Who benefits from better Internet connectivity? Evidence from the labor market in South Africa

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Abstract

I study how expansion of fast Internet availability affect job outcomes and the extent to which online job information can substitute for social networks. I use a two-way fixed effects identification strategy with continuous treatment at district level, and find that Internet availability has a positive impact on average employment and total income. Jobseekers are more inclined to search for job information online with increased access, while their reliance on social networks remains unchanged. The study also finds that young workers tend to search more through both online and network channels, suggesting that personal connections could complement internet job searching for some individuals. Workers without a primary education are discouraged from searching online and have worse employment outcomes. Constraints on effective uses of Internet job search and Internet activities, such as social networking, could help explain the results.

Keywords: Unemployment, Job Search, Internet, Social Networks

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1 Introduction

A lack of information is arguably one of the key frictions in labor markets, and growing evidence has shown that information frictions can impede transitions into employment (Abebe et al., 2021; Caria, Lessing and Hermes, 2019; Carranza, Garlick and Orkin, 2020; McCasland and Hardy, forthcoming).Seminal works have done modeling the use of social networks by firms and jobseekers to overcome information frictions in job search (Calvó-Armengol and Jackson, 2004; Granovetter, 1973; Montgomery, 1991; Pellizzari, 2010). In many developing countries, social networks are especially important because it is the main or only information source for many individuals when making labor market decisions (Beaman, Keleher and Magruder, 2018; Caria, Franklin and Witte, 2020).[1] Referrals are also used as key methods for filling vacancies in these countries (Abel, Burger and Piraino, 2020; Beaman and Magruder, 2012; Heath, 2018). In recent years, the growth of Internet adoptions and expansion of job sites have lowered the cost of acquiring and disseminating job related information (Autor, 2001; Kuhn and Skuterud, 2004). Internet-based job search is by now one of the predominant ways of searching for jobs (Kuhn and Mansour, 2014). An important question is: does more access to Internet improve jobseekers labor market outcomes? If so, to what extent can a market mechanism like online job search and hiring, open to all and anonymous, substitute for exclusionary personal connections.

Existing studies solely focus on Internet impacts on job outcomes such as employment rate and income. My study aims to contribute by providing evidence on how the Internet may change job search activities. Individual's job search effort response have key implications for aggregate labor market outcomes. Understanding the choice of search channels is also critical for designing policies that can be used to address information frictions.[2] In this paper, I estimate how broadband Internet availability affects job outcomes for workers with different skill levels and age

[1] Caria, Franklin and Witte (2020) calculated that over 50 percent jobseekers in developing countries heard about current job from a social contact, based on the 2017 International Social Survey Program (ISSP) data by Sapin et al. (2020).

[2] For example, training on using LinkedIn (Wheeler et al., 2022), reference letters from previous employers (Abel, Burger and Piraino, 2020), or detailed job search plan (Abel et al., 2019).

groups in South Africa, and how search methods used by workers and firms respond to faster and more Internet access. To the best of my knowledge, this is the first paper examining whether Internet access has an impact on the choice of job search methods.

I first present a simple model of jobseekers' utility maximization to show that search effort is the key to how employment changes with Internet access. Comparative statics predicts that if more Internet availability brings down the cost of search and increases the marginal productivity of search, a jobseeker will search more and has higher probability of being employed.

I match Internet connection data published in Hjort and Poulsen (2019), with spatially coded panel data of job search activities from South Africa, the National Income Dynamic Studies (NIDS), and compare individuals in locations with different Internet penetration rates, during the gradual roll out of first undersea cables in South Africa. This undersea cable brought much faster speed and traffic capacities. For example, South Africa's average download speed increased from 1,101kbps in January 2008 to 5,616kbps in June 2014.[3] The time required to load key job search websites decreased from 14 seconds to 5 seconds.[4] NIDS is the first and only national household panel survey in South Africa. Over 32,000 individuals across 52 districts from 2008 to 2014 are included in the final data set.

I address the endogeneity issues in two ways. First, I use both location fixed effects and year fixed effects to explore the temporal and spatial variation in the Internet availability across 52 districts in South Africa. This identification is similar in spirit to a difference-in-difference (DID) design at district level with a continuous treatment. Variations in Internet treatment intensity make it possible to evaluate a "does-response" relationship, which policy makers may care more about than the effect of the existence of Internet. Recent literature shows that TWFE estimators may not be robust to heterogeneous treatment across groups and over time (Goodman-Bacon, 2021). Thus, I access the robustness using the estimator proposed by de

[3]Sources: Speedtest Global Index by Ookla, which uses data from millions of Internet speed tests performed on the Speedtest.net platform.

[4]Author's own calculation using http://www.webpagetest.org. The main job search website in South Africa careers24.co.za is tested.

Chaisemartin and D'Haultfœuille (2020), and find larger but imprecisely estimated impacts of Internet on job outcomes and searches. Second, I analyze the timing of changes in Internet access, and find that the timing does not appear to be systematically related to key observable correlated of employment. Lagged productivity variables such as employment rate, education level, age, and industry distributions do not predict current Internet penetration rates.

I find positive effects of Internet availability on employment and total income. A one-standard-deviation improvement in Internet availability (about 10 percentage points) increases the employment rate for an average jobseeker in the district by 3.6 percent, and increases his or her total income by 8 percent. As to search methods, more Internet availability induces jobseekers to use online job information by about 10 percent more, but more access does not change reliance on personal networks or government agencies. The total number of different search methods ever used by jobseekers declines, driven by less uses of other methods such as contacting other employers or waiting at the side of roads. These estimates are robust to inclusion of a set of time-varying controls for potential productivity factors, as well as allowing for different time trends across areas.

Heterogeneous analysis by age group and education attainment contribute to our understanding of distributional effects of Internet technology change. When more Internet becomes available in the area, both young (between 15 to 24 years old) and older workers increase their employment rates, but only older workers' total income increases. Young workers will use more search methods, and increase their searches through not only online but also personal networks. Compared with skilled workers with beyond primary education, unskilled workers are discouraged from online job search, less likely to be employed, and earn less.

Considering choices of search channels made by young and unskilled workers respond to more Internet differently than older and skilled workers, I provide additional evidence on other constraints preventing them from using this technology for effective job search. Computer ownership and computer literacy are low for less-educated workers. Internet activities like social networking can also help maintain relationships or form new links with a wide network of weak ties. Thus, personal networks could complement the Internet in the job search process for some workers. For example, young workers are more likely to own a computer and know how to use it. Besides using this technology to search for job information online directly, they also use it to enhance personal networks that could be used for sharing job information.

Since the Internet variations are at a district level, cheaper information brought by the Internet are available for both jobseekers and firms. The results on employment and income should reflect the equilibrium outcomes of both labor supply and labor demand. Without employers or firms' data, I cannot say much about how employers' job creation decisions respond to more Internet access empirically. Instead, I use the search and matching theory of unemployment and vacancies, the Diamond-Mortensen-Pissarides(DMP) model (Diamond, 1982; Mortensen, 1986; Pissarides, 1985). I simulate the Internet access shock by changing the parameter value of matching technology or the value of unemployment income, and numerically solve the new general equilibrium. The results show that Internet can change the equilibrium outcomes by decreasing the job search costs for workers, or increasing matching efficiency for firms. The effect on wage is unambiguously positive, but the aggregate effect on employment depends on the relative importance of these two forces.

Understanding the impacts of Internet on labor market in South Africa is salient and has important policy implications. Despite being Africa's most industrialized economy, South Africa still has extremely high levels of unemployment. The recent Covid-19 lockdown has pushed the unemployment rate to a record high above 30% in 2021.[5] In particular, unemployment has been inordinately high for young workers (Figure A1), who may have less access to referral networks and limited information about their employment prospects. The challenge for policymakers is to ensure that all current and future workers can seize the growing economic opportunities that accompany the spread of digital technologies.

This paper adds developing country evidence to a limited literature assessing the linkages between Internet and labor market outcomes. More than 60 per cent of the world's employed population earn their livelihoods in the informal economy, most of them in emerging and developing countries (Bonnet, Vanek and Chen, 2019). For

[5] Source: Statistics South Africa, 2021

many informal jobs in which workers' effort is important but difficult to induce, formal institutions for firms to share information about workers are absent (Heath, 2018). Given these labor market frictions, it remains questionable if findings for broadband Internet expansion implemented in developed countries are applicable to developing countries. To date, the only direct evidence on the average and distributional effects in developing countries is provided by Hjort and Poulsen (2019) focusing on the Africa continent. They leverage the gradual arrival of sub-marine Internet cables in Africa, and find large positive effects on employment and incomes, particularly for higher-skill occupations, due in part to the technology's impact on firm entry, productivity, and export.

Existing studies in high-income countries show mixed impacts. Kroft and Pope (2014) analyze the expansion of Craigslist in the US, and find that Craigslist significantly lowered classified job advertisements in newspapers, but had no effect on the unemployment rate. Dettling (2017) uses state-wide shares of multifamily residences to instrument for the diffusion of Internet access across the U.S., and finds increases in labor force participation rates of married women, and no corresponding effect for single women or men. Bhuller, Kostol and Vigtel (2019) document that broadband expansions in Norway increase online vacancy-postings, lower the average duration of a vacancy, resulting in higher job-finding rates and starting wages, and more stable employment relationships after an unemployment-spell. Akerman, Gaarder and Mogstad (2015) finds the same Internet expansion improves the labor market outcomes and productivity of skilled workers only. The stronger effects of Internet I found in this paper could suggest that limited information may exacerbate other labor markets frictions such as high migration costs or limited public transportation in sprawling cities in less-developed countries (Ardington, Case and Hosegood, 2009; Bryan, Chowdhury and Mobarak, 2014; Franklin, 2018).

My paper complements a growing experimental literature considering the role of limited information in labor market matches in developing countries. Abebe et al. (2021) shows that job application workshop for young jobseekers can help them signal skills better, and generate large and persistent improvements in their labor market outcomes. The effects are larger when combined with formal certificates provided to firms (Carranza, Garlick and Orkin, 2020). Firms may have poor knowledge of candidates, and providing information directly to firms can improve match quality (Abel, Burger and Piraino, 2020; Banerjee and Chiplunkar, 2020). Online platforms such as LinkedIn can help address supply-side information frictions by allowing jobseekers to learn more about job prospects, and also address demand-side frictions by allowing firms to learn more about potential candidates (Wheeler et al., 2022).

My findings on the distributional effects are at odds with the notion that active labor market programs such as training or employment subsidies have larger employment effects for more disadvantage groups(Card, Kluve and Weber, 2018).This could partly because the most disadvantaged group in my study may not have direct access to the Internet technology even if it is made more available in their areas. I provide evidence showing that when Internet becomes available, it is more likely adopted in places where complementary factors such as computer ownership and computer literacy are abundant. In addition, cheaper information are available at a larger scale, and both sides of the labor market respond to this information provision.

This paper also extends the literature on the role of information and communications technology (ICT) in developing countries. ICT such as mobile phones has been attributed with reducing price dispersion across markets and increasing welfare for producers and consumers (Aker and Mbiti, 2010; Goyal, 2010; Jensen, 2007). ICT such as mobile money can help reduce transaction costs and potentially improve informal risk sharing networks (Jack and Suri, 2014). ICT can even influence fertility patterns and bring cultural changes to the society (La Ferrara, Chong and Duryea, 2012). My paper shows that ICT such as Internet can provide cheaper access to job information directly, or reduce communication costs for sharing job information among family and friends, impact the job search methods used by jobseekers, and improve employment outcomes in the labor market.

The rest of the paper proceeds as follows. Section 2 provides a simple model analyzing how Internet availability affects jobseekers' search effort and employment. In Section 3 I present the data, and in Section 4 the estimation strategy. The average and heterogeneous results are in Section 5. In Section 6, I show additional evidence how Internet access may affect employment and search behavior. Section 7 concludes with policy implications.

2 Conceptual model

I present a simple model illustrating the relationship between employment, job search, and Internet access. With exogenously provided Internet access, how employment changes depends on the optimal search effort. If search cost decreases while marginal productivity of search increases with more Internet access, jobseekers will exert more effort, and are more likely to find a job.

A jobseeker lives two periods: in the first period, an unemployed individual receives some unemployment benefit b and decide how much effort to spend for job searching s. Cost of job search $\tau(\theta)$ depends on amount of Internet access, and the probability of finding a job depends on both the search effort and amount of Internet access: $p(s,\theta)$. In the second period, if the individual becomes employed, assuming labor supply is inelastic, a fixed income will be given as w. In this set up, internet access amount θ and wage w are given exogenously.[6] The jobseeker chooses job search effort and maximizes the expected lifetime utility as follows:

$$\begin{aligned}
\max_{s} \quad & u\left(c_1\right)+\beta E u\left(c_2\right) \\
\text{s.t.} \quad & c_1=b-\tau(\theta) s \\
& c_2=\begin{cases} w & \text{w.p. } p(s,\theta) \\ b & \text{w.p. } 1-p(s,\theta) \end{cases} \\
& 0 \leq p(s,\theta) \leq 1
\end{aligned} \tag{1}$$

where utility $u(c)$ is assumed to be increasing and strictly concave in consumption.

An interior solution should satisfy the following first order condition:

$$\tau(\theta) u'=\beta \frac{\partial p(s,\theta)}{\partial s}\left[u\left(w\right)-u\left(b\right)\right] \tag{2}$$

[6] I include a search and matching model allowing wage to be determined endogenously in section 6.4. Simulation results show a positive impact of Internet on equilibrium wage.

which implies that the individual chooses search effort s optimally such that the marginal utility of giving up consumption equals the expected utility gain from searching for work, which is the difference between employment and unemployment utility in the second period.

For this paper, I am interested in how employment probability may change with the Internet access given exogeneously. The comparative statics is,

$$\frac{d}{d\theta}p(s(\theta),\theta) = \frac{\partial p}{\partial s}s'(\theta) + \frac{\partial p}{\partial \theta} \tag{3}$$

Assuming the marginal productivity of search and Internet are both positive ($\frac{\partial p}{\partial s}, \frac{\partial p}{\partial \theta} > 0$), the effect on employment will depend on $s'(\theta)$. In order to see how optimal search effort $s^{\star}(\theta)$ changes with Internet access θ, we can differentiate the first order condition equation 2 with respect to θ:

$$s'(\theta) = \frac{\tau' u' - \beta p_{s\theta}(u^{emp} - u^{unemp})}{\tau u'' + \beta p_{ss}(u^{emp} - u^{unemp})} \tag{4}$$

where u^{emp}, u^{unemp} represent the utility being employed and unemployed in period 2 respectively.

Assume $u'' < 0$ and $p_{ss} < 0$, and u$^{emp} > u^{unemp}$ is a necessary condition for the existence of an interior solution, the denominator in equation 4 is negative. The sign of the numerator depends on two parts. First, $\tau'(\theta)$, the change in the cost of job search given more Internet access. If we think more Internet means that jobseekers have cheaper access to more job information, the cost of job search should be lower, $\tau'(\theta) < 0$. Second, $p_{s\theta}$ the change in the marginal productivity of search in response to more Internet access. $p_{s\theta} > 0$ if job search by the jobseekers is made more productive with more Internet, eg. Internet technology can help job candidate send out more resumes, or firms can screen candidates and match them with vacancies faster.[7] Then the numerator of equation 4 should be negative too. With positive change of optimal search effort($s'(\theta) > 0$), equation 3 indicates that employment will

[7]The marginal productivity of search p_s is not necessarily linear in θ.For example, too much information online can be a distraction from job searching, or ghosted postings can make searches a waste of time. Thus, the marginal productivity of search in response to more Internet access can be negative, $p_{s\theta} < 0$. Then the impact on optimal search effort and employment is unclear.

increase as well.

Internet can also change the utility of leisure, which will impact the trade off between searching for jobs and staying unemployed. I solve a version of this model including leisure in the jobseeker's utility function in appendix A. The comparative statics predictions are similar.

Using published data from a field experiment that Abel et al. (2019) have done with South Africa youth, I find suggestive evidence that online job search is correlated with higher effort exerted. The original experiment is to test the effects of plan making on job search and employment. Table 1 shows the regression results using panel data over two follow-up periods, with only baseline control group observations included. In a period of about 12 weeks, individuals who search jobs online spend 2 hours more, and send out 2.6 more number of applications in total. They are also more likely to receive responses and job offers from the employers.

Table 1: Effects of Online Search on Search Behaviors and Employment Outcomes

	(1) Search Hours	(2) Applications	(3) Empl Responses	(4) Job Offers	(5) Employed
Search online	2.091	2.626^{***}	0.535^{***}	0.091^{***}	0.016
	(1.300)	(0.320)	(0.061)	(0.026)	(0.031)
Mean Dep Vars	14.087	3.821	0.543	0.131	0.116
Obs	818	828	828	819	857
R-squared	0.026	0.079	0.048	0.026	0.011

* Notes: Baseline control group observations of Abel et al. (2019) are used. All specifications control for age, gender, education, round, and location fixed effects. Standard errors (in parentheses) are clustered at the individual level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

3 Data

In the main analysis, I use the South Africa National Income Dynamic Studies (NIDS) for labor market data. NIDS is the first and only national household panel survey in South Africa, and is implemented by the Southern Africa Labour and Development Research Unit (SALDRU) based at the University of Cape Town's School of Economics. The study began in 2008 with a nationally representative sample of over 28,000 individuals in 7,300 households across the country. Stratified random sampling was implemented, whereby 1500-3000 enumerator areas are randomly selected and subsequently 10 households per enumerator area are interviewed. The core survey continued to be repeated with these same household members every two years to three years, with the latest round being conducted in 2017. NIDS provides information about changes in broad themes, including poverty, education, health, household structure, labor market participation and economic activity, migration, and social capital.

I focus on the labor market module in the survey, where working age adults were asked about their labor market participation and economic activity, including employment status, income (wages or the profits of self-employed workers), contract types, and industry. In addition, individuals were asked to check all the job search methods used, including family and friends, online ads, government agency, previous employers, and others.

Table 2 provides the summary statistics of working age (15 - 65) individuals used in the analysis. This sample has a balanced representation of urban and rural population. 59 percent of the sample are female. Average worker's age is 33, and 37 percent are between 15 and 24 years old. 52 percent have finished primary education. Cellphone ownership is high (71 percent) compared to computer ownership (5 percent). About one third of the sample report they know how to use a computer. 37 percent of the sample are employed, among which 27 percent have a job paid with regular salary, and 5 percent are self employed. On average, individuals work around 40 hours per week, and earn 3233 ZAR(230 USD) per month. The standard deviation of log income is large, because I put zero for unemployed individuals' income. Network (25 percent) is the most widely used job searching method, while 6 percent of the sample report that they have used online search. Internet is available to 10 percent of the population in an average district with a standard deviation of 14 percentage points.

I use the Internet infrastructure and speed data published in Hjort and Poulsen (2019). Using Mahlknecht's map of submarine cables to measure landing points

Table 2: Sample Summary Statistics

	Obs	Mean	SD
Individual characteristics			
Urban area	38,497	0.47	0.50
Age	38,520	33.49	14.29
Female	38,520	0.59	0.49
Youth(15-24)	38,520	0.37	0.48
Not primary	38,436	0.06	0.23
Primary	38,436	0.39	0.49
Secondary	38,436	0.29	0.45
Higher	38,436	0.26	0.44
Parents with primary education	24,156	0.19	0.39
Own a cellphone	35,311	0.71	0.46
Own a computer	35,301	0.05	0.22
Is computer literate	34,386	0.29	0.46
Household characteristics			
HH owns a cellphone	38,124	0.85	0.36
Spent money on cellphone monthly	29,108	0.74	0.44
HH owns a computer	38,069	0.11	0.31
Spent money on internet monthly	29,144	0.01	0.11
Labor market outcomes			
Employed	37,108	0.37	0.48
Salary job	35,654	0.27	0.44
Self employed	35,651	0.05	0.21
Total income (adjusted)	37,108	2.05	3.68
Salary income(adjusted)	34,696	3.69	6.57
Has permanent duration	9,307	0.54	0.50
Weekly hours	10,516	39.70	17.15
Job search methods			
Network	32,923	0.25	0.43
Online	32,923	0.06	0.24
Government	32,923	0.03	0.17
Others	32,923	0.15	0.36
Internet connection at district level			
% population connected	38,520	0.10	0.14

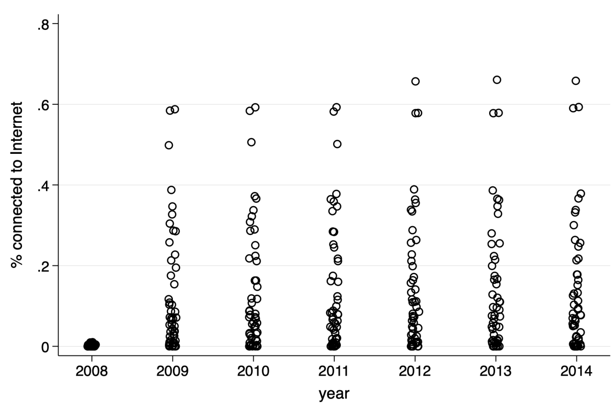
* Notes: Only workers between age 15 and 65 are included. The income for unemployed workers is assumed to be zero, and inverse hyperbolic sine is used.

and times (Mahlknecht 2014), and www.africabandwidthmaps.com and AfTerFibre's (AfTerFibre 2014) maps of terrestrial backbone networks to measure locations' connectivity, Hjort and Poulsen (2019) document whether a city is connected to the Internet quarterly from 2007 to 2014. Average Internet speed for the same locations is also provided by network service company Akamai Technology.

I match this Internet connection data from Hjort and Poulsen (2019) with the NIDS survey data using the geocode and year. While the converge data are available at the city level, individuals in the NIDS outcomes data can only be identified at higher levels of geographies, such as province and district. I aggregate the city-level connection data to district-level by calculating the percentage of cities with connection in one district by year, weighted by its population. 52 districts across 4 waves from 2008 to 2014 are included in the final data set.

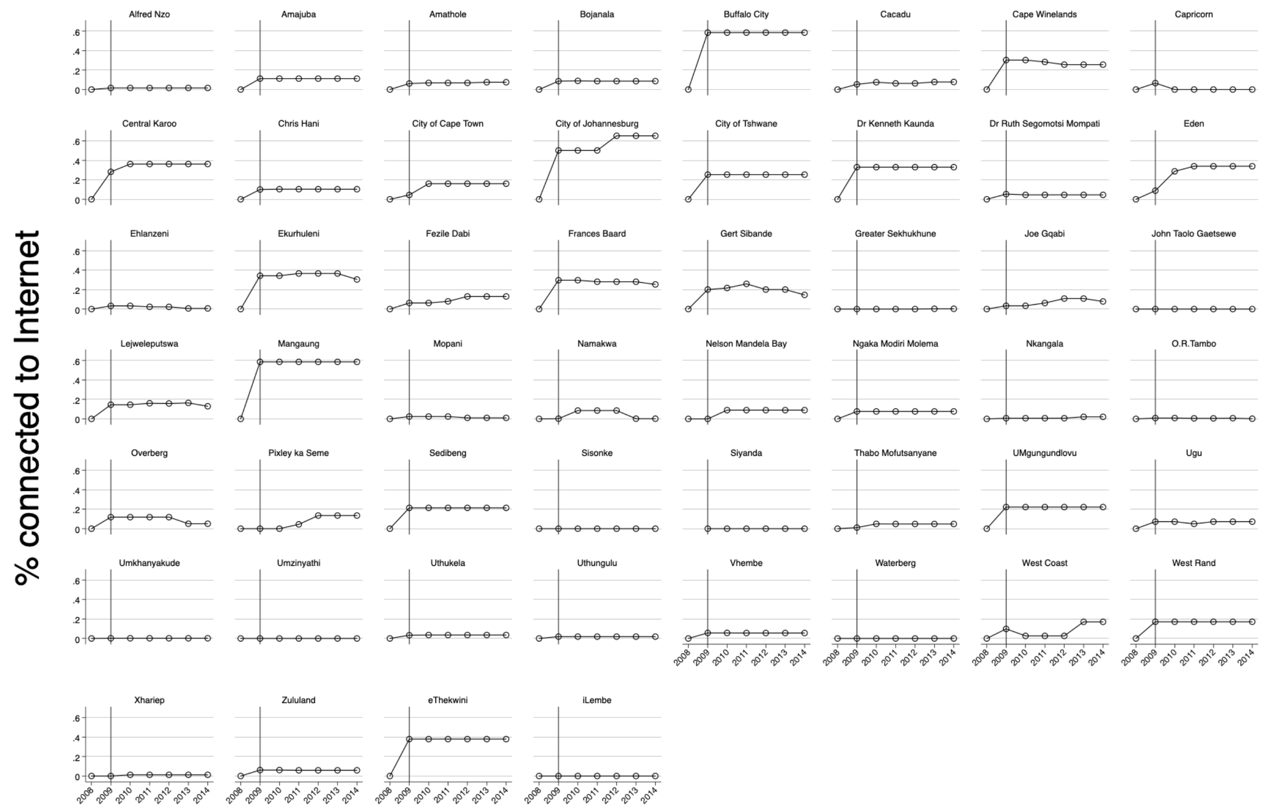
Figure 1 and 2 show the variation in percent of cities connected over time and across districts. In 2008, all cities have no fast Internet connection. Over the years, more cities gained access and more districts achieved higher availability rates in 2014. There are also differences in connection timing and access intensity within districts, which generate a continuous measure of availability rates that I exploit as the key variations in my empirical analysis.

Figure 1: Comparing Internet availability rates over years



Notes: Each dot represents one single district.In 2008, the percent of populations connected to fast Internet are zero for all districts. The first fast Internet cable was connected in 2009.

Figure 2: Comparing Internet availability rates across districts



Notes: Each sub plot represents one district.The vertical line indicates the connection of first fast Internet cable in 2009. Some districts experienced drops in connectivity due to infrastructure deterioration, which could be caused by natural disasters or a lack of maintenance.

4 Empirical Strategy

My empirical approach is a two-way fixed effects (TWFE) estimation that controls for location and year fixed effects. I compare individuals across locations with varying degrees of Internet coverage, during the gradual roll out of undersea Internet cable in South Africa. This is motivated by two features of this Internet expansion. First, most of the confounding supply and demand factors are accounted for by the location fixed effects. Second, the timing of the expansion is unlikely to co-vary with key correlates of employment.

4.1 Two-way Fixed Effects estimation

I run the following two-way fixed effects estimation as the main specification.

$$Y_{ijt} = \beta PercentConnected_{jt} + X'_{ijt}\alpha + \gamma_t + \theta_j + \epsilon_{ijt} \tag{5}$$

where Y_{ijt} is the labor market outcomes for worker i in district j at time t. The set of outcomes of interest are individual-level labor market outcomes, including employment, employment with formal contracts, income, network search, and online search. $PercentConnected_{jt}$ is the percent of population in district j connected to the Internet at time t. This measure allows me to exploit variation within the set of connected districts in their intensity of treatment.

All specifications include both location fixed effects, θ_j, time fixed effects,γ_t, and an idiosyncratic error term, ϵ_{ijt}. X_{ijt} is a vector of individual-specific controls, including age,gender,and education level. Since there could be other unobserved individual-level factors that are endogenous to the choice of search channels, I also include a individual fixed effect in some analyses. In all analyses, standard errors are clustered at the district level.

Within such a set up, as long as there are not omitted idiosyncratic shocks correlated with both Internet connection rate and labor market outcomes, the causal effect of Internet, β, is identified off of comparison between the change in outcomes for locations that gain (more) access to Internet in a given year and the change in outcomes for other locations that without or gain less access at the same time.

Given that I am controlling for fixed effects for districts and years, the core of this design is similar to a difference-in-difference setup at the district level. Districts fixed effects act as controls for the "preperiod" outcomes of workers in the same area that never received Internet, which is the first difference. Treatment and control groups can be defined as workers within a year that had different exposure to Internet access. Comparing the treatment group outcomes from the control group yields the second difference. Because the treatment variable $PercentConnected$ is continuous, I effectively weight these double differences by the difference in Internet connection rates.

4.2 Tests for parallel trend assumption and timing of the expansion

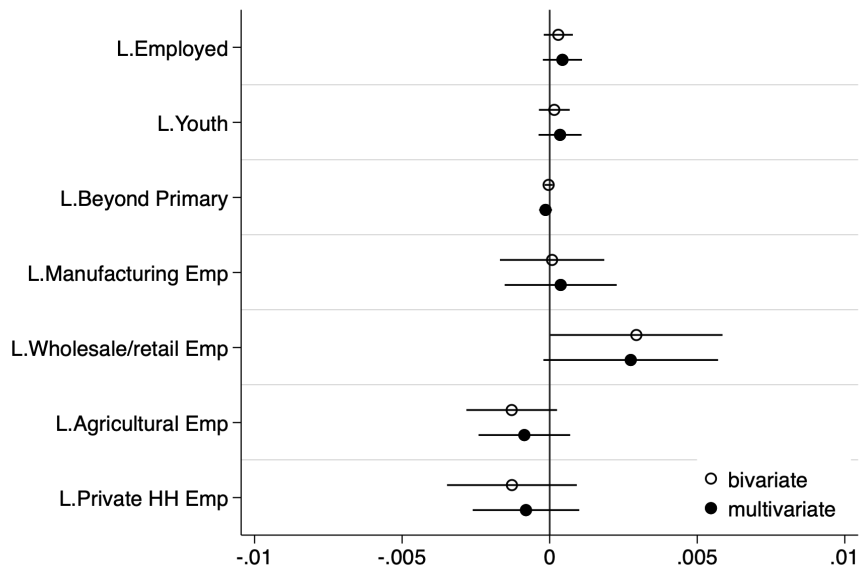
Another threat to identification is that the timing of the expansion might be related to different underlying trends across locations. The parallel trend assumption of difference-in-difference models requires that in the absence of treatment, the difference between the "treatment" and "control" group is constant over time. Two limitations prevent me from producing the standard parallel trend test. First, I only have one time period (2008) prior to the access boost in 2009. Second, since the variation in coverage rate is a continuous variable, I do not have a clear "control" and "treatment" group.

Instead, I test if current Internet allocation is determined by lagged productivity variables as follows:

$$PercentConnected_{jt} = \gamma_t + \theta_j + \lambda c_{j,t-1} + \epsilon_{jt} \tag{6}$$

where $PercentConnected_{jt}$ is the Internet availability for location j at time t, γ_t is year fixed effect, and θ_j is location fixed effect, and $c_{j,t-1}$ is district-level variables related to productivity at previous year, including employment rate, education level, percent of young workers, and industry distribution.

Figure 3: Internet connectivity and lagged productivity variables



Notes: The bivariate coefficients are from models regressing internet connectivity on a single lagged productivity variable. The multivariate coefficients are from a regression of internet connectivity on all productivity variables.

The coefficients plot of γ in Figure 3 shows that most lagged productivity variables do not predict Internet connectivity rates. Though the impact of wholesale/retail sector employment rate is significantly different from zero but small. So I also check that including it as an additional control in the main specifications does not change the estimation results.

5 Results

5.1 Main effects

In Table 3, I show the regression results for specification in 5, including district and year fixed effects and demographic controls. I find that one standard deviation increase in Internet connection (about 10 percentage point) increases the probability that an individual is employed by 1.3 percentage point, or 3.5 percent increase off a baseline of 36.6 percent average employment rate (column 1). This result is similar in magnitude to Hjort and Poulsen (2019), where they find the employment increases by 3.1 percent for South Africa in their cross-country sample of Africa countries.[8] Workers can earn an average of 8 percent more in total income when the Internet connectivity in their areas rise by 10 percentage point (column 2).[9]

To see what extent these increases reflect additional economic activity, I use more detailed work-related questions that only employed individuals were asked in the NIDS. Given the truncation by survey design, results in column 3-5 should not be interpreted as casual effects of Internet, but rather should be viewed as an intensive channel of the overall effects. For individuals already working, they will earn more while work less hours with additional Internet (column 3, 4). The estimated effect on having a formal contract is close to zero and insignificant (column 5). This helps rule out the situation that the additional employment comes from formalization of existing informal jobs.

To further explore how individuals job search behavior might change with Internet access, I show results on the search methods in Table 4.One standard deviation (about 10 percentage point) increase in Internet availability will induce jobseekers to look for information online by 0.64 percentage points more, which is about 10 percent increase from the mean (column 1). Internet's negative impact on network search is small and not statistically significant, suggesting that network channel can be resilient to the Internet access shock (column 2). The impact on use of government agencies for job search is close to zero and insignificant (column 3). The number of different search methods average individuals used declines by 0.91 percentage points or 3.6 percent (column 4). This decline is driven mostly by less use of other search methods such as contacting other employers directly, or waiting at the side of roads. If this total number of methods can be viewed as a proxy for search effort, this result

[8]The results are not identical, because Hjort and Poulsen (2019) used a different labor force survey, the South Africa Quarterly Labor Force Survey (QLFS), a repeated cross-sectional data. Their Internet connection treatment is binary at a smaller geographic level - enumeration area.

[9]60 percent of the observations are reported not employed and not earning any income, and I put zero as their income.

could suggest that Internet access leads to lower search effort.

Table 3: Impacts of Internet Connection on Job Outcomes

Outcome	Employed (0/1)	Total income (asinh)	Salary wage (asinh)	Weekly hours (asinh)	Formal contract (0/1)
% connected	0.135**	0.702**	1.610***	-0.199	0.007
	(0.065)	(0.312)	(0.521)	(0.162)	(0.078)
	[0.068]	[0.042]	[0.032]	[0.204]	[0.932]
Mean of outcome	0.366	2.048	3.692	3.533	0.688
Observations	37,034	37,034	10,487	10,487	9,319
R-squared	0.160	0.190	0.162	0.076	0.121

* Notes: Only workers between age 15 and 65 are included. All regressions include both district and year fixed effects, and controls for age, gender and education. Employed equals to 1 if the individual is employed with a salary job or self-employed. Hours and income are summed across each of the individual's jobs if more than one is reported. Total income are calculated using monthly income if salary employed, profit if self-employed, and as zero if unemployed. Inverse hyperbolic sign transformation are done to total income and salary wage. Only employed individuals are asked about wage, working hours, and contract types, so the number of observations for column 3-5 are small. Standard errors (in parentheses) are clustered at the district level. The wild bootstrap p-values [in brackets] are calculated following Cameron, Gelbach and Miller (2008). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: Impacts of Internet Connection on Search Methods

Outcome	Online (0/1)	Network (0/1)	Government agency (0/1)	Number of search methods
% connected	0.064***	-0.017	0.013	-0.091*
	(0.017)	(0.064)	(0.016)	(0.051)
	[0.009]	[0.803]	[0.436]	[0.062]
Mean of outcome	0.061	0.247	0.030	0.251
Observations	32,856	32,856	32,856	32,856
R-squared	0.085	0.053	0.022	0.031

* Notes: Only workers between age 15 and 65 are included. All regressions include both district and year fixed effects, and controls for age, gender and education. Network, Online and Government variables are equal to 1 if workers have used this method when searching for jobs. "Number of search methods" is the total number of different methods ever used by the individual in the past four weeks. Besides online, network, and government agencies, other search methods include contacting other employers directly, waiting at the side of roads, placing ads, or seeking financial assistant to start own business. Standard errors (in parentheses) are clustered at the district level. The wild bootstrap p-values [in brackets] are calculated following Cameron, Gelbach and Miller (2008). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

5.2 Robustness checks

The first set of robustness checks examines whether the timing of the broadband Internet roll out correlates with time-varying covariates and/or trends. Column 1 shows the results without any controls, and column 2 repeats the main results with time-varying covariates. In column 3, I include linear trends interacted with baseline (year 2008) demographic covariates. In column 4, I allow for municipality-specific linear trends. I also show results including individual fixed effects in column 5. The point estimates are similar across these specifications, except for the estimations on network.

Table 5: Main results robustness checks

	TWFE β_{fe}					DID_m
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable						
Employment	0.109*	0.135**	0.102	0.175*	0.101	0.170
	(0.063)	(0.065)	(0.065)	(0.099)	(0.079)	(0.255)
Total Income	0.649**	0.702**	0.609*	0.933	0.481	0.692
	(0.317)	(0.312)	(0.347)	(0.671)	(0.373)	(1.500)
No.of Methods	-0.085*	-0.091*	-0.140**	-0.023	-0.221***	-0.111
	(0.049)	(0.051)	(0.054)	(0.145)	(0.074)	(0.365)
Online	0.067***	0.064***	0.060***	0.079**	0.027	0.019
	(0.019)	(0.017)	(0.018)	(0.036)	(0.019)	(0.068)
Network	-0.029	-0.017	-0.063	0.093	-0.055	0.132
	(0.063)	(0.064)	(0.064)	(0.080)	(0.065)	(0.213)
Observations	32,923	32,856	32,817	32,856	32,923	20,306
Location FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Time-varying covariates		Y	Y	Y		
Trends interacted with						
baseline covariates			Y	Y		
location FE				Y		
Individual FE					Y	

* Notes: Each cell is from a separate regression where the independent variable is *PercentConnected*. Column 1-5 use the standard TWFE estimator, and column 6 uses the robust estimator DID_m proposed by de Chaisemartin and D'Haultfœuille (2020). Less observations are included for the DID_m because comparison between later treated and early treated groups are dropped. Standard errors (in parentheses) are clustered at the district level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The second set of robustness checks are related to recent research on TWFE with heterogeneous treatment effects. TWFE regressions are unbiased for an ATE only if the treatment effect are constant between groups and over time. With heterogeneous treatment effects and under a parallel trends assumption, TWFE may estimate a weighted sum of treatment effects across periods and units, with some negative weights.The negative weights could bias the treatment coefficient in TWFE regressions close to zero or negative, even if the treatment effect is positive for every unit $\times$ period (de Chaisemartin and D'Haultfœuille, 2022; Goodman-Bacon, 2021). Several alternative difference-in-difference (DID) estimators robust to heterogeneous effects have been proposed recently. Most of them apply to binary treatments that follow a staggered design (Borusyak, Jaravel and Spiess, 2022; Callaway and Sant'Anna, 2021; Sun and Abraham, 2021). Only one estimator DID_m proposed by de Chaisemartin and D'Haultfœuille (2020) can be extended for continuous treatments, which applies to my research design. The DID_m estimator is a weighted average, across treatment intensity d and period t, of DIDs comparing the $t-1$ to t outcome evolution of groups whose treatment goes from d to some other value, and of groups with a treatment equal to d at both dates, normalized by the intensity of the treatment change experienced by the switchers.

I first estimate the weights attached to TWFE estimator $\hat{\beta_{fe}}$, and find that 45 percent are positive, 55 percent are negative. The negative weights indicate that $\hat{\beta_{fe}}$ may not be robust to heterogeneous effects, although the negative weights only sum to -0.09. The correlation between the weights attached to $\hat{\beta_{fe}}$ and the year t is equal to 0.08 (t-stats = 9.7), suggesting that the effect of Internet may be different in the early years than in the later years of the panel. Given the heterogeneous treatments, I compute the robust DID_m estimator using *did_multiplegt* in Stata. Table 5 column 6 shows that the DID_m estimates share the same sign but with larger effects from the TWFE estimates, except for network search. Although network search results are imprecisely estimated using the standard TWFE. The standard errors of DID_m estimations are larger, probably because less variations are used after dropping comparisons between later and early treated groups as suggested by de Chaisemartin and D'Haultfœuille (2020).

5.3 Heterogeneous effects

Given the high unemployment rate among young people in South Africa, I examine the heterogeneous effects of Internet exposure on job outcomes and search channels by workers' age. I use equation 7 where I interact $PercentConnected$ with a dummy variable for young workers between 15 and 24 years old. Estimation results are reported in Table 6.

$$
\begin{aligned}
Y_{ijt} = \alpha &+ \beta_1 (PercentConnected_{jt} \times Youth_i) \\
&+ \beta_2 PercentConnected_{jt} + \beta_3 Youth_i + X'_{ijt}\delta + \gamma_t + \theta_j + \epsilon_{ijt} \quad (7)
\end{aligned}
$$

where the dummy variable $Youth_{it}$ indicates whether individual i is between 15 and 24 years old at time t.

Compared with older workers in areas with more Internet, young workers share similar probability of getting a job (column 1), but earn significantly less (column 3). They will try more number of search methods (column 5), and are more likely to increase searching through personal networks (column 9). These results suggest that young workers spend more effort searching for jobs, but the methods they choose are not as effective as the experienced. Their increasing reliance on personal networks suggests that Internet could make it easier to communicate with family and friends using tools such as emails or social media. I test if the Internet has an impact on the strength of social capital in section 6.2.

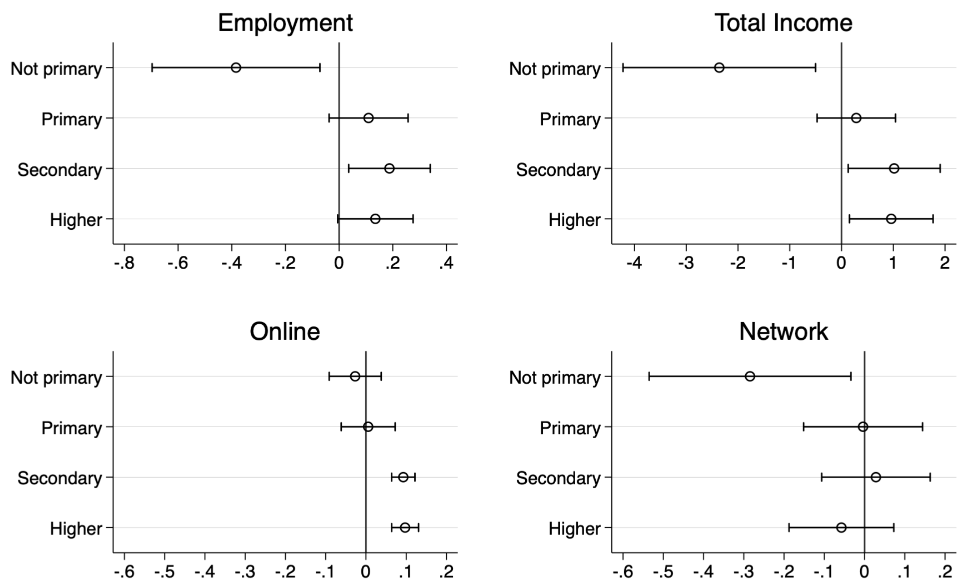
Family networks are particularly important to the labor outcomes of youth when transitioning from school to work (Kramarz and Skans, 2007). Thus, I include parents' education level and its interaction with Internet access to account for social economic status and network quality. The results on job outcomes are comparable when including these variables (column 1-4). As for search behaviors, Internet will cause workers whose parents have primary education to use less number of search methods, more likely to use online search, and less dependent on network search. These results suggest that existing social network variances can play a role in the young workers' choice of job search methods.

Considering how Internet can be a skill-biased technology as documented in many rich countries (Akerman, Gaarder and Mogstad, 2015; Michaels, Natraj and Van Reenen, 2014), I test if this is true in South Africa by interacting Internet penetration rate with educational attainment dummies for no school, primary, secondary, and tertiary education. The education level is used as a proxy for skill level here.

Results in figure 4 indicate that Internet connection increases the employment and income among the more educated workers the most. This finding is similar to Hjort and Poulsen (2019). However, individuals with no education do not benefit from Internet connection. This group of workers search less with both online and network channels, are less likely to find a job, and their total income will decrease. The results on uneducated workers contrast with Hjort and Poulsen (2019), where they find fast Internet reduces unemployment inequality across all education groups.[10] I also test if parents' education level is a confounding factor in Table A1. Including the interaction terms of Internet and parents' education, main effects of Internet on workers with and without primary education do not change much. The coefficients on parents education interaction term are statistically significant, suggesting that existing social economic differences may play a role in the job outcomes and search methods for jobseekers.

[10] Though Hjort and Poulsen (2019) find the employment outcomes for workers with no education in eight other African countries do not benefit from fast Internet either.

Figure 4: Internet effects by education level



Each panel plots the coefficients of Internet penetration rate and highest education level interaction, from regressions of labor outcomes and search channels on Internet connectivity. All models include location and year fixed effects, and control for age and gender. 95% confidence intervals are displayed.

*Notes: Each panel plots the coefficients of Internet connectivity rate and highest education level interaction, from regressions of labor outcomes and search channels on Internet connectivity. All models include location and year fixed effects, and control for age and gender. 95% confidence intervals are displayed.

Table 6: Impacts of Internet Connection on Job Outcomes by Age

Outcome	Employed		Income		No.of Methods		Online		Network	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
% connected	0.141*	0.109	1.330***	0.838*	-0.196***	-0.118	0.065***	0.060***	-0.191	-0.132**
	(0.073)	(0.083)	(0.392)	(0.483)	(0.060)	(0.084)	(0.013)	(0.021)	(0.126)	(0.064)
... × youth	0.007	0.053	-1.376**	-1.048	0.332***	0.541***	-0.003	0.011	0.353**	0.412***
	(0.055)	(0.057)	(0.625)	(0.670)	(0.103)	(0.189)	(0.025)	(0.032)	(0.175)	(0.083)
... × w.educated parents		-0.016		-0.144		-0.180**		0.046		-0.095**
		(0.040)		(0.468)		(0.085)		(0.044)		(0.046)
youth	-0.354***	-0.381***	-2.599***	-2.895***	-0.229***	-0.226***	-0.056***	-0.063***	-0.282***	-0.279***
	(0.013)	(0.015)	(0.143)	(0.158)	(0.023)	(0.026)	(0.006)	(0.007)	(0.011)	(0.015)
w.educated parents		-0.012		0.029		-0.035		0.027***		-0.049***
		(0.012)		(0.126)		(0.022)		(0.008)		(0.011)
p-values(youth)	0.017	0.029	0.868	0.739	0.150	0.057	0.052	0.115	0.324	0.001
Mean of outcome	0.366	0.399	2.340	2.681	0.251	0.253	0.061	0.067	0.247	0.265
Observations	37,034	23,993	32,411	21,015	38,436	24,112	32,855	21,300	32,856	21,301
R-squared	0.209	0.199	0.237	0.244	0.037	0.042	0.090	0.106	0.090	0.087

* Notes: Only workers between age 15 and 65 are included. All specifications include year, location fixed effects. Control variables include age, gender, education, and baseline demographic covariates interacted with time trends. Standard errors (in parentheses) are clustered at the province level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

6 Additional Mechanism Evidence

In this section, I discuss how Internet might affect employment and job search behaviors by skill levels and workers' age.

6.1 Access constraints

In Table 4, I find more Internet access enhances the use of online information search, and has little impact on the use of social network search. In section 5.3, I show choices of search channel made by uneducated or young workers respond to more Internet availability differently than their peers. Even after Internet is made more available in their areas, individuals without primary education will not use online search, and young workers will increase their reliance on personal networks.

One possible explanation is that there are other constraints prevent disadvantaged workers from accessing the Internet for online job search. Figure A2 shows that the high cost of equipment is the most important reason for not having Internet access at home, according to the General Household Survey (GHS) in 2018.

If we consider the computer a tool necessary for online job search, computer ownership can be used as a proxy to test if accessing costs are different for heterogeneous workers.[11]I use both the individual and household survey data from NIDS, and show how Internet affects computer ownership, literacy, and spending in Table 7. All regressions include individual fixed effects in additional to location and year fixed effects.

For skilled workers, their probability of owning a computer is 9 percentage point higher than unskilled workers, and they are more likely to be computer literate (Table 7,panel A column 1-2). Their households are also more likely to spend money on Internet (column 5). Interestingly, I find cellphone ownership are lower for the skilled workers than the unskilled (column 3, 6). Young workers are obviously more tech-savvy: more likely to own a computer or cellphone, and know how to use a computer (Table 7,panel B column 1-3). However, it seems that they are not using this technology to search for job information online directly, but rather to enhance personal networks for sharing job information. Most people probably communicate with families and friends or use social networking websites through a cellphone, so the more widely available cellphone could suggest no significant cost difference in accessing the Internet for network job search. This could explain why we do not see large differences in using network search for the skilled and unskilled in column 9-10 Table A1.

The findings about computer ownership and literacy suggest that technology may not make a difference if there are other constraints. Similar result are found in rural South Africa, where the rollout of mobile phone networks increased employment among women, but only for those who did not have significant family responsibilities (Klonner and Nolen, 2008).

6.2 Internet activities - social networking

Job search response could also depend on the various uses of Internet technology. Table A2 Panel B shows that social networking is the most important Internet activity (44.5%), while only about 12% survey respondent uses Internet for job search.[12] It is possible that internet communication may provide a cheap way for people to maintain relationships with people outside of their primary groups, such as classmates, former colleagues, or acquaintances (Armona, 2021; Gee, Jones and Burke, 2017). Social networking might also provide a way through which individuals can form new links by associating with others online who share specific interests. If Granovetter (1973)'s strength of weak ties hypothesis can be applied to online relationship, having a wide network of "weak" ties will provide greater quantity of job information. Then personal networks may complement the Internet in the job search process.

To test if the Internet affects the strength of social capital, I use favor exchanges behaviors with people outside of the household in the past year from the NIDS

[11]Smartphones which cost less can be a substitute for computers for many functions. However, in a survey of people who used smartphones to apply for a job, 47% had difficulties accessing content that did not display properly, 38% had difficulties entering in a large amount of text, 37% had difficulties submitting required files and supporting documentation, and 23% had difficulties bookmarking saved job applications for later(Smith 2015)

[12]Source: Research ICT Africa (RIA)

Table 7: Impacts of Internet Connection on Cell and PC Ownership

	Individual			Household			
	own a computer	computer literate	own a cellphone	own a computer	spent money on internet	own a cellphone	spent money on cellphone
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: by education level							
% connected	-0.005	-0.179***	-0.012	0.023	0.005	0.176**	0.054
	(0.014)	(0.050)	(0.105)	(0.032)	(0.015)	(0.075)	(0.165)
... × beyond primary	0.090***	0.256***	-0.157***	0.107	0.034*	-0.228***	-0.236*
	(0.026)	(0.061)	(0.054)	(0.071)	(0.020)	(0.047)	(0.124)
beyond primary	-0.008	0.080***	0.182***	-0.013*	-0.001	0.025**	0.042**
	(0.005)	(0.015)	(0.016)	(0.007)	(0.004)	(0.011)	(0.019)
p-values(primary)	0.002	0.248	0.073	0.084	0.189	0.322	0.070
Observations	33,829	32,850	33,841	35,715	26,777	35,768	26,724
R-squared	0.530	0.670	0.493	0.583	0.444	0.384	0.446
Panel B: by age							
% connected	0.034	-0.057	-0.155*	0.079	0.030	0.031	-0.108
	(0.021)	(0.044)	(0.085)	(0.052)	(0.023)	(0.064)	(0.113)
... × youth	0.093***	0.209***	0.304***	0.030	-0.010	0.020	0.086
	(0.029)	(0.060)	(0.082)	(0.028)	(0.020)	(0.037)	(0.096)
youth	-0.025***	-0.089***	-0.050***	-0.010	-0.001	0.003	-0.034**
	(0.007)	(0.017)	(0.018)	(0.007)	(0.004)	(0.013)	(0.017)
p-values(youth)	0.000	.059	0.279	0.030	0.407	0.481	0.858
Observations	33,767	32,788	33,779	36,696	27,629	36,750	27,580
R-squared	0.532	0.671	0.492	0.579	0.436	0.380	0.440
Mean of outcome	0.051	0.292	0.714	0.107	0.012	0.851	0.738
Individual FE	Y	Y	Y	Y	Y	Y	Y

* Notes: Only workers between age 15 and 65 are included. All specifications include individual, location and year fixed effects. Standard errors (in parentheses) are clustered at the district level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

as dependent variables. Table 8 panel A shows that Internet does not impact the favor exchanges activities much differently for more or less educated workers. However, the negative coefficient on $PercentConnected$ on panel B suggests that older workers' social networks might be hurt by the Internet. And the coefficients on $PercentConnected \times youth$ are large, positive, and statistical significant for all favor exchange activities, implying that young workers are more likely to enhance their networks when Internet becomes more available in their areas. This can help explain why we see with more Internet, young people increasingly rely on personal networks for job information previously in Table 6. So for young workers without much social capital, they prefer to strength their networks and find job information through their personal networks, rather than using the Internet to search for jobs online directly.

6.3 Adoptions by household and firms

In previous analysis, the key variable of interest $PercentConnected$ represents the Internet availability rate in the district where the worker is living, it does not directly reflect the actual Internet access of the households or individual. As a supplement source, I use the General Household Survey (GHS) by Statistics South Africa to show some first stage correlations between Internet availability and adoption.The target population of the GHS survey consists of all private households in all nine provinces of South Africa and residents in workers' hostels. The sample size is about 24 thousand households each year, from 2009 to 2021. This survey includes information about whether households had at least one member who had access to or used the Internet, which can be used as proxy for direct Internet adoption rate.

Households in South Africa are generally more likely to have access to the Internet at work than at home or at Internet cafes or at educational institutions. In 2021, Internet access using mobile devices (66%) is the most common way compared to access at home (6%), at work (16%) and elsewhere (15%) (Figure A3).

I match the Internet access types data from the GHS with the key variable of interest $PercentConnected$ by province and year, and find a positive impact of broadband Internet availability in the local area on households' Internet adoption rates.

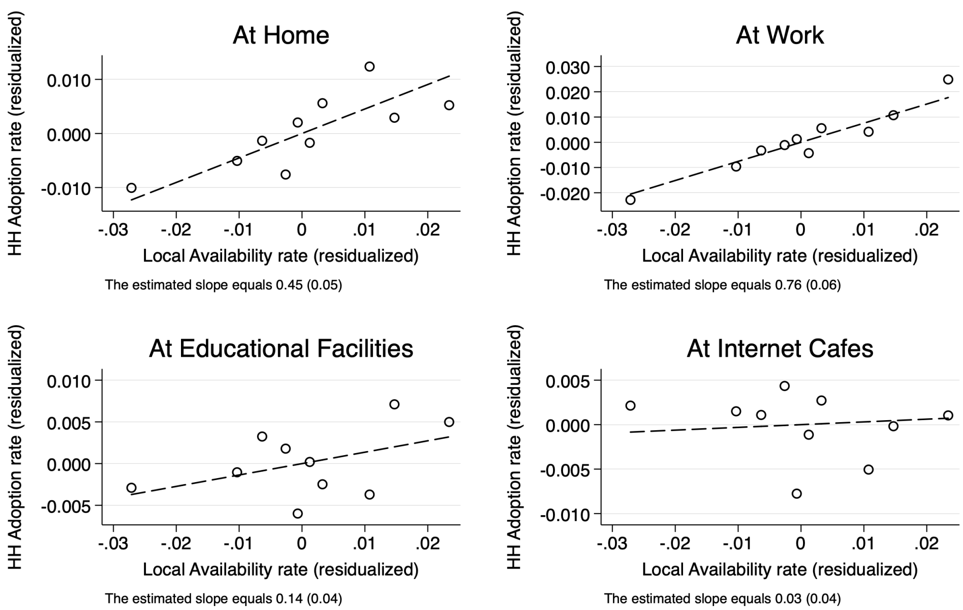
Table 8: Impacts of Internet Connection on Favor Exchanges

	exchanged favors (1)	gave favors (2)	received favors (3)
Panel A: by education level			
% connected	-0.092	-0.102	-0.003
	(0.085)	(0.089)	(0.047)
... × beyond primary	-0.012	0.033	-0.038
	(0.055)	(0.054)	(0.037)
beyond primary	0.020	-0.012	0.029***
	(0.013)	(0.010)	(0.010)
p-values(primary)	0.122	0.194	0.266
Observations	34,526	34,205	34,525
R-squared	0.369	0.363	0.366
Panel B: by age			
% connected	-0.130*	-0.095	-0.044
	(0.069)	(0.062)	(0.037)
... × youth	0.186***	0.091**	0.101**
	(0.060)	(0.039)	(0.049)
youth	-0.037***	-0.042***	0.001
	(0.014)	(0.012)	(0.012)
p-values(youth)	0.498	0.958	0.337
Observations	34,534	34,213	34,533
R-squared	0.370	0.363	0.366
Mean of outcome	0.138	0.055	0.090
Individual FE	Y	Y	Y

* Notes: Dependent variables equal 1 if individuals have exchanged, gave or received favors with people outside of their household in the past year. All specifications include individual, location and year fixed effects. Standard errors (in parentheses) are clustered at the district level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure 5 shows scatterplots of the Internet adoption rate by places of access, against the Internet availability rate in the province, after taking out provincial and year fixed effects. The x-axis reports residuals from a regression of percent of populations connected to broadband on province and year fixed effects, and the y-axis reports residuals from a regression of households having Internet by access types on province and year fixed effects.

Figure 5: Internet availability and household adoption rate, by places of access



Note: The scatter plot shows average (residual) adoption at (residual) availability deciles, by places of access

The figure is based on the following regression that uses the sample of households for which we observe whether or not they have Internet access at home, work, nearby Internet cafes, or educational facilities:

$$d_{ijt} = \delta PercentConnected_{jt} + \gamma_t + \theta_j + \nu_{ijt} \tag{8}$$

where d_{ijt} equals one if household i in province j at time t had Internet access at home (or at work, at educational facilities, at nearby Internet cafe) and is zero otherwise.

The coefficient on the availability rate δ is about 0.43 with a standard error of 0.07 for Internet access at home. This estimate implies that a 10 percentage point increase in broadband availability will induce 4.5 percent of households to gain Internet access at home. Adoption at work responses the most, while access from Internet cafes do not change much. These findings illustrate that when Internet becomes available, adoption is not universal; instead, it is more likely adopted in places in which complementary factors are abundant, including computer ownership and computer literacy.

Table 9: Impacts of Internet Connection on Adoptions by Place of Access

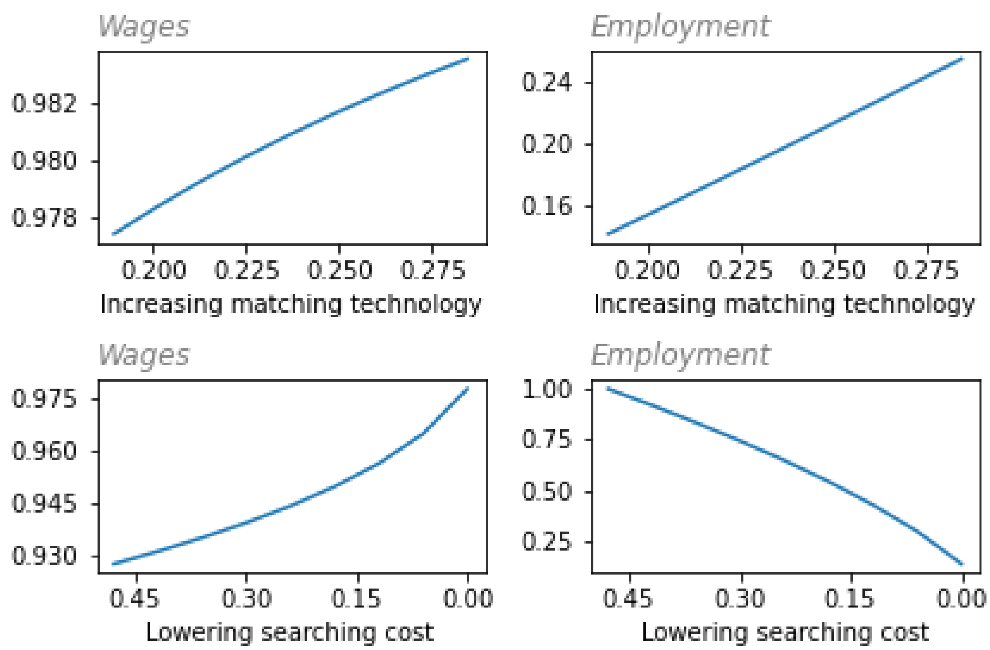
	Anywhere	At home	At work	Educational facilities	Internet cafes
	(1)	(2)	(3)	(4)	(5)
% connected	0.946***	0.427***	0.805***	0.158*	0.086
	(0.173)	(0.073)	(0.113)	(0.090)	(0.135)
Mean of outcome	0.220	0.075	0.133	0.058	0.048
Observations	127,024	126,349	126,349	127,024	127,024
R-squared	0.106	0.046	0.069	0.033	0.029

* Notes: All specifications include location and year fixed effects. Standard errors (in parentheses) are clustered at the province level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

6.4 General equilibrium impacts

Internet can affect both the labor supply and the labor demand, and the results on employment and wages in Table 3 and Table A1 should reflect the equilibrium outcomes. Without employers or firms' data, I can not say much about how employers' job creation decisions respond to more Internet access empirically. Instead, I study the expected general equilibrium impacts of Internet using the theory of unemployment and vacancies, the Diamond-Mortensen-Pissarides(DMP) model (Diamond, 1982; Mortensen, 1986; Pissarides, 1985). I simulate the Internet access shock by changing the parameter value of matching technology or the value of unemployment income, and solve the model numerically. Expected equilibrium changes of wage and employment are summarized in Figure 6. A brief description of the DMP framework is presented in Appendix B.

Figure 6: New equilibrium simulation using DMP model



Notes: By changing the parameter value of matching technology A_t and the value of unemployment income b, I numerically solve the new equilibrium after a Internet access shock. The baseline parameter values are from Hagedorn and Manovskii (2008).

The first mechanism that Internet could impact the labor market is an improvement in matching efficiency. A key process in the DMP-framework is the "matching function", which uses job vacancies and jobseekers as input, and produces a number of firm-worker matches given a matching technology A. Upper panel, Figure 6 show that with higher values of A, more hires can be generated from the same number of jobseekers and vacancy, thereby increasing the employment rate. Since jobseekers expect to be matched faster, their outside option improves, which will drive up wages in new employment relationships.

Internet access can also reduce the cost of learning about and applying for jobs. Unemployment income in the DMP model include both actual unemployment transfer and imputed value of time to unemployed workers. Lower searching cost implies higher value of leisure, thereby increasing the value of unemployment income. Everything else equal, this increasing unemployment benefits exerts an upward pressure on the equilibrium wage. This lowers the profits employers receive from filled jobs, leading to a decline in vacancy creation. Lower vacancies imply a lower job finding rate for workers, which leads to an decrease in employment as shown in lower panel, Figure 6.

Combining these two mechanisms, the effect on wages is unambiguously positive, but the total effect of the Internet on employment depends on the relative importance of these two.

7 Conclusion

This paper provides evidence on how Internet availability affects job market outcomes and job search activity in South Africa. By comparing individuals in areas with various Internet penetration rates, I find that jobseekers in locations with better connectivity have higher employment rates and income, and the impact is driven by a significant increase in employment of experienced and skilled workers. When Internet is made more available, only skilled ones increase their use of online job search. Young workers will search through more methods, while rely more on personal networks.

These findings suggest that not everyone stands to benefit from improved Internet availability automatically. Associated labor market disruptions can be painful and can result in higher inequality. High cost remains the largest barrier for Internet usage.[13] The low-skilled or less-educated almost exclusively use mobile phones to access the Internet. Poor computer literacy could limit the productive use of this technology. Besides improving Internet infrastructure, complementary policies aim-

[13] Table A2 Africa ICT access survey, Fig A2

ing at updating skill and digital literacy are critical for ensuring the overall benefits be shared broadly.

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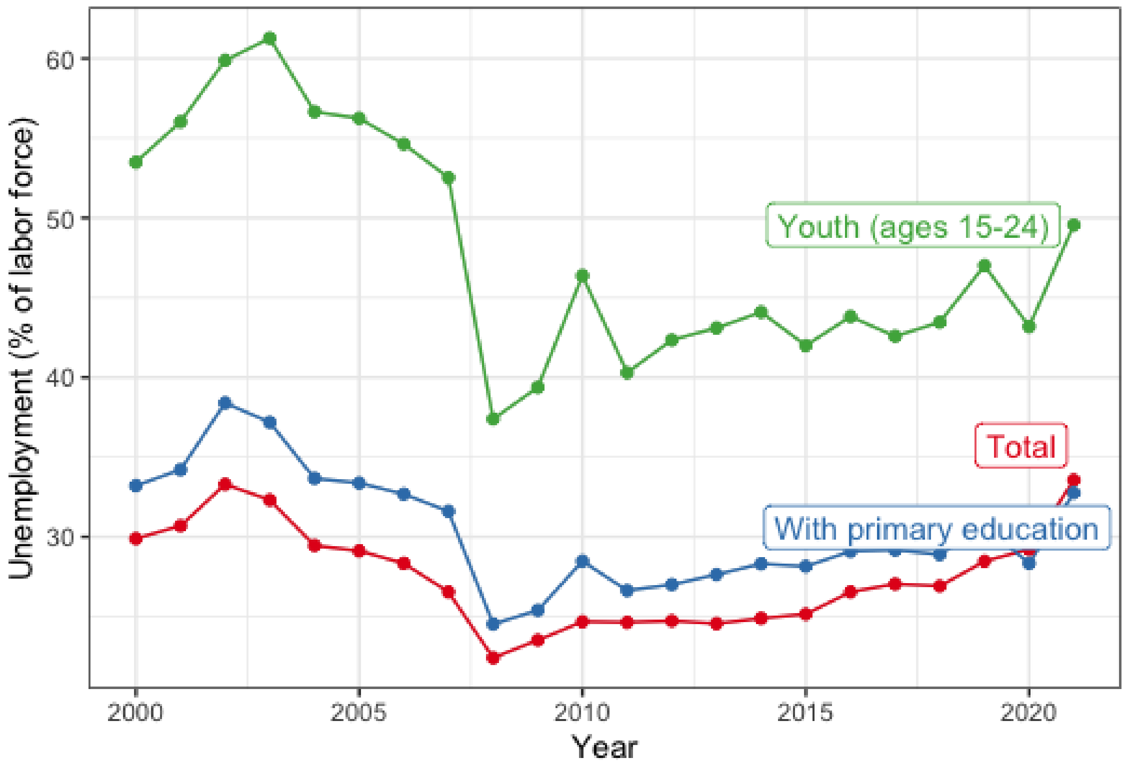
Appendices

Figure A1: Unemployment Rate in South Africa



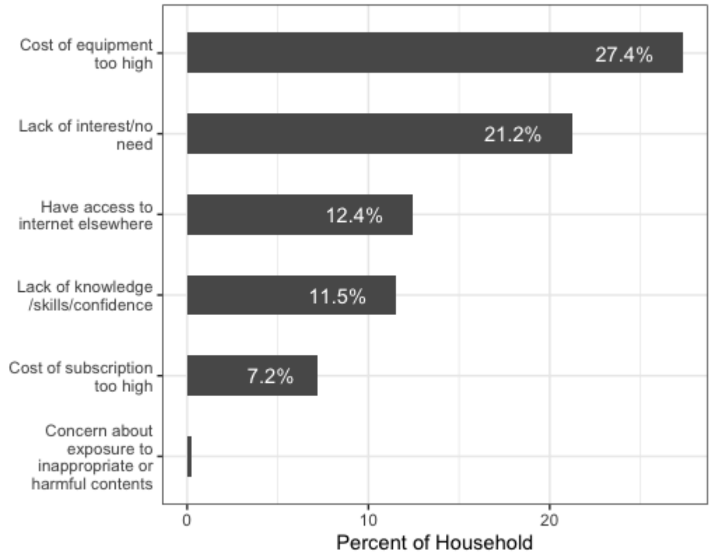
Source: World Development Indicators.

Table A1: Impacts of Internet Connection on Job Outcomes by Education

Outcome	Employed		Income		No.of Methods		Online		Network	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
% connected	0.081	0.054	0.133	-0.268	-0.082	0.015	-0.010	-0.030	-0.016	0.008
	(0.075)	(0.090)	(0.453)	(0.653)	(0.061)	(0.068)	(0.034)	(0.043)	(0.074)	(0.075)
... × beyond primary	0.074	0.126	0.999	1.374*	-0.044	-0.024	0.118***	0.112**	-0.019	0.016
	(0.071)	(0.084)	(0.624)	(0.686)	(0.075)	(0.078)	(0.038)	(0.045)	(0.049)	(0.049)
... × w. educated parents		-0.134***		-0.969**		-0.189***		0.122***		-0.283***
		(0.041)		(0.457)		(0.064)		(0.045)		(0.055)
beyond primary	0.163***	0.163***	1.524***	1.666***	0.186***	0.166***	0.090***	0.099***	0.094***	0.079***
	(0.010)	(0.013)	(0.101)	(0.134)	(0.017)	(0.018)	(0.006)	(0.007)	(0.010)	(0.011)
Mean of outcome	0.367	0.399	2.356	2.685	0.258	0.254	0.062	0.067	0.248	0.265
Observations	36,892	24,032	32,278	21,050	37,485	24,151	32,724	21,335	32,725	21,336
R-squared	0.147	0.137	0.168	0.173	0.031	0.034	0.060	0.069	0.053	0.051
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Location FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y

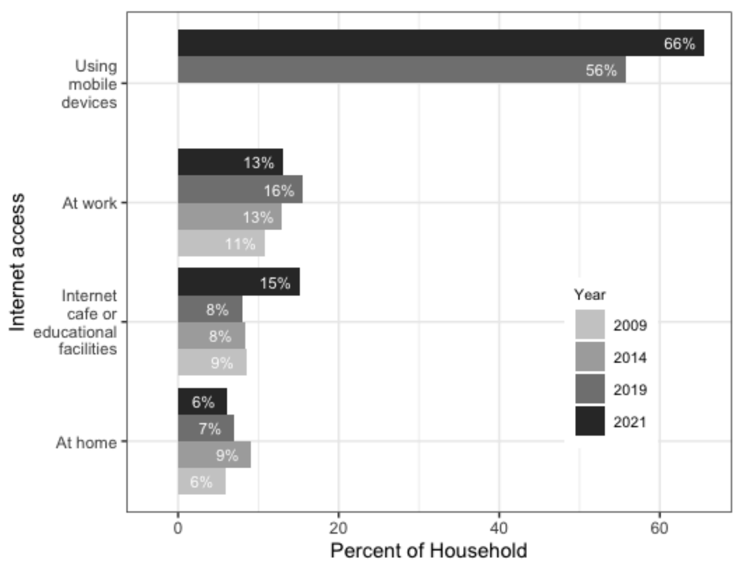
* Notes: Only workers between age 15 and 65 are included. All specifications include year, location fixed effects, age and gender control variables. Standard errors (in parentheses) are clustered at the district level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure A2: Reasons for not having Internet access at home



Source: General Household Survey, 2018, Statistics South Africa.

Figure A3: Households' Internet Access by Place of Access



Source:General Household Survey, Statistics South Africa.

Table A2: South Africa ICT access survey

	2017-2018	2011-2012	2005-2008
Panel A: household attributes			
HH has internet connection	11.6%	16.2%	6.5%
HH with Internet: highest education level			
No school	0.9%		
Primary	1.4%		
Secondary and above	97.6%		
Reasons not having internet			
Cost too high	48.3%		
Not available in the area	5.9%		
Do not need	20.4%		
Do not know how to use it	12.4%		
Others	12.9%		
Panel B: Individual usage			
Used Internet before	68.6%	33.0%	18.6%
Internet usage			
Once a day	50.4%	64.8%	64.4%
Once a week	30.8%	24.6%	24.9%
Once a month	10.3%	9.1%	7.0%
Less than once a month	8.6%	1.5%	3.6%
Most important internet activity			
Social networking	44.5%		
Education	23.5%		
Job search	12.4%		
Work related	11.3%		
Online banking	2.5%		
Others	5.7%		
Limitation for use of the internet (multiple responses)			
Cost	46.6%	62.9%	45.3%
Speed	25.6%	10.1%	8.8%
No interesting content in my language	7.1%		13.0%
Difficult to use	2.8%	73.2%	1.5%
Reason not using internet(single choice)			
Cost	50.6%		
No interest	19.3%		
Do not know how to use it	8.9%		
Not available in my area	3.4%		
Others	17.9%		

Source: Africa ICT access survey.

A A model of jobseeker's utility maximization with leisure

I include leisure in the utility function for jobseekers in this version of the conceptual model. A jobseeker lives two periods with a supply of Internet access θ. In the first period, an unemployed individual receives some unemployment benefit b, and needs to allocates his time (normalized to 1) between job searching s and leisure l. The probability of finding a job depends on the search effort and amount of Internet access: $p(s, \theta)$. In the second period, if the individual becomes employed, the wage and labor supplied will be given as w and h. The jobseeker chooses job search effort and maximizes the expected lifetime utility as follows:

$$\begin{aligned}
\max_{s} \quad & u\left(c_1, \ell_1, \theta\right) + \beta E u\left(c_2, \ell_2, \theta\right) \\
\text{s.t.} \quad & c_1 = b \\
& \ell_1 = 1 - s \\
& c_2 = \begin{cases} wh & \text{w.p. } p(s, \theta) \\ b & \text{w.p. } 1 - p(s, \theta) \end{cases} \\
& \ell_2 = \begin{cases} 1 - h & \text{w.p. } p(s, \theta) \\ 1 & \text{w.p. } 1 - p(s, \theta) \end{cases} \\
& 0 \leq s, p(s, \theta) \leq 1
\end{aligned} \tag{A1}$$

An interior solution should satisfy the following first order condition:

$$\frac{\partial u\left(b, 1 - s, \theta\right)}{\partial l_1} = \beta \frac{\partial p(s, \theta)}{\partial s} \left[u\left(wh, 1 - h, \theta\right) - u\left(b, 1, \theta\right)\right] \tag{A2}$$

which implies that the individual chooses search effort s optimally such that the marginal utility of giving up leisure equals the expected utility gain from searching for work, which is the difference between employment and unemployment utility in the second period.

For this paper, I am interested in how employment probability may change with the Internet access, which is provided exogenously. That is,

$$\frac{d}{d\theta}p(s(\theta),\theta) = \frac{\partial p}{\partial s}s'(\theta) + \frac{\partial p}{\partial \theta} \tag{A3}$$

Assuming the marginal productivity of search and Internet are both positive ($\frac{\partial p}{\partial s}, \frac{\partial p}{\partial \theta} > 0$), the effect on employment will depend on $s'(\theta)$. In order to see how optimal search effort $s^\star(\theta)$ changes with Internet access θ, we can differentiate the first order condition equation A2 with respect to θ:

$$s'(\theta) = \frac{\beta p_{s\theta}\left(u^{emp} - u^{unemp}\right) + \beta p_s \frac{\partial}{\partial\theta}\left(u^{emp} - u^{unemp}\right) - u_{\ell\theta}}{-u^1_{\ell\ell} - \beta p_{ss}\left(u^{emp} - u^{unemp}\right)} \tag{A4}$$

where u^1, u^{emp}, u^{unemp} represent the utility in period 1, being employed and unemployed in period 2 respectively.

Since $u^{emp} > u^{unemp}$ is a necessary condition for the existence of an interior solution, the denominator in equation A4 is positive. The sign of the numerator depends on three parts. First, $p_{s\theta}$, the change in the marginal productivity of search in response to more Internet access. Second, $\frac{\partial}{\partial\theta}\left(u^{emp} - u^{unemp}\right)$, the difference between employment and unemployment utility in response to more Internet access. Third, $u_{\ell\theta}$, the change in marginal utility from leisure in response to more Internet access.

B DMP framework

I summarize the standard equilibrium search and matching model briefly in this appendix.

The hiring process is governed by a matching function that produces worker-employer pairs using job vacancies and jobseekers as inputs,

$$H_t = A_t v_t^{\alpha} u_t^{1-\alpha} \tag{A5}$$

where u_t is the number of jobseekers, v_t is the number of vacant jobs, and A_t is the efficiency of the search and matching process.

The probability of finding a job match for the unemployed worker is given by

$A_t(v_t/u_t)^\alpha = A_t(\theta_t)^\alpha$, where θ_t represents the labor market tightness.

All workers face the same constant unemployment risk λ. At steady states, the flow into unemployment $\lambda(1-u)$ should equal the flow out of unemployment $A\theta^\alpha u$. Unemployment can be solved in terms of two transition rates,

$$u = \frac{\lambda}{\lambda + A(\theta)^\alpha} \tag{A6}$$

Workers maximize the net present value of income and randomly search for vacant jobs while unemployed. The flow value of being unemployed is $rU = b + A(\theta)^\alpha(W - U)$, and the flow value of working is $rW = w + \lambda(U - W)$. Firms receive a flow value of profits for active jobs according to $rJ = p - w - \lambda J$, and the flow value of vacancy is $rV = -c + A(\theta)^{\alpha-1}(J - V)$. In profit-maximizing equilibrium, the expected value of a vacancy is driven to zero by free entry of new vacancies. We can derive the job creation condition as,

$$p - w - \frac{(r+\lambda)c}{A(\theta)^\alpha} = 0 \tag{A7}$$

The wage is assumed to be derived from a Nash bargaining solution: the w that maximizes the weighted product of the worker's and the firm's net return from the job match.

$$w = \arg\max\, (W - U)^\beta\, (J - V)^{1-\beta}\,, \tag{A8}$$

where β can interpreted as a relative measure of labor's bargaining strength, and it is between 0 and 1. First order condition gives the wage setting condition as,

$$w = (1-\beta)b + \beta p(1 + c\theta) \tag{A9}$$

Equilibrium is a unique set of (u, θ, w) that satisfies the flow equilibrium condition A6, the job creation condition A7, and the wage equation A9. By changing the parameter value of matching technology A_t and the value of unemployment income b, I numerically solve the new equilibrium after a Internet access shock. The simulated results are shown in Figure 6.