	0.102 (0.119)	0.077 (0.118)
Rung_5				-0.255 (0.175)	-0.263 (0.200)	-0.291 (0.194)
Rung_6				0.042 (0.256)	0.243 (0.180)	
Occupation and Industry Controls						
Legislators					0.528*** (0.142)	0.483*** (0.137)
Professionals					0.520*** (0.110)	0.508*** (0.110)
Technicians					0.314** (0.124)	0.299** (0.122)
Clerks					0.224** (0.101)	0.188* (0.100)
Sales					0.009 (0.095)	0.029 (0.095)
Skilled agriculture					-0.172* (0.093)	-0.187** (0.092)
Crafts					0.174* (0.099)	0.177* (0.098)

Operating					0.077 (0.093)	0.078 (0.093)
Agriculture					0.043 (0.096)	0.039 (0.095)
Mining					0.716*** (0.143)	0.687*** (0.139)
Manufacturing					0.147 (0.097)	0.153 (0.097)
Electricity					0.026 (0.147)	0.038 (0.134)
Construction					0.124 (0.151)	0.108 (0.147)
Trade					0.099 (0.104)	0.113 (0.104)
Transport					0.426*** (0.162)	0.428*** (0.160)
Finance					0.202* (0.115)	0.151 (0.116)
Community service					0.298*** (0.101)	0.316*** (0.101)
Tenure 0 – 1 year					-0.376*** (0.088)	-0.368*** (0.089)
Tenure 2 – 5 years					-0.358*** (0.083)	-0.363*** (0.084)
Tenure 6 – 10 years					-0.226*** (0.084)	-0.243*** (0.084)
Tenure 11 – 20 years					-0.249*** (0.080)	-0.246*** (0.080)
Constant	2.192*** (0.035)	2.226*** (0.138)	1.996*** (0.158)	1.937*** (0.160)	2.168*** (0.177)	2.175*** (0.177)
R^2	**0.2477**	**0.3716**	**0.4762**	**0.4797**	**0.5373**	**0.5439**
N	**2834**	**2834**	**2823**	**2822**	**2558**	**2558**

Source: NIDS, 2008
Note: Data are weighted, standard errors in parentheses
Sample is of working-age individuals (18-65)
*** p< 0.01, **p<0.05 , *p< 0.1
Omitted variables: Male, White, Rural, Age 58- 65, Western Cape, No schooling, Not proficient inEnglish, Rung 1, Elementary occupations, Private households and exterritorial organisations, Tenure 20+ years.

Model one shows the association between computer literacy and the log of hourly earnings of regular workers (excluding those who are in self-employment) without any controls. The results suggest that an absolute change from not being computer literate to being computer literate accounts for an increase in hourly earnings of 278%[3]. The magnitude of the effect of

[3] The calculation for converting the coefficients of dummy variables into percentages are in the log earnings equation:
$100.g = 100\{\exp (c)-1\}$
where *g* is the relative effect of the dummy variable on the dependent variable; and *c* is the coefficient on the dummy variable.

computer literacy on earnings is large due to the fact that computer literacy is correlated with many other variables (such as age and education for example) which also influence earnings.

Demographic characteristics such as gender, race, area type, age, and province are included in model two. This model indicates that being computer literate attracts a 146% premium in hourly earnings compared to those who are not computer literate. Females are found to earn on average 31% less than males. Those who are African and Coloured earn significantly less (66% and 72% respectively) than their White counterparts. Holding everything else constant, the results suggest that living in an urban area is correlated with a 51% advantage in hourly earnings compared to living in a rural area. The findings also show that age is significantly associated with higher earnings, as age to a certain degree will reflect potential experience. Individuals between the ages of 18- 27 are likely to earn 21% less than those between the age of 58- 65. However those between 28-37 years are likely to earn approximately 32% more than individuals aged between 58- 65 years. Being between the ages of 38-47 and 48-57 is associated with a 51% and 53% increase in hourly earnings respectively. This inverted U-shaped relationship between age and earnings is well documented and is likely picking up a depreciation of human capital in the older cohorts. Six out of the eight provinces have no statistically significant earnings differentials from that of the Western Cape. Living in the Eastern Cape is correlated with an hourly earnings penalty of 40% compared to those living in the Western Cape, while living in the Free State is associated with a penalty in hourly earnings of 25% compared to their counterparts living in the Western Cape.

When the education and English proficiency variables are included in the regression in Model 3, the hourly earnings premium for computer literacy drops from 146% to 46%. This large fall is expected due to the high correlation between computer literacy and other forms of human capital. Although the premium for computer literacy drops substantially, the effect of computer literacy on earnings is still quite large and remains significant. The penalty for being African or Coloured decreases when education is controlled for, however, Africans and Coloureds still earn less on average compared to Whites. The correlations between living in an urban area and age and earnings also decrease when the human capital variables are included. There is no statistically significant earnings difference between those with primary school education compared to those with no education. Having incomplete secondary education is associated with a 42% increase in hourly earnings compared to having no schooling. Having a matric is associated with a 92% earnings premium compared to those with no schooling. Those with higher educational levels are likely to earn significantly more than those with no schooling, even after controlling for language proficiency and computer literacy. Individuals with degrees earn the highest premium, where having a degree results in an average earnings advantage of 371% compared to individuals with no schooling, while those with a diploma earn on average 165% more. Those who are fluent in English earn 32% more than those who are not fluent in English.

In Model four, a set of variables that indicates family background is added to the model together with all previous independent variables. The results show that the premium for being computer literate drops marginally by 3 percentage points when perceived relative economic standing at age 15 is added. Being computer literate is still associated with a 43% earnings premium compared to those who are not computer literate, while holding demographic characteristics, human capital, and family socioeconomic background constant. The results show that there is a marginally statistically significant earnings return for employed individuals who reported that their family was on rung 3 on the relative economic standing ladder compared to the lowest rung. All the coefficients on the other rungs on the poverty ladder are statistically insignificant. This variable has been used elsewhere (Casale and Posel, 2011) to capture the social network/capital benefits of coming from a wealthy family background (for instance, parents in good jobs can set up their children in good jobs). These variables may generally not be significant because this effect is already being picked up by the race variables.

Part of the premium on computer literacy might be due to computer literacy being correlated with better jobs; either because being computer literate helps people obtain better jobs or because being in better jobs means that people acquire greater computer skills. Also, being in a job for longer would afford the individual greater opportunity to acquire computer skills. Model 5 therefore also includes job characteristics namely, industry, occupation type, and years of tenure. The results in Model 5 suggests that there is indeed a statistically significant earnings premium for being computer literate in South Africa, after controlling for these variables. The coefficient on computer literacy does fall substantially, from 0.361 in Model 4 to 0.263 in Model 5, but remains sizeable and significant. This suggests that being computer literate is associated with earning up to 30% more on average compared to not being computer literate, taking into account the kinds of jobs people get and their length of time in the job. The size of the gender, race, urban, age and other human capital effects is also reduced somewhat when job characteristics are controlled for, indicating that these variables are correlated with the kinds of jobs people are in. Most notable is the change in the education coefficient, where having a matric compared to no schooling is now associated with an increase in earnings of 59% compared to 92% in the previous model. Similarly the effect of having a degree decreases substantially, where having a degree increases earnings by about 190% relative to those with no schooling, compared to the premium of 385% in the previous model.

Occupations such as legislators, professionals, technicians and clerks, all have statistically significant positive returns compared to individuals who work in elementary occupations. Legislators and professionals, for example, earn on average 70% more per hour than an elementary worker. This model shows that there are no statistical earnings differences in occupations such as sales, skilled agriculture, craft and related trade, and operating machinery compared to elementary workers. Individuals who work in the mining, transport, and community service industry have higher returns compared to individuals working in private households and exterritorial organisations. Years of tenure are statistically significantly associated with earnings. Individuals who have worked between 0-1 year earn on average 46% less per hour than their counterparts who have worked for more than 20 years. Similarly those who have worked between 11- 20 years earn approximately 28% less than those who have worked for more than 20 years.

In the final column of the regression table, Model 6 disaggregates the computer literacy variable into basic use and highly literate. In this Model there are no stark differences in the association between each variable and computer literacy compared to model 5. All coefficients that were statistically significant in Model 5 remain significant in model 6 with marginal changes in the size of the coefficients. The results suggest that there is a positive association between being highly computer literate and having basic computer use and earnings. Model 6 shows that individuals who are highly computer literate earn on average **60**% more than individuals who are not computer literate, and individuals who have basic use earn 17% more than the employed who are not computer literate. This study therefore finds that the premium for basic use is similar to that found in the existing literature in developed countries, where the earnings premium for computer literacy (in general) is said to be between 12%- 21%. The earnings premium found for a high level of literacy in South Africa is, however, much higher than this.

As with employment, it could be argued that earning higher wages increases the ability to invest in human capital such as computer literacy. Also, those earning higher wages are likely to have been in jobs for longer, and therefore may have acquired greater skills. Table 5.4 therefore presents the results on the association between computer literacy and earnings among the youth who are employed as regular workers. The sample is again restricted to youth so that the effects of reverse causality can be controlled for to some extent. By restricting the sample to youth this reduces the effect of work experience on computer literacy, and reduces the timeframe in which individuals would have been able to make further investments in their computer skills.

Table 5.4: Ordinary Least Squares regression analysis of the log of hourly earnings for youth (18- 25) who are regular workers

	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**
Computer Literacy						
Computer literacy	0.780*** (0.127)	0.671*** (0.139)	0.384** (0.150)	0.351** (0.142)	0.311** (0.126)	
High computer literacy						0.576*** (0.184)
Basic computer use						0.187 (0.124)
Demographic Characteristics						
Female		-0.125 (0.124)	-0.201* (0.120)	-0.198* (0.119)	-0.215* (0.114)	-0.218* (0.114)
African		-0.220 (0.218)	-0.303 (0.219)	-0.289 (0.211)	0.108 (0.257)	0.147 (0.257)
Indian		0.233 (0.315)	-0.125 (0.274)	0.096 (0.322)	0.618* (0.354)	0.800** (0.348)
Coloured		0.048	-0.211	-0.228	0.131	0.124

		(0.280)	(0.210)	(0.199)	(0.274)	(0.269)
Urban		0.308** (0.153)	0.204 (0.156)	0.242 (0.149)	0.275** (0.138)	0.266* (0.136)
Province controls	No	Yes	Yes	Yes	Yes	Yes
Human Capital						
Primary school			0.048 (0.173)	-0.023 (0.175)	-0.088 (0.190)	-0.080 (0.184)
Incomplete secondary school			0.367** (0.186)	0.284 (0.182)	0.150 (0.195)	0.170 (0.188)
Matric			0.551** (0.216)	0.447** (0.215)	0.320 (0.239)	0.292 (0.235)
Diploma			0.873*** (0.309)	0.841*** (0.285)	0.512* (0.310)	0.441 (0.299)
Degree			1.647*** (0.334)	1.679*** (0.336)	1.069*** (0.351)	0.891** (0.349)
English proficiency			0.049 (0.163)	0.070 (0.159)	0.101 (0.144)	0.087 (0.143)
Family socioeconomic background (relative economic standing)						
Rung_2				0.388*** (0.128)	0.226* (0.118)	0.190* (0.115)
Rung_3				0.259 (0.181)	0.207 (0.146)	0.115 (0.144)
Rung_4				0.172 (0.197)	0.288 (0.239)	0.206 (0.245)
Rung_5				-0.566 (0.552)	-1.145* (0.590)	-1.343** (0.589)
Rung_6				0.351 (0.297)	. .	. .

Occupation and Industry Controls						
Legislators					-0.214 (0.275)	-0.237 (0.278)
Professionals					0.760*** (0.262)	0.740*** (0.258)
Technicians					0.246 (0.332)	0.291 (0.326)
Clerks					0.180 (0.205)	0.150 (0.197)
Sales					0.013 (0.157)	0.044 (0.158)
Skilled agriculture					-0.103 (0.142)	-0.111 (0.142)
Crafts					0.001 (0.175)	0.034 (0.179)
Operating					0.011 (0.222)	0.011 (0.222)
Agriculture					0.021 (0.215)	0.008 (0.216)
Mining					0.735** (0.321)	0.717** (0.319)
Manufacturing					0.150 (0.192)	0.147 (0.197)
Electricity					0.189 (0.301)	0.212 (0.287)
Construction					-0.001 (0.302)	-0.020 (0.294)
Trade					-0.111 (0.198)	-0.083 (0.201)

Transport					0.567 (0.392)	0.567 (0.396)
Finance					0.280 (0.257)	0.238 (0.253)
Community service					-0.031 (0.223)	0.016 (0.222)
Tenure 0 – 1 year					0.536 (0.358)	0.530 (0.343)
Tenure 2 – 5 years					0.567 (0.362)	0.561 (0.345)
Constant	1.919*** (0.087)	1.565*** (0.283)	1.561*** (0.260)	1.423*** (0.285)	0.593 (0.491)	0.629 (0.472)
R^2	**0.1704**	**0.2215**	**0.3069**	**0.3492**	**0.4573**	**0.4700**
N	**432**	**432**	**431**	**431**	**391**	**391**

Source: NIDS, 2008
Note: Data are weighted, standard errors in parentheses
Sample is of working-age individuals (18-25)
*** p< 0.01, **p<0.05 , *p< 0.1
Omitted variables: Male, White, Rural, Western Cape, No schooling, Not proficient in English, Rung 1, Elementary occupations, Private households exterritorial organisations, Tenure 6+ years.

In this regression the sample size is now much reduced; nevertheless, the results shown in Model 1 reveal that there is a statistically significant earnings return for youth who are computer literate compared to youth who are not computer literate. Being computer literate is associated with a 118% increase in earnings compared to youth who are not computer literate, without controlling for any other variables.

When demographic characteristics are included in Model two, the coefficient for computer literacy drops to 0.67. This implies that youth who are computer literate earn approximately 95% more per hour than their counterparts who are not computer literate. The largest drop in the coefficient is in Model three when the other human capital variables are included. The results indicate that the returns to computer literacy among young South Africans remain significant, where youth who are computer literate earn on average 47% more in hourly earnings compared to youth who are not computer literate. Holding computer literacy fixed, as the educational level of the youth increases, so do their earnings compared to those with no schooling. Having a degree is associated a 419% higher return compared to individuals with no schooling.

The size of the computer literacy effect does not change much in Models 4 and 5 when family economic background, industry, and occupation controls are added. Few of the additional variables are significant – some exceptions are living in an urban area, being in a professional occupation, and working in the mining industry.

In Model six being highly computer literate is associated with a 58% increase in earnings compared to youth who are not computer literate, while having basic computer use is no longer statistically significant. After controlling for various characteristics which include demographic, human capital, family background, occupation and industry, the analysis finds that there is still an economic premium for being computer literate among youth in South Africa, but that a high degree of literacy (compared to basic use) is important, probably reflecting the kinds of skills-biased jobs that are becoming available to this youngest cohort in the past decade or so.

5.4 Limitations of the study

One of the major limitations of this study is the issue of reverse causality. Instead of computer literacy resulting in a greater likelihood of employment and higher earnings**,** the causation could run in the opposite direction; being employed or having higher earnings could create the opportunity for individuals to learn computer skills on the job or to invest in computer literacy skills. I attempted to mitigate for the effect of reverse causality by restricting the sample to youth aged 18-25 to control for the fact that for older cohorts, computer skills may be more likely to be learnt on the job, or higher incomes may provide the necessary resources to invest in computer skills. Although these adjustments were made it is still noted that reverse causality could still be at play.

In both sets of regressions (on employment and earnings) there may be other confounding effects/unobserved heterogeneity which cannot be controlled for using this dataset. For example, individuals who have greater inherent ability or motivation, may be more likely to acquire greater computer skills and more likely to gain employment, and once employed, gain higher earnings. This problem could be dealt with using panel data and controlling for individual fixed effects, but this is beyond the scope of this dissertation.

Sample selection is another noteworthy issue. The earnings regressions are run for the subset of individuals who are employed, and this group might not be a random sample of all labour market participants or of all working-age individuals. The implementation of the Heckman selection model to try and correct for sample selection bias is also beyond the scope of this work. Further, implementing this model also requires a number of identifying variables (instruments) at each stage of selection, and suitable variables are generally not available in the surveys.

5.5 Conclusion

Using NID 2008 data, this study investigated the relationship between computer literacy and employment, and computer literacy and earnings among working-age adults. Probit regression analysis was used to examine the relationship between computer literacy and employment and Ordinary Least Squares (OLS) regression analysis was used to measure the association between computer literacy and earnings. In both regression models a range of variables were controlled for namely demographic characteristics, family socio-economic background, education, English proficiency, and in the earnings regressions, industry, occupation type, and years of tenure. The main variable of interest was the dummy variable capturing computer literacy, and in some of the specifications this was disaggregated further into having basic computer use and being highly literate.

The results showed that computer literacy is associated with an increased chance of employment among working-age adults (age 18-65), even after various demographic, human capital and family background controls were included in the regression. In an attempt to mitigate for reverse causality, the same regression was run restricting the sample to only working-age youth (aged18-25), and excluding the not economically active from the reference group. These results were somewhat weaker than for the full sample, however they still showed that computer literacy, and especially a higher level of skill, is likely to increase the chance of employment among working-age youth.

In the earnings regressions, it was found that computer literacy is positively associated with earnings; where having computer skills results in higher earnings compared to not being computer literate. After controlling for various demographic, human capital, family background, and job characteristics, the results showed that working-age adults who are employed in regular work and who are computer literate earn up to **30**% more per hour than their counterparts who are not computer literate. It must be noted again that regular work in this instance excludes individuals in self-employment. The results also suggest that having basic computer use and being highly computer literate are both associated with a significant earnings premium.

Similar results were generated for the youth sample. Youth who are employed in regular work are likely to earn approximately 36% more than their counterparts who are not computer literate. Being highly computer literate is associated with an earnings premium of approximately 78% among the youth. However, as with the employment probability regression, among youth who are employed in regular work, having basic computer use is not statistically different from not being computer literate. This difference among the youth cohort may be due to a greater diffusion of computer skills in the workplace necessitating more advanced skills to secure higher earnings; or it may be that the jobs available to the youth are becoming increasingly skills-biased.

Although the findings above are certainly consistent with findings in the international literature, it must still be noted that key limitations exist, namely reverse causality, not being able to control for unobservable traits of individuals (such as motivation and innate ability), and possibly selection bias. These results do however provide some insight into the link between computer literacy and employment and earnings and set a platform for further research in this area.

Chapter 6: Discussion and Conclusion

The technological revolution, and the associated skills-biased change in employment, occupies a key role in proposed explanations of both economic growth and the changing distribution of wages in many developing countries, where there has been an increased demand and competition for individuals with higher skill levels (Gush et al, 2004; Borghans, Green and Mayhew, 2001). Skills development, and in particular development of skills in the area of computer literacy, is likely to be crucial for strengthening the economy and reducing inequality internationally and nationally. Academics studying the links between computer use and economic growth postulate that computer literacy will be as important for economic growth in the 21st century as reading, writing, and mathematics were in the previous century (Hawkins and Paris, 1997). It is believed that inequalities in access to computer-based technology in the so called "Information Age" will further marginalise the economically disadvantaged in society. Previous work done on computer skills development in South Africa, all of which has involved small-scale case study work (such as the "Hole in the Wall", "Digital Doorway", and "iEarn" initiatives), suggests important benefits of computer literacy (Thinyane et al, 2006). These programs aimed to introduce computers and other forms of technology in marginalised and semi-marginalised communities in South Africa.

In this study I attempted to contribute to the broader discussion on the importance of computer literacy in increasing the skills of the national workforce and reducing inequality, by investigating (i) the extent of computer literacy among South African adults; (ii) the correlates of computer literacy, i.e. who is more likely to be computer literate in South Africa; and iii) whether or not there is a positive association between computer literacy and the probability of employment, and computer literacy and earnings (among the employed) in South Africa.

Data from the NIDS 2008 survey, the first national survey to collect information on computer literacy in South Africa, suggests that only 30% of working-age adults (18-65 years) are computer literate, based on a self-assessment question. Of these about 40% are highly literate, while the rest have basic use skills only. This rate of computer literacy is much lower than has been reported in other developed countries in particular. However, as with other forms of human capital in South Africa, these overall figures mask large disparities in the rates of computer literacy between various groups. Previous studies in other countries have highlighted that the demographic and socioeconomic determinants of computer literacy tend to mirror existing inequalities. The descriptive results presented in Chapter 4 on what proportion of individuals are computer literate by various demographic and socioeconomic characteristics, support this general finding.

In South Africa, a slightly greater proportion of males are computer literate compared to females. In this study, I also found striking differences in the proportion of Africans who are computer literate compared to all other race groups. The rate of computer literacy among Whites for example is almost four times greater than the rate among Africans, evidence of very stark disparities in computer literacy in South Africa across racial lines. Elsewhere, education has been found to have a positive impact on the probability of computer use. The results in Chapter 4 confirm this for South Africa; those with higher levels of education are much more likely to be computer literate, and to have a high level of skills rather than basic use. In addition, those living in rural, tribal and urban informal areas; those living in the poorest provinces; the unemployed; individuals who work in private households (mostly domestic workers), and those in elementary occupations, are least likely to be computer literate. Further, the oldest cohorts have the lowest levels of computer literacy, as would be expected given changing technology. The descriptive results presented in this study therefore broadly show that individuals who are/were most marginalised in society are less likely to be computer literate, consistent with findings elsewhere that disparities in computer literacy are simply an extension of the inequality that already exists in society.

As elaborated on in the literature review, human capital theory provides a theoretical foundation for the positive relationship between computer literacy and earnings, especially given the pace of technological change in many industries. The basis for acquiring computer skills is motivated by the perception that one would be compensated sufficiently for that particular skill, and only if the payoff for such an investment is an increase in future earnings would individuals be motivated to acquire computer skills (Peng and Eunni, 2011). Literature, mostly from developed countries, using a mix of cross-sectional and longitudinal data, finds a computer skills premium in the region of 10% to 20% (Krueger, 1993; Oosterbeek, 1996; Dolton and Makepeace, 2002; Entorf, Gollac, and Kramarz, 1998; Di Nardo and Pishke, 1997; Di Pietro, 2007; and Zoghi and Pabilonia, 2007). It was noted however, that while many studies examine the link between computer literacy and earnings (although none in South Africa), very few studies in other countries interrogate the relationship between computer literacy and employment. In South Africa, given very high rates of unemployment, understanding whether computer literacy benefits one's chances of finding employment in addition to securing higher earnings, is an important topic. In this study therefore both the links between computer literacy and the probability of employment, and between computer literacy and earnings in South Africa, were explored, with the aim of starting to fill this gap in the national labour market literature.

The results from the probit regression analysis showed that computer literacy is associated with an increased chance of employment among working-age adults (18-65 years), even after various demographic, human capital and family background controls were included in the regression. In an attempt to mitigate for reverse causality, the same regression was run restricting the sample to only working-age youth (aged 18-25), and excluding the not economically active from the reference group. These results were somewhat weaker than for the full sample, however they still showed that computer literacy, and especially a higher level of skill, is likely to increase the chance of employment among working-age youth.

In the earnings regressions, it was found that computer literacy is positively associated with earnings; where having computer skills results in higher earnings compared to not being computer literate. After controlling for various demographic, human capital, family background, and job characteristics, the results showed that working-age adults who are employed in regular work (which does not include those who are self-employed) and who are computer literate earn up to 30% more per hour than their counterparts who are not computer literate. The results also showed that having basic computer use and being highly computer literate are both associated with a significant earnings premium, although the premium is much larger for a high level of skill (60% compared to 17%). Similar results were generated for the youth sample. Youth who are employed in regular work are likely to earn approximately 36% more than their counterparts who are not computer literate. Being highly computer literate is associated with an earnings premium of approximately 78% among the youth. However, as with the employment probability regression, among youth who are employed in regular work, having basic computer use is not statistically different from not being computer literate. This difference among the youth cohort may be due to a greater diffusion of computer skills in the workplace necessitating more advanced skills to secure higher earnings; or it may be that the jobs available to the youth are becoming increasingly skills-biased.

It is feared that the disparities across various groups in computer literacy will further perpetuate inequality in South Africa, where due to technological change and computer diffusion, those who are already disadvantaged become further isolated from gaining access to work and securing higher earnings in the labour market. Understanding these relationships can give insight into how computer literacy or the lack thereof can lead to differences in the chances of gaining employment, and the returns to being computer literate in South Africa. Government policies and programmes aimed at bridging the digital divide are of paramount importance. Countries like South Africa need to increase the level of skills of its workforce in order to maintain global competitiveness and keep abreast of global market trends.

One such policy is the development and to some extent implementation of the South African White Paper on e-Education (2004) which broadly stipulated that all school-leaving leaners would be computer literate by 2013. A part of this strategy is to implement ICT's in all FET (Further Education and Training) and GET (General Education and Training) institutions, and to fully integrate ICT's into the teaching and learning process at schools. The development and implementation of policies such as this is vital for ensuring that no segments of the population are left behind in a technologically advancing society. The ability to access information, and interact with technology, is becoming more and more important in daily life as well as for participation in the labour market. The diffusion of technology in the workplace can have adverse effects on the low-skilled who, if they do not adapt to technological change, may become obsolete and put a further burden on the state. It is therefore important that government together with the private sector and other stakeholders increases the skills of the national workforce through teaching computer skills in the schooling arena as well as through computer training programmes in the workplace.

This study has illustrated that computer literacy is a vital component of the nation's human capital stock in today's technologically changing environment. I find that there is indeed a positive association between computer literacy and employment and computer literacy and earnings, where computer literacy is associated with an increase in the likelihood of employment among working-age adults, and also with increased earnings among those who are employed. Although this study provides useful insights on these relationships, it does however acknowledge the limitations of the data and the methods employed to examine the data. The study contributes to the existing body of knowledge by being the first in South Africa to use nationally representative data to explore these relationships and can be used as a platform for further research in this area using panel data and more advanced methods.

Appendix

Table 1: Probit regression analysis on the probability of employment among working-age youth, 18 – 25 years, excluding the not economically active (coefficients displayed)

	Model 1	Model 2	Model 3	Model 4	Model 5
Computer literacy					
Computer literacy	0.339*** (0.090)	0.171* (0.096)	0.166 (0.104)	0.175* (0.105)	
Highly computer literate					0.424*** (0.156)
Basic computer use					0.084 (0.115)
Demographic Characteristics					
Female		-0.629*** (0.086)	-0.619*** (0.087)	-0.612*** (0.087)	-0.628*** (0.087)
African		-0.852*** (0.314)	-0.848*** (0.312)	-0.988*** (0.261)	-0.875*** (0.261)
Indian		-0.121 (0.511)	-0.126 (0.527)	-0.237 (0.486)	-0.106 (0.505)
Coloured		-0.689** (0.339)	-0.735** (0.333)	-0.861*** (0.293)	-0.748*** (0.287)
Urban		-0.016 (0.098)	-0.020 (0.100)	-0.005 (0.100)	0.005 (0.100)
Province controls					
Human Capital					
Primary school			-0.500 (0.380)	-0.497 (0.381)	-0.491 (0.381)
Incomplete secondary school			-0.452 (0.367)	-0.436 (0.368)	-0.420 (0.369)
Matric			-0.451 (0.375)	-0.435 (0.377)	-0.429 (0.377)
Diploma			-0.451 (0.402)	-0.442 (0.403)	-0.487 (0.404)
degree			0.496 (0.523)	0.504 (0.520)	0.370 (0.516)
English proficiency			-0.054 (0.098)	-0.045 (0.098)	-0.064 (0.098)
Family socioeconomic background (relative economic standing)					
Rung 2				-0.012 (0.102)	-0.015 (0.103)
Rung 3				-0.088 (0.122)	-0.117 (0.122)
Rung 4				-0.001 (0.177)	-0.028 (0.177)
Rung 5				-0.655* (0.373)	-0.716* (0.383)

Rung 6				0.215 (0.509)	0.213 (0.512)
constant	-0.094* (0.050)	1.339*** (0.338)	1.843*** (0.486)	1.967*** (0.469)	1.883*** (0.467)
F	14.28	8.42	6.39	5.69	5.75
Prob>F	0.000	0.000	0.000	0.000	0.000
N	1944	1944	1939	1939	1939

Source: NIDS, 2008

Note: Data are weighted, standard errors in parentheses

Sample is of working-age individuals (18-25)

*** p< 0.01, **p<0.05 , *p< 0.1

Omitted variables: Male, White, Rural, Western Cape, No schooling, Not proficient in English, Rung 1.

Table 2: Probit regression analysis on the probability of employment among all age cohorts, excluding the not economically active (coefficients displayed)

	Model 1	Model 2	Model 3	Model 4	Model 5
Computer literacy					
Computer literacy	0.417*** (0.051)	0.414*** (0.060)	0.266*** (0.071)	0.263*** (0.072)	
Highly computer literate					0.552*** (0.099)
Basic computer use					0.153** (0.075)
Demographic characteristics					
Female		-0.549*** (0.048)	-0.549*** (0.048)	-0.550*** (0.047)	-0.555*** (0.047)
African		-0.291** (0.132)	-0.250* (0.135)	-0.280** (0.133)	-0.230* (0.132)
Indian		0.134 (0.260)	0.158 (0.271)	0.178 (0.251)	0.199 (0.256)
Coloured		-0.215 (0.156)	-0.140 (0.156)	-0.168 (0.156)	-0.098 (0.155)
Urban		-0.001 (0.054)	-0.015 (0.055)	-0.014 (0.055)	-0.008 (0.054)
Age 18-27		-1.135*** (0.160)	-1.115*** (0.162)	-1.109*** (0.161)	-1.140*** (0.157)
Age 28-37		-0.642*** (0.161)	-0.656*** (0.161)	-0.655*** (0.161)	-0.679*** (0.157)
Age 38-47		-0.416** (0.162)	-0.440*** (0.159)	-0.438*** (0.159)	-0.460*** (0.156)
Age 48-57		-0.160 (0.169)	-0.186 (0.166)	-0.182 (0.166)	-0.196 (0.162)
Province controls	No	Yes	Yes	Yes	Yes
Human Capital					
Primary school			-0.049 (0.096)	-0.051 (0.095)	-0.043 (0.095)

Incomplete secondary			-0.159 (0.100)	-0.164 (0.100)	-0.138 (0.100)
Matric			0.033 (0.116)	0.029 (0.115)	0.036 (0.115)
Diploma			0.210 (0.131)	0.214* (0.129)	0.181 (0.129)
Degree			0.944*** (0.212)	0.959*** (0.215)	0.865*** (0.218)
fluenteng1			-0.030 (0.061)	-0.030 (0.061)	-0.045 (0.061)
Family socioeconomic background (relative economic standing)					
Rung 2				0.115** (0.054)	0.114** (0.054)
Rung 3				0.002 (0.066)	-0.008 (0.066)
Rung 4				0.110 (0.101)	0.085 (0.102)
Rung 5				-0.325 (0.206)	-0.334 (0.206)
rung6				-0.363 (0.375)	-0.366 (0.391)
Constant	0.370*** (0.024)	1.800*** (0.216)	1.848*** (0.222)	1.840*** (0.224)	1.789*** (0.222)
F	67.13	28.60	22.41	19.09	18.87
Prob>F	0.000	0.000	0.000	0.000	0.000
N	8382	8382	8346	8345	8345

Source: NIDS, 2008
Note: Data are weighted, standard errors in parentheses
Sample is of working-age individuals (18-65)
*** p< 0.01, **p<0.05 , *p< 0.1
Omitted variables: Male, White, Rural, Western Cape, Age 58- 65, No schooling, Not proficient in English, Rung 1.

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