NBER WORKING PAPER SERIES

THE ARRIVAL OF FAST INTERNET AND EMPLOYMENT IN AFRICA

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Working Paper 23582
http://www.nber.org/papers/w23582

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
July 2017

We thank Sebastian Axbard, Niklas Bengtsson, Martina Björkman-Nyqvist, Greg Bruich, Esther Duflo, Ray Fisman, Oded Galor, Francois Gerard, Amit Khandelwal, Erik Lindqvist, Mushfiq Mobarak, Kalle Moene, Eva Mörk, Anders Olofsgård, Michel Serafinelli, Kjetil Storesletten, Eric Verhoogen, Tim Waters, Frank Windmeijer, Chris Woodruff, and seminar participants at Barcelona Summer Forum, Bocconi, Brown, Columbia, Harvard, IGC Growth Week, NBER Summer Institute, Oslo, Oxford, Stockholm School of Economics, UBC, and Uppsala for comments and suggestions, and Sawal Acharya, Patrick Kennedy, and Roxanne Rahnama for great research assistance. We are especially grateful to Henrik Sigstad and Matthieu Teachout for many helpful conversations, and to Akamai, Steve Song, and the World Bank for data access. Hjort thanks the Center for Development Economics and Policy at Columbia University for financial support. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

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NBER Working Paper No. 23582
July 2017
JEL No. D20,J20,O10

ABSTRACT

To show how fast Internet affects employment in Africa, we exploit the gradual arrival of submarine Internet cables and maps of the terrestrial cable network. Robust difference-in-differences estimates from three datasets covering 12 countries show large positive effects on employment rates, with little job displacement across space. A decrease in workers' likelihood of holding unskilled jobs is offset by a bigger increase in employment in higher-skill occupations. Less educated workers' employment rate also rises. Firm level data available for some countries indicate that increased firm entry, productivity, and exporting lead to higher job-creation (and/or -saving). Average incomes and wealth rise.

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1 Introduction

Traditional trade theory predicts a decrease in inequality in developing countries during periods of integration in the global economy. The slow economic progress of poor workers in many parts of Africa, Asia, and Latin America during the last few decades therefore surprised economists. Two potential explanations were proposed and compared: skill-biased technological change (SBTC) and features of international trade—such as outsourcing (see e.g. Feenstra & Hanson, 1996, 1999, 2003) and quality upgrading (see e.g. Verhoogen, 2008; Frías *et al.* , 2009)—that could alter the logic underlying expectations of job growth and greater equality in unskilled labor-abundant countries post-integration (Feenstra & Hanson, 2003; Goldberg & Pavcnik, 2007; Harrison *et al.* , 2011; Goldberg, 2015). Two decades of research led to wide agreement that both explanations play a role, and that they probably interact (Wood, 1995; Acemoglu, 2003; Attanasio *et al.* , 2004; Burstein *et al.* , 2013; Koren & Csillag, 2016; Raveh & Reshef, 2016). But this conclusion was built on studies of *trade-induced* technological change. To date, there is no direct evidence on the average and distributional economic effects in poor countries of the spread of the modern information and communication technologies (ICT) that help explain increasing inequality in rich countries' labor markets.

In this paper, we estimate how fast Internet—"the greatest invention of our time" (The Economist, 2012)—affects poor countries' economies.[1] To do so, we compare individuals and firms in locations in Africa that are on the terrestrial network of Internet cables to those that are not. We compare these two groups during the gradual arrival in coastal cities of submarine cables from Europe that greatly increase speed and capacity on the terrestrial network. We show how employment rates, occupational employment shares, job inequality across the educational attainment range, and the underlying extensive (Internet take-up) and intensive (Internet speed) margin, respond. We also show evidence on three particular mechanisms through which take-up and speed may affect employment: changes in firm entry; changes in productivity in existing firms; and changes in exporting. Finally, we show how average incomes and wealth in locations that see changes in employment patterns with the arrival of fast Internet respond.

It has been difficult to study SBTC directly because, other than in local experiments, ICT technologies are not randomly allocated, but introduced where economic benefits are expected. While this is true everywhere, developing countries additionally tend to lack systematic and detailed labor market and firm level data, especially in the poorest regions of the world, where the economic environment differs the most from the West (see Katz & Autor (1999); Bond & Van Reenen (2007); Goldin & Katz (2007) for overviews of the SBTC literature on rich countries). We overcome the first obstacle by interacting time variation generated by the gradual arrival of submarine Internet cables in landing point cities on Africa's coast in the late 2000s and early 2010s with cross-sectional variation in whether a given location is connected to the terrestrial "backbone" network that starts at the landing point cities.[2] That a given submarine cable reaches different countries at different times and in a geographically determined order, and that we consider 10 different cables, a priori lowers concerns about non-parallel prior trends in economic outcomes in locations on versus off the backbone network. The collection of datasets we use enables an extensive battery of tests that supports a causal interpretation of our results.

We overcome the second obstacle by combining employment data from representative household surveys (panels at location level) from 12 African countries with a combined population of roughly half a billion people with firm level datasets (panels at firm or location level) from Ethiopia, South Africa, and

[1] We are not aware of existing causal evidence on this relationship. See World Bank (2016) for an overview of the existing correlational evidence, and more details below.

[2] During this period, each coastal country effectively had its own separate backbone network, as explained in Section 2.

a group of six African countries.[3] We use the firm level data to show evidence on three especially important mechanisms—firm entry, productivity, and exporting—through which fast Internet may affect employment.[4] We also use data on Internet speed and take-up of the Internet to tie the reduced form estimates to the intensive and extensive margin of use. Finally, we use individual level data on wealth and data on night lights from satellite images to study how fast Internet ultimately affects average incomes and wealth.[5]

Our approach differs from much of the related literature in that employment rates, rather than wages (among the employed), are our primary outcomes of interest. This is partly for data availability reasons, but it is also a sensible choice in a developing region context.[6] "Job inequality" captures inequality in human capital accumulation, future labor market prospects, and income that is due to (i) current (un)employment—a component of first order importance in Africa that focusing on wage inequality would miss (see e.g. Magruder, 2012; Hardy & McCasland, 2015)—and (ii) the "quality" of the individual's job (if any) (see also Davis & Harrigan, 2011; Card *et al.* , 2013, 2016). Moreover, changes in the probability of a worker being employed in a position belonging to a given type of occupation are informative not only of demand for qualified workers, but also of trends in "structural change" in developing economies.

Our three main sets of results are as follows. First, we find that the probability that an individual is employed increases by 4.4 and 10 percent respectively in the two groups of countries covered by our household survey datasets, and by 4.2 percent in South Africa, when fast Internet becomes available. We show that the increase in employment in connected areas in the first group of countries and South Africa is not due to displacement of jobs in unconnected areas, but that such displacement may explain some (though not all) of the especially large effect in connected areas in the second group of countries.[7]

Second, we find that the probability of being employed in a position belonging to a skilled occupation increases, and the probability of holding an unskilled job decreases, when fast Internet becomes available in Africa. These two broad International Labour Organization categories (ISCO level 2-4 versus 1) can be further broken down into four underlying occupational skill levels. In both South Africa and the eight poorer countries covered by a household survey that records occupation information, employment in "highly skilled" (ISCO level 4) and "moderately skilled" (ISCO level 2) occupations increases and employment in unskilled occupations (ISCO level 1) decreases. In South Africa, there is also an increase in employment in "somewhat skilled" occupations (ISCO level 3). While the impact on overall trends in structural change is likely modest, fast Internet thus appears to shift employment shares somewhat out of low-productivity occupations (such as small-scale farming and "elementary" work) and towards higher-productivity ones.

Third, inequality in employment outcomes falls when fast Internet arrives in Africa. In South Africa, it is those who completed primary or secondary school who see an increase in "any" and skilled employment.

[3]One household survey (Afrobarometer) covers Benin, Ghana, Kenya, Madagascar, Mozambique, Nigeria, Senegal, Tanzania, and South Africa; and the other (DHS) Benin, D.R. Congo, Ghana, Kenya, Namibia, Nigeria, Togo, and Tanzania. (We follow Young (2012) and McMillan & Harttgen (2014) in using DHS surveys to study the evolution of African economies). We refer to these 12 countries jointly as "Africa" for simplicity. We also use a labor force survey from South Africa, and firm data from Ethiopia and Ghana, Kenya, Mauritania, Nigeria, Senegal, and Tanzania.

[4]We study a diverse subset of the world's poorest countries and a transformative technology that may affect employment patterns through many different channels. Data limitations thus prevent us from investigating *all* such potential channels, or determining what share of the identified changes in employment patterns firm entry, productivity, and exporting account for. The literature on information frictions in developing countries, for example, hints at additional mechanisms that may also play a role (Bloom *et al.* , 2007; Antrás *et al.* , 2008; Magruder, 2010; Beaman & Magruder, 2012; Allen, 2014; Eaton *et al.* , 2015; Hardy & McCasland, 2015; Atkin *et al.* , 2017; Mitra *et al.* , 2016).

[5]See Henderson *et al.* (2012); Bleakley & Lin (2012); Michalopoulos & Papaioannou (2013); Lowe (2014) on night lights as a proxy for average incomes.

[6]While inequality is closely tied to unemployment also in advanced economies (see e.g. Galbraith, 2008), it has been natural in studies of tight(er) labor markets to focus primarily on wages. Results for employment shares are often presented as well.

[7]Interestingly, Atasoy (2013) finds correlations between broadband access and employment rates of only slightly smaller magnitude in rural and isolated areas of the U.S.

In other African countries, the employment rate increases for those with primary, secondary or tertiary education, but skilled employment increases most for those with secondary or tertiary education.

To compare these results to the existing evidence on recent SBTC in developed countries, we distinguish between the skill level of *jobs* and *workers*. Our findings suggest that fast Internet in Africa affects employers' relative demand for skilled and unskilled positions similarly to "computerization" and broadband Internet in rich countries (Autor *et al.* , 1998, 2003, 2008; Goos *et al.* , 2014; Katz & Margo, 2014; Akerman *et al.* , 2015), although the increase in employment in skilled occupations is notably bigger in Africa.[8] In contrast, while ICT tends to increase inequality across the educational attainment range in rich countries[9], fast Internet decreases (un)employment inequality in Africa. In South Africa, the technology also enables workers of low and intermediate educational attainment to shift into higher-skill jobs to a greater extent than highly educated workers. These results underscore that the factor bias of new technologies varies by context.

The changes in employment patterns observed when submarine Internet cables arrive in Africa occur through a combination of extensive margin (new users) and intensive margin (different use of the Internet by existing users) responses. We find a significant increase in firm entry (in South Africa), especially in sectors that use ICT extensively (e.g. finance), and in the productivity of existing manufacturing firms (in Ethiopia). The latter finding comes from a procedure where we first estimate how factor output elasticities change with fast Internet, controlling for a possible simultaneous change in firm level productivity (see De Loecker, 2011) to uncover the technology's (positional) skill bias in Ethiopia. In the last step of the procedure, we impose additional structure to estimate how firm level productivity responds, and find a significant increase. We also use firm level data from World Bank Enterprise Surveys to show that exports, website communication with clients, and on-the-job training increase among firms in Ghana, Kenya, Mauritania, Nigeria, Senegal, and Tanzania, after they get access to fast Internet.

In sum, the evidence we present indicates that greater and cheaper access to information and communication due to availability of fast Internet increases employment rates in Africa, and that in at least some countries, this happens in part due to the technology's impact on firm entry, productivity, and exports. In the final part of the paper, we show that, as expected, average incomes and wealth rise in the areas that see changes in employment when fast Internet arrives.

This paper contributes to the literatures on the relationship between globalization and jobs, poverty, and inequality; structural change; and constraints on firm growth in developing countries. The "new" features of international trade uncovered in the recent body of work on globalization (see Feenstra & Hanson (2003); Goldberg & Pavcnik (2007); Harrison *et al.* (2011); Goldberg (2015) for overviews) are important in part because they alter traditional models' prediction that locally relatively abundant factors necessarily gain the most from global integration.[10] A parallel literature convincingly demonstrated SBTC's role in slowing wage growth and rising unemployment among less educated workers in rich countries.[11] The

[8] Of course, the types of skilled positions that exist in Africa may differ from those in rich countries.

[9] Acemoglu & Autor (2011) and Michaels *et al.* (2014) find that, if three skill levels are considered, ICT technologies substitute most for middle-skill workers in rich countries.

[10] Most existing studies find that trade liberalization tends to increase productivity in developing countries (Goldberg & Pavcnik, 2007), with more varied effects on poverty (Topalova, 2010; Winters *et al.* , 2004) and employment rates (see e.g. Currie & Harrison, 1997; Revenga, 1997; Harrison & Revenga, 1998; Marquez & Pages-Serra, 1998; Levinsohn, 1999; Moreira & Najberg, 2000). Currie & Harrison (1997) is an exception in that they study (trade reform in) Africa (Morocco). Fajgelbaum & Khandelwal (2015) show that trade benefits the poor through another a channel, i.e. because their consumption is relatively concentrated in traded goods.

[11] The relative demand for college graduates increased from the late 1980s onwards with take-up of computers in Europe and the U.S. (Krueger, 1993; Berman *et al.* , 1994; DiNardo & Pischke, 1997; Autor *et al.* , 1998; Machin & Van Reenen, 1998; Autor *et al.* , 2003; Beaudry & Green, 2003, 2005; Beaudry *et al.* , 2010; Acemoglu & Autor, 2011; Goos *et al.* , 2014; Katz & Margo, 2014; Michaels *et al.* , 2014). The explanation lies not only in "direct" factor complementaries, but also in associated worker sorting and organizational change (Bartel & Sicherman, 1999; Caroli & Van Reenen, 2001; Bresnahan *et al.* , 2002; Crespi *et al.* , 2007; Bloom *et al.* , 2012). Akerman *et al.* (2015) document an increase in the relative wages and productivity of high-skill workers when broadband Internet became available

ICT technologies shown to be skill-biased in the West spread also in poor countries. It was thus widely accepted that technological change was partly responsible for rising inequality there too.[12] However, to our knowledge there was never any direct evidence on the causal relationship between employment rates, inequality, and incomes in developing countries and the ICT technologies that were shown to adversely affect the relative labor market outcomes of low-skill workers in rich countries (Goldberg & Pavcnik, 2007).[13]

To date, research on the factor bias of new technologies in developing countries has largely focused on how technology-driven improvements in agricultural productivity affect the movement of labor in and out of agriculture (see Syrquin (1988) and Foster & Rosenzweig (2008) for overviews, and Bustos *et al.* (2016) for a prominent recent example). Such movement is a form of structural change (Clark, 1940; Lewis, 1955; Banerjee & Newman, 1993; Baumol, 2012; Herrendorf *et al.* , 2014), i.e. a change in the relative size of different sectors and occupations. Recent work on structural change has emphasized the importance of the manufacturing sector (Gollin *et al.* , 2002; Lagakos & Waugh, 2013; Gollin *et al.* , 2014; Rodrik, 2015); improvements in trends in structural change in Africa in the 2000s (McMillan & Harttgen, 2014; McMillan & Rodrik, 2014); and how trade liberalization can shift workers across sectors and across firms within sectors (see e.g. Attanasio *et al.* , 2004; Davis & Harrigan, 2011; Young, 2014). Beyond the role of agricultural productivity and openness to trade, the drivers of structural change are not well understood.

The literature on firms in developing countries has made considerable progress in the last decade and a half. The benefits of importing, exporting, and government contracts suggest that the size of the input and output markets that can be accessed is important even conditional on a firm's initial productivity (see e.g. Frías *et al.* , 2009; Goldberg *et al.* , 2010a,b; Amiti & Davis, 2012; Brambilla *et al.* , 2012; Atkin *et al.* , 2015; Ferraz *et al.* , 2015). Greater demand from richer consumers abroad has in turn been shown to enable firms to learn, and to produce higher quality products that may require more skilled workers (Verhoogen, 2008; Frías *et al.* , 2009; Atkin *et al.* , 2015). Existing evidence also indicates that firm performance is enhanced by improved coordination with suppliers, access to credit, and good management (Bloom *et al.* , 2007; McKenzie *et al.* , 2008; Bloom *et al.* , 2013; Casaburi *et al.* , 2013; Macchiavello & Miquel-Florensa, 2015). But we know little about what drives job creation, productivity, and exporting among firms in developing countries. This is especially true when the focus is on the poorest countries and/or specific technologies or inputs. The existing literature reviewed here, the role of ICT in the resurgence of U.S. productivity growth (Draca *et al.* , 2007; Oliner *et al.* , 2007; Jorgenson *et al.* , 2008; Syverson, 2011), and a considerable body of important correlational evidence from developing countries all underscore the promise of fast Internet.[14]

in Norway. More generally, SBTC studies that focus on advanced Internet technology in rich countries find positive correlations with local wage levels (see e.g. Czernich. *et al.* , 2011; OECD, 2013), and mixed results for the relative wage effects in richer versus poorer U.S. counties (Forman *et al.* , 2012; Champion *et al.* , 2012; Atasoy, 2013). Atasoy (2013) finds that a U.S. county gaining access to broadband services is associated with a 1.8 percentage points higher employment rate, with larger correlations in rural and isolated areas, among college-educated workers, and in industries and occupations that more heavily utilize college-educated workers. De Stefano *et al.* (2014) find no significant effect of broadband Internet on the performance of British firms.

[12] Interestingly, while income inequality has increased in many African countries in recent decades, the picture for Africa as a whole is less clear than for Asia and Latin America (Harrison *et al.* , 2011; Dabla-Norris *et al.* , 2015).

[13] There are important existing studies of mobile phones, mobile money, and TV in poor countries that focus on price variation across space, risk sharing, and cultural change as outcomes (Jensen, 2007; Jensen & Oster, 2009; Aker, 2010; Chong *et al.* , 2012; Jack & Suri, 2014). Jensen (2007)'s innovative study also shows that fishermen's profits increased and consumer prices decreased when mobile phones helped eliminate price dispersion across markets in Kerala. There is also important indirect evidence on SBTC in developing countries from studies that use trade liberalization episodes or exchange rate variation that simultaneously affect trade and technological change for identification, including Harrison & Hanson (1999); Acemoglu (2003); Attanasio *et al.* (2004); Aghion *et al.* (2005); Amiti & Cameron (2012); Frazer (2013); Raveh & Reshef (2016). Another indirect form of evidence that has been taken to suggest that SBTC has occurred in Latin America and India in recent decades is that the share of skilled workers has increased in most industries there (see Goldberg & Pavcnik (2007, p. 27)). Goldberg & Pavcnik (2007) note that the skill premium increased around the same time as trade reform occurred in several Latin American countries and India, but that inequality *decreased* in several South East Asian countries and China when they opened up their markets (see also Wood, 1999; Wei & Wu, 2002).

[14] Qiang & Rossotto (2009) find that, across developing countries, a 10 percent increase in broadband penetration is associated with

Relative to the literature, we make three main contributions. First, we use quasi-random variation in access to ICT technology to provide direct evidence on its consequences for employment rates, job inequality, and incomes in 12 developing countries. The results are important because they suggest that the factor bias of modern technologies differ in Africa. This implies that the primary explanation for rising inequality in poor countries may not be SBTC.

Second, we provide evidence on the relationship between structural change and ICT technology. This represents a first step towards understanding what drives structural change beyond the role of agricultural productivity and openness to trade. Our results qualify negative views of (other manifestations of) globalization in that fast Internet appears to increase both the share of skilled jobs and average incomes in Africa, and—at least in the Ethiopian context—productivity and employment in manufacturing.

Finally, we demonstrate how fast Internet affects employment, productivity, and exporting in African firms, expanding the body of evidence on why firms tend to grow slowly, and ways to stimulate job growth, in poor countries. Our findings on fast Internet and exports represent evidence of an interaction between technological change and trade that differs from trade-induced SBTC as analyzed by the existing literature.[15]

The rest of the paper is organized as follows. In Section 2 we lay out the background on Internet and jobs in Africa, and discuss examples of job creation often attributed to the submarine cables. In Section 3 we present our data, and in Section 4 the empirical strategy. The paper's main results are in Section 5, and in Section 6 we analyze *how* fast Internet affects employment in Africa. Section 7 explores the ultimate impact on employment-related living standards outcomes (incomes and wealth). Section 8 concludes.

2 Background

2.1 Internet infrastructure and use in Africa

In 2000, Africa as a whole had less international Internet bandwidth than the country of Luxembourg (ITU, 2000). By 2013, 13 percent of all Africans used the Internet, compared to 36 percent globally (Internet Society, 2013), and more than half of urban African adults owned Internet-capable devices (McKinsey Global Institute, 2013). Listed in decreasing order of average speeds and increasing order of frequency in Africa, the forms of Internet infrastructure that reach users—the "last mile"—are fiber cables, copper cables, wireless transmission using cell towers, and satellites (de M. Cordeiro *et al.* , 2003; Gallaugher, 2012). Prior to the last mile, Internet traffic travels through a national "backbone" of bigger (typically fiber) cables, as depicted in Figure I for South Africa.[16] The backbone was built by a national telecom in almost all countries, sometimes with "branches" added by private telecoms. Since Internet traffic was initially transmitted through telephone cables, the majority of the backbone network cables date back many decades (ITU, 2013).

In the 2000s, submarine Internet cables to Africa from Europe were built by consortia made up of private investors, African governments, and/or multilateral organizations (OECD, 2014).[17] The submarine cables were brought to shore at various landing points along the coast, typically one in each country passed by

a 1.38 percentage point higher GDP per capita growth rate. Clarke & Wallsten (2006) find that a 1 percentage point increase in Internet users is associated with 3.8 percentage points higher exports from low-income to high-income countries. Paunov & Rollo (2015) find that use of the Internet correlate positively with firm performance in a range of poor countries. Basant *et al.* (2011), using more detailed data on Brazilian and Indian manufacturing firms and more extensive controls, find the same for ICT technologies. Their novel results point to much higher rates of return to investment in ICT in Brazil and India than in developed countries.

[15] Here, causality runs from technological change to trade, rather than the other way around.

[16] Some experts include a "middle mile" in their categorization of Internet infrastructure.

[17] One of the 10 submarine cables that arrived in Africa during our data period connected the continent with both Europe and India, and another one with the U.A.E. We refer to the connection point of the submarine cables outside of Africa as "Europe" for simplicity.

the cable. Landing points were usually located just outside of a big city that was connected to the national backbone, such as Mombasa in Kenya. Figure II shows the 10 submarine cables that arrived in Africa during 2006-2014, as reported by Mahlknecht (2014).

Once plugged in, the submarine cables brought much faster speed and traffic capacities on Internet traffic to and from Europe and other continents to locations in Africa connected to the terrestrial network.[18] On a fiber-optic cable network, the technologically feasible increase in speeds and traffic post-submarine cable plug-in decays with cable length to the landing point to a negligible extent. In general, technological bottlenecks therefore arise at the backbone level only where networks owned by different owners connect to each other. In such cases, the Internet service providers (ISPs) operating on network A will transmit content to network B directly only if the two networks are not only physically connected, but also collaborating, for example through "peering" (ITU, 2013). If not, the fees that African networks charge each other for the exchange of traffic ("transit") are such that content stored on network A would likely be sent via other continents to users on network B ("tromboning"). While this partly explains the submarine cables' predicted effect on "experienced" speed and capacity, a more important fact is that "evidence suggests that in Africa very little Internet content is sourced locally, with the vast majority sourced internationally—including local content that is hosted overseas." (Kende & Rose, 2015, p. 15).[19] For example, Chavula *et al.* (2014) found that on average 75 percent of the traffic originating in Africa that is destined for African universities traverse links outside the continent, and Kende & Rose (2015) report that all of the top 14 commercial websites in Rwanda are hosted in Europe or the U.S.

The need for African Internet traffic to travel overseas is important for this paper. In combination with each country being covered by a single backbone network, the lack of "spillovers" from one coastal country's submarine connection to neighboring countries means that each country has a specific "treatment date"—the date when the first cable has arrived at the country's landing point and is plugged in.[20]

In Table I we show the mean and standard deviation of Internet speeds and use of the Internet across locations in Africa before the submarine cables arrived. The average (measured) speed was 307 kbps, with a standard deviation of 353 kbps.[21] These moderately high numbers partly reflect the fact that our speed data measure non-mobile connections. (In Section 3 we describe the data in detail; some limitations of the speed measure are discussed in Sub-section 5.1). The proportion of individuals who used the Internet daily and weekly was 9 and 17 percent on average, with standard deviations of 28 and 38 percent.

2.2 Jobs and firms in Africa

Given their diversity, we do not attempt to describe an average labor market among the 12 countries in our sample here. Instead Table I displays, for the groups of countries covered by our respective datasets, and focusing again on the period before fast Internet became available, the proportion of individuals that have a job, and the proportion that have a job in a skilled occupation. In Benin, D.R. Congo, Ghana, Kenya, Namibia, Nigeria, Togo, and Tanzania (the DHS sample), the employment rate is on average 70 percent, with a standard deviation of 46 percent. In Benin, Ghana, Kenya, Madagascar, Mozambique, Nigeria, Senegal,

[18] Being reached by submarine Internet cables from Europe implies a faster connection also to North America and other continents because of the extensive Internet infrastructure that connects Europe with other continents.

[19] The main reason is cost: "one content developer reported spending USD 49.99 per year for up to 150GB capacity overseas, compared to a Rwandan offer of over USD 900 for 50GB capacity" (Kende & Rose, 2015, p. 3). Africa pays over USD 600 million a year for within-Africa traffic exchange that is carried outside the continent (Internet Society, 2013).

[20] We exclude landlocked countries from our analysis because the extent to which they get treated (through coastal neighbors) is unclear.

[21] These numbers exclude the four biggest cities in each country (see Table II).

Tanzania, and South Africa (the Afrobarometer sample), the employment rate is on average 58 percent, with a standard deviation of 49 percent. In South Africa, the employment rate is 71 percent, with a standard deviation of 45 percent.

In the first group of countries, 53 percent have a job that belongs to a skilled occupation as defined by the International Labour Organization (ILO), with a standard deviation of 50 percent.[22] We also observe the type of occupation to which an individual's job belongs in South Africa; there, 49 percent have a skilled job, with a standard deviation of 50 percent.

It is worth noting that the 2006-2014 period we focus on was a period of high growth in many African countries (see also Young, 2012). In his book on 17 newly "emerging" African countries, Radelet (2011) includes five of the 12 countries in our sample. He argues that the unusually high growth rates since the late 1990s in the 17 countries he focuses on are explained by a combination of democratization, improved economic policies, debt reduction, new technologies, and a new generation of energetic leaders. However, some countries in our sample, especially South Africa, were badly affected by the 2008 global financial crisis.

In the third panel of Table I, we show the average number of workers, and workers in skilled positions, per firm in respectively Ethiopia and Ghana, Kenya, Mauritania, Nigeria, Senegal, and Tanzania (World Bank Enterprise Survey countries. See Section 3 for information on the firms included). In the latter group of countries, firms have 36 employees on average, with a standard deviation of 132 across firms, while large- and medium-sized Ethiopian manufacturing firms have 84 employees on average, with a standard deviation of 231. The number of skilled positions per firm, as proxied respectively by high salary positions and non-production positions, is 24 in Ethiopia and 10 in the first group of countries.

We return to the comparison between eventually treated and untreated locations in Section 4.

2.3 Examples of new job creation after the arrival of fast Internet

There are many articles in the media and case studies of new, and new types, of jobs in Africa being created after the arrival of fast Internet. Scruggs (2015) reports that "In 2009, a submarine fiber-optic cable landed on the beaches of Mombassa [...] Six years later, Nairobi is bursting with technology startups like Shop Soko, a sort of Etsy for Africa that allows shopkeepers to sell handmade goods to consumers worldwide. The Kenyan capital has also emerged as [a] base for high-tech heavyweights such as Google, IBM and Intel. From 2002 to 2010, the value of Kenya's tech exports rose from USD 16 million to USD 360 million." Nairobi's iHub incubator had according to McKinsey Global Institute (2013) helped develop more than 150 new technology businesses by 2013. Similarly, Harris (2012) reports that "With the landing of new submarine telecom cables off South Africa's coastline starting with Seacom in 2009, bandwidth prices began to tumble, removing one of the most significant barriers to the global competitiveness of the country's IT industry. That was a catalyst for the explosion of Cape Town's tech scene [...] [and] stature as a business process outsourcing [BPO] and offshoring hub." In 2013 there were more than 54,000 jobs in South Africa's new BPO sector, and Morocco's was at similar scale (McKinsey Global Institute, 2013). Growth in the technology sector also has add-on benefits in other sectors, for example construction.[23]

Nigeria is one of the African countries where "eCommerce" has taken off, driven in part by major online retailers such as Konga and Jumia (Rice, 2013), which also operate in Egypt, Ivory Coast, Kenya, and Morocco. Online purchases in Nigeria stood at more than USD 1 billion in 2014, tripling in three years (Atuanya & Augie, 2013). Adepetun (2014) of the online news site AllAfrica.com argues, based on interviews with

[22] ILO's definition of skilled occupations is fairly wide; in Section 5.5 we consider each of the underlying categories.

[23] Scruggs (2015): "In Nairobi's Kilimani area, where the tech scene is centered, ten-story office buildings are shooting up."

officials and industry executives, that Nigeria's ICT sector from 2004 to 2014 created 100,000 direct jobs, and 1.1 million jobs indirectly, increasing its contribution to the country's services sector from 0.04 to 19 percent, and that eCommerce and ICT's success in Nigeria is due in part to the arrival of the submarine cables.

Kenya, Nigeria and South Africa all now have a manufacturing sector producing Internet-capable devices for the African market, such as low-cost cell phones and computers (McKinsey Global Institute, 2013).

There are also signs that the arrival of fast Internet helped make supply chain coordination easier. For example, Mozambican moWoza and similar start-ups in other African countries use smartphone apps and websites to deploy taxi drivers and others to deliver parcels from wholesalers to traders, and the bureaucracy required to import and export in Ghana can now be done online, which has decreased delays considerably (McKinsey Global Institute, 2013). Such improvement in coordination along the supply chain are believed to enhance productivity in agribusiness and manufacturing. For example, the adoption of cloud-based supply-chain management solutions by the Kenyan Tea Development Agency connected around 60 tea factories with the farmers that supply them. This reportedly reduced delays at collection points and fraud, and increased tea factories' productivity and farmers' incomes (Business Daily, 2009; GIZ, 2014).

Technology start-ups, BPO, eCommerce, new forms of manufacturing, and innovative supply-chain management companies and regulatory agencies that make doing business easier for factories and farmers are of course only examples of the ways in which fast Internet may enable greater job creation. But the technology may also eliminate jobs in some occupations, or conceivably even on average, for example due to automation or increased exposure to Asian competition. In the next section we present the data that we use to investigate the causal impact of fast Internet on employment in Africa.

3 Data

Our outcome data come from the following sources:

Afrobarometer surveys are nationally representative repeated cross-sections conducted every two-three years in many African countries. The order in which locations are surveyed is randomly determined. We geo-code the location based on information provided on the respondent's residence. Men and women of voting age are interviewed. The survey asks socioeconomic questions, and records opinions about a range of political topics. We use Afrobarometer data from coastal countries that had survey rounds both before and after submarine cable arrival in the relevant country: Benin, Ghana, Kenya, Madagascar, Mozambique, Nigeria, Senegal, Tanzania, and South Africa.

From Afrobarometer we construct an outcome variable for the individual being employed.[24] We also use variables on educational attainment and Internet use.

Demographic and Health Surveys (DHS) are nationally representative repeated cross-sections. The order in which sampling clusters are surveyed is randomly determined. GPS coordinates for sampling clusters are recorded. Women and men between 15 and 49 years old are interviewed.[25] The survey asks questions about labor market participation, health, and demographic background. We use DHS data from coastal countries that had survey rounds both before and after submarine cable arrival in the relevant country:

[24] The question states "Do you have a job that pays a cash income?".

[25] While DHS surveys both women and men, its primary focus is on women (and children): the "Man's Questionnaire" is shorter, and fewer men are surveyed. About 30 percent of the DHS sample we use is male. Note also that, for two of the countries in our DHS sample (Tanzania and Togo), the pre-treatment survey round we use was conducted in the late 1990s, rather than in the years preceding the arrival of submarine cables as for the other DHS countries (these two countries did not have a survey round in the years preceding the arrival of submarine cables). Our results are essentially unchanged if these two countries are excluded from the sample. In Afrobarometer, Tanzania was surveyed in 2008.

Benin, D.R. Congo, Ghana, Kenya, Namibia, Nigeria, Togo, and Tanzania.

From DHS we construct outcome variables for the individual being employed[26] and being employed in a specific type of occupation. We also use educational attainment variables and a wealth index.

The South Africa Quarterly Labor Force Survey (QLFS) is a nationally representative repeated cross-section. Unlike in Afrobarometer and DHS, QLFS surveys are carried out every quarter. GPS coordinates for enumeration areas are recorded. The current version of the survey began in 2008.[27]

From QLFS we construct outcome variables for the individual being employed[28] and being employed in a specific type of occupation. We also use educational attainment variables.

South African companies are required to register with the **Companies and Intellectual Property Commission (CIPC) Firm Registry**. The resulting zip-code×date level panel registry captures entry and exit of formal firms. CIPC provided us with data from 2007 quarter 1 to 2014 quarter 4. We code up each firm's sector when its name contains sufficient information to do so.[29]

The Ethiopia Large and Medium Scale Manufacturing Industries Survey (LMMIS) is an annual survey of all Ethiopian manufacturing establishments that engage 10 or more persons and use power-driven machines. We use the 2006 to 2013 rounds. The survey collects information on employees, inputs, production, sales, and assets, and is used to construct the country's national accounts.

From LMMIS we construct an outcome variable for the number of employees per firm. As proxies for skilled and unskilled positions, we use high-salary and low-salary positions.[30] When estimating production functions, we also use measures of output (value added), capital (total book value), and intermediate inputs.

The World Bank Enterprise Survey (WBES) is a nationally representative sample of formal firms with five+ employees from all sectors. The survey asks about the business environment, operations, output, and input use. We use WBES data from coastal countries that had survey rounds both before and after submarine cable arrival in the relevant country: Ghana, Kenya, Mauritania, Nigeria, Senegal, and Tanzania. The surveys for these countries were carried out in 2006, 2007, 2013, and 2014.

From WBES we use measures of national sales, indirect exports, and direct exports; communication with clients through a website and email; and whether the firm provides training to its employees. As proxies for skilled and unskilled positions, we use non-production and production positions.

We also use Internet infrastructure and speed data. We use **Mahlknecht's map of submarine cables** to measure landing points and -times (Mahlknecht, 2014), and **www.africabandwidthmaps.com** and **AfTerFibre** (AfTerFibre, 2014)'s maps of terrestrial backbone networks to measure locations' connectivity.[31]

Our data on Internet speeds come from the "content delivery network" **Akamai** Technologies, Inc., which owns servers worldwide and serves 15-30 percent of all Internet traffic. Akamai averages the speeds recorded for residential users, educational institutions, government offices, and firms in a given location×quarter, excluding those who connect via mobile networks. (We discuss a limitation of this measurement method in Sub-section 5.1). Akamai provided us with quarterly data on average connection speeds for ∼900 African locations during the 2007-2014 period. These locations are shown in Appendix Figure A1.

[26] The question states "Aside from your own housework, have you done any work in the last seven days?".

[27] From 2010 quarter 3 onwards, the QLFS changed the way observations are linked to enumeration areas and locations. We thus restrict attention to the period prior to then. The results are not sensitive to this decision.

[28] The question states "In the last week, did you work for a wage, salary, commission or any payment in kind (including paid domestic work), even if it was only one hour?".

[29] The procedure is described in the Appendix. We were able to assign a sector to 67 percent of the firms based on their names.

[30] LMMIS does not contain information on occupational categories. Skilled (high-salary) / unskilled (low-salary) positions are defined as those where salary is higher/lower than 800 Birr per year, approximately the sample salary median.

[31] Note that we consider Ethiopia (eventually) "treated" because it is well-documented that the country's backbone became internationally connected via the submarine cable landing point in Djibouti, which was planned and built to also cover Ethiopia (Giorgis, 2010; Oxford Business Group, 2015).

4 Empirical Strategy

We analyze the relationship between employment patterns in a given location and time period on the one hand and whether or not the location is connected to submarine Internet cables from Europe via the terrestrial backbone network on the other. We run

$$y_{i\mathbf{j}(i)t} = \alpha + \beta \text{SubmarineCables}_{it} \times \text{Connected}_i + \delta_{\mathbf{j}(i)} + \eta_t + \epsilon_{i\mathbf{j}(i)t} \tag{1}$$

where $y_{i\mathbf{j}(i)t}$ is an outcome for individual i in grid-cell $\mathbf{j}(i)$ and time period t. The 0.25×0.25 degree (∼25×25 km) grid-cell fixed effects[32]—$\delta_{\mathbf{j}(i)}$—and time period (quarter or year) fixed effects[33]—η_t—control for any time- or location-invariant differences in employment outcomes that may be correlated with access to fast Internet. SubmarineCables$_{it}$ is a dummy variable equal to one if the backbone network in the country individual i is in has been connected to at least one submarine cable at t, and Connected$_i$ is a dummy variable equal to one if individual i's location is connected to the backbone network. We cluster the standard errors at the grid-cell level.[34] Most of our outcome variables are 0/1; the ones that are not are highly skewed. We transform these using the inverse hyperbolic sine (asinh).[35]

We define a location as *connected* if it is near infrastructure that makes availability of fast Internet possible, i.e. the country's backbone network. (We refer to a location as "treated" at t if additionally at least one submarine cable has arrived in the country at t). We use maps of Africa's backbone networks prior to the arrival of the 10 submarine cables to define such connectivity.[36] Using Southwestern South Africa and the QLFS dataset as an example, Figure I displays the grid-cells that we use to define location fixed effects, the area's backbone network, as well as dots that represent the location of each enumeration area.

In Sub-section 2.1 we discussed how the technologically feasible increase in traffic and speeds post-submarine cable arrival decays with cable length *along* fiber backbone networks to a negligible extent. Connectivity *is* lower further away from than close to the backbone network, but the connectivity reach beyond the backbone network depends on the last mile infrastructure in place in a given area (Commonwealth Telecommunications Organisation, 2012; Banerji & Chowdhury, 2013). Since we lack information on last mile infrastructure at the local level, we define as connected those locations that are less than 500 meters from the backbone network.[37] Dividing the sample into two groups facilitates easy inspection of possible differences in pre-trends in the outcomes across connected versus unconnected locations, and this approach also simplifies interpretation of the estimates. In Section 5, we show that our results are robust to varying the radius used to define connectivity, and relax the binary definition of connectivity.[38]

[32]These grid-cells correspond to the commonly used Equal-Area Scalable Earth Grid constructed by NASA (Brodzik *et al.* , 2012).

[33]We use the quarter in which the survey was conducted (or to which the observation belongs) to designate a given observation as pre- versus post- submarine cable arrival in all our outcome datasets as this is the time level at which Mahlknecht (2014)'s map of submarine cables reports arrival times in the various landing point cities along the coast.

[34]Our results are robust to instead clustering the standard errors at the level of administrative units and to computing standard errors using methods designed to account for spatial correlation, as discussed in Section 5.

[35]The asinh function closely parallels the natural logarithm function, but is well defined at 0 (see Card & DellaVigna, 2017).

[36]To construct our map of the initial backbone network, we start with AfTerFibre's 2013 map (which is publicly and freely available, and for which corresponding GIS shape files are provided). We then use a map of backbone networks in Africa from www.africabandwidthmaps.com that is available (for purchase, and without shape files) both for 2009 quarter 2 and 2013 quarter 2 to identify the (few) backbone segments built during that period. Finally, we "remove" these new segments from the AfTerFibre map. In Section 5 we vary the measurement and definition of connectivity in various ways.

[37]We calculate the distance between an individual, firm or location in the sample and the nearest point on the country's backbone network. For DHS and Afrobarometer, we define the location of an individual as the GPS coordinates provided for his or her sampling cluster or village/neighborhood. For QLFS, we observe the location of the (∼80,000) enumeration areas individuals belong to. In QLFS we thus define the location of the individual as the GPS coordinates of the centroid of his or her enumeration area.

[38]Our empirical strategy may underestimate the true effect of fast Internet in treated locations since locations further than 500 meters from the backbone network may also benefit from the arrival of submarine cables, even if they do so to a lesser extent. It is also possible

The identifying assumption is that locations close to and further away from the terrestrial backbone network were on parallel trends in employment outcomes prior to the arrival of submarine Internet cables in Africa, and did not experience systematically different idiosyncratic shocks after the submarine cables arrived. Table I includes, in addition to the overall employment rates by groups of countries covered by our respective datasets, the breakdown by connected versus unconnected areas. Differences in employment rates are small in most countries; in the DHS and Afrobarometer countries the employment rate is respectively three and two percentage points higher in unconnected areas, while in South Africa the employment rate is seven percentage points higher in connected areas. The rate of employment in skilled positions is five percentage points higher in connected areas in the DHS countries, and eight percentage points higher in connected areas in South Africa. Firms on average employ 13/5 and 25/20 workers in skilled positions in connected/unconnected areas in the WBES countries and Ethiopia respectively. Internet speeds and take-up rates are essentially equal in connected and unconnected areas.

Location fixed effects control for level differences in employment patterns between connected and unconnected areas. In Sub-section 5.3 we investigate possible violations of the identifying assumption of parallel trends. We show that our results are robust to varying the radius around the backbone network used to define connectivity status; to varying the size of the grid-cells used to define location fixed effects; to defining the backbone network as the intersection of cables reported by two different data sources; to excluding landing point locations; to excluding locations far from the backbone network; to including "placebo treatments" that interact $\text{SubmarineCables}_{it}$ with proximity to roads, electricity networks or 3G coverage; to including country×year fixed effects; to controlling for location-specific linear and non-linear trends in the outcomes; to including leads and lags of $\text{SubmarineCables}_{it}$; and to two alternative ways to compute standard errors. We also show direct evidence of parallel pre-trends, and that our estimates remain significant if we use a non-parametric permutation test for inference.

Figure II shows the submarine cables that had arrived in different landing point cities along the coast at various times during our data period. The figure illustrates two important aspects of the identifying variation we exploit. First, submarine cables arrive at many different points in time, and at different points in time in different countries. This means that we compare connected and unconnected locations across many different points in time rather than a single date.[39] Second, the order in which different countries are reached by a given submarine cable is geographically determined. It is thus a priori unlikely that arrival times correlate with temporal variation across countries in differences between the economic trajectories of connected and unconnected areas.

5 Results

5.1 Submarine cable arrival and Internet speed and use

Before analyzing how access to fast Internet affects employment in Africa, we document that the arrival of submarine cables from Europe increases both average speeds and use of the Internet. Columns 1 to 5 of Table II shows results from running (1) with the outcome variable defined as the average Internet speed in a given location×quarter as measured in Akamai's data. We find that submarine cable arrival increases measured speed in connected locations, relative to unconnected locations, by 25 percent in the full

that neighboring locations suffer (or benefit) from the greater increase in access to fast Internet in connected locations. In Section 5 we vary the connectivity radius and compare locations close to, far from, and intermediate distance from the backbone network.

[39] Appendix Table A1 lists when the countries in our sample were surveyed and when they were reached by submarine cables.

sample; 25 percent when we leave out the biggest cities in each country; and by 41 percent when we also restrict to location×quarters where Akamai's average speed measure is based on more than 10 underlying IP addresses.[40] When we control for country×year fixed effects and connected×year fixed effects in columns 4 and 5, the estimated coefficient on the access to fast Internet indicator is 37 and 45 percent respectively. (We motivate and discuss these controls in detail in Sub-section 5.3).

Akamai informed us that, because only a fraction of their African speed tests were "sent" to servers on other continents during our data period, the coefficients estimated in columns 1 to 5 of Table II are likely much smaller than the true effect of the submarine cables on speeds experienced by users.[41] This is line with numerous media reports and existing analyses documenting large increases in speed with the arrival of submarine cables in Africa (see e.g. BBC, 2009; CNN, 2009; State of the Internet Report, 2012).

In the Afrobarometer surveys, respondents are asked if they use the Internet daily or weekly, which we take as proxies for work-related use. In columns 6 and 9 of Table II, we show results from again running (1), except that the outcome variable is now a dummy for the individual reporting that he or she uses the Internet. We find that submarine cable arrival increases the probability that an individual uses the Internet daily in connected relative to unconnected locations by about five percent on average, and the probability that she uses the Internet weekly by nine percent. When we control for country×year fixed effects and connected×year fixed effects in columns 7+10 and 8+11, the estimated effect of access to fast Internet on daily and weekly Internet use is 7/10 and 10/10 percent respectively.

There are likely two reasons why use of the Internet increases with submarine cable arrival. First, the technology becomes more useful to potential users. Second, the arrival of the submarine cables led to "drastic falls in prices for international capacity" (Kende & Rose, 2015, p. 15); a cost decrease that ISPs likely partly pass on to users via lower prices. Of course, the increase in take-up by *employers* after the arrival of the submarine cables may be greater than the effect for individuals that we can identify in the Afrobarometer sample. In Section 6, where we use firm level data to explore channels through which fast Internet may effect employment, we analyze how firms' use of websites and email responds.

We conclude that, while data limitations prevent us from pinning down the exact magnitude of the increase in experienced speeds and commercial use of the Internet with the arrival of fast Internet infrastructure in Africa, both rise considerably. This highlights that an impact on employment patterns may arise both through inframarginal users increasing and changing their use of the Internet, and through take-up by new users. In Section 6 we analyze the economic channels through which effects on employment may arise.

5.2 Fast Internet and employment rates

In Table III we report this paper's first main findings: the estimated effect of the arrival of fast Internet on employment rates in Africa. In the eight countries for which we have DHS data—Benin, D.R. Congo, Ghana,

[40] As explained in more detail in the notes to the table, the 500 meter connectivity radius may misclassify the biggest, connected cities in Akamai's sample as unconnected, and Akamai recommends restricting attention to locations where their speed measure is based on many IP addresses. Our preferred approach is thus to leave out the biggest cities and #unique IP<10 locations. As seen in the table, the estimated effect of fast Internet is of similar magnitude and significant also in the full sample.

[41] The reason is that Akamai's technology normally tests a user's speed of connection to a nearby server. In general, during our data period, the speed recorded was that to a server in another country—typically in or via Europe—only in cases where Akamai did not own a server that was located within the user's ISP's own network or directly upstream. It is, however, primarily speeds on traffic to other continents that are affected by the submarine cables, as discussed in Sub-section 2.1. Almost all Internet traffic from Africa did indeed travel to or via other continents during our data period, as also discussed in Sub-section 2.1. Despite significant efforts, we have not managed to find Internet speed data covering our data period that explicitly measure speeds between specific locations in Africa and other continents over time. We also attempted to obtain information from Akamai that would allow us to separate out the speed tests that were sent to other continents, but data on the individual tests, locations of their servers, and the algorithms determining where tests from a given location is sent are intellectual property Akamai is unwilling to share with us.

Kenya, Namibia, Nigeria, Togo, and Tanzania—we find a 3.1 percentage point, or 4.4 percent, increase in the probability that an individual is employed when fast Internet arrives. In the nine countries for which we have Afrobarometer data—Benin, Ghana, Kenya, Madagascar, Mozambique, Nigeria, Senegal, Tanzania, and South Africa—we find an even bigger 5.8 percentage point, or 10 percent, increase in the employment rate. In South Africa—for which we use labor force survey data—we see a 3 percentage point or 4.2 percent increase in employment.

Given the large magnitude of these estimates, one may wonder to what extent they reflect "real" additional economic activity. In Panel B of Table III, we use more detailed work-related questions available in the QLFS dataset to investigate this. In column 1, we show that access to fast Internet increases hours worked by 14 percent on average. This helps rule out, for example, that fast Internet simply allows individuals to smooth out their work hours over time (which could affect how they answer employment questions in a survey). The increase in hours worked also helps explain why the technology reduces the probability that an individual "wants to work more" by 3 percent, as seen in column 2. Another possibility is that the estimates in the top panel of Table III reflect formalization of pre-existing informal jobs rather than additional employment. This is unlikely because all the surveys we use ask about employment status in a way that should capture also informal employment (see Section 3). The QLFS survey explicitly records both formal and informal employment. As seen in columns 3 and 4 of Panel B, the estimated increase in formal employment is bigger than the estimated increase in any employment, while the estimated effect on informal employment is zero.

The evidence thus suggests that "real" employment in Africa increases substantially when fast Internet becomes available. In the next sub-section we probe the identifying assumption underlying our causal interpretation of the estimates in depth.

5.3 Robustness

We start by confirming that the estimated effect of fast Internet is not sensitive to the radius around the backbone network used to define locations' connection status. In Table IV, we show how the results change with both smaller and bigger increases and decreases in the connectivity radius. In almost all cases, the estimate remains highly significant and quantitatively very similar to that in Table III. In Appendix Table A2, we show that the results are also not sensitive to the size of the grid-cells used to define location fixed effects.

In Table V, we vary the backbone cables used to define connection status and the sample analyzed in several ways. We first use the intersection of the AfTerFibre and www.africabandwidthmaps.com maps to define connectivity.[42] It is reassuring that the estimated effect of fast Internet is essentially unchanged when we use only backbone cables reported by both these sources to define connectivity, as seen in Panel A.

In Panel B of Table V, we exclude from the sample all individuals located less than 20 kilometers from a landing point. The locations that were chosen as landing points are, in addition to being on the coast, typically in or near large cities. If such locations were on a different trend in employment before the arrival of submarine cables, we may incorrectly attribute an estimated treatment effect to the arrival of fast Internet. However, the results are essentially unchanged when we exclude near-landing point locations.[43]

[42]The drawback of this approach is that we can only implement it with "post-treatment"—2013—backbone maps (see Section 4). However, few backbone cables were finalized and "turned on" during our data period.

[43]Note that this finding also implies that an increase in demand due to the building of the submarine cables themselves cannot explain the effect on overall employment rates. Locations near the landing points are presumably places where a lot of the submarine cable- driven increase in construction and related employment would have occurred.

In panels C and D of Table V, we exclude from the sample all observations in locations that are respectively more than 10 and 5 kilometers from the backbone network itself. Though there are arguments for including remote locations in the sample—they are presumably less likely to be indirectly affected by the arrival of fast Internet than unconnected locations closer to the backbone—such locations likely differ more from connected locations. The estimates in panels C and D make clear that our findings in Table III are not driven by the inclusion of remote, less comparable locations in the analysis sample.

In Table VI we include additional controls. In most African countries, a part of the backbone network runs parallel to other infrastructure such as roads or electricity cables (see Appendix Figure A2). If locations near such infrastructure saw faster employment growth over time, irrespective of whether they were also connected to the Internet backbone, there is a risk of misattributing employment growth to the arrival of submarine cables. We thus use maps of Africa's road and electricity network to define each location's "road-connectivity" and "electricity-connectivity" status, exactly as we do for Internet backbone-connectivity.[44] We interact these with the arrival of submarine Internet cables—analogously to the construction of $\text{SubmarineCables}_{it} \times \text{Connected}_i$ in (1)—to construct placebo road- and electricity treatments. When these are included, the estimated effect of fast Internet remains essentially unchanged and the estimated coefficients on the placebo treatments are small and insignificant, as seen in columns 1, 4, and 7 of Table VI.

In column 7 of Table VI, we also include a placebo treatment that interacts $\text{SubmarineCables}_{it}$ with an indicator for the location having 3G mobile coverage at t, similarly to the approach for roads and electricity connectivity (except that 3G coverage varies over time). This is possible when we use the QLFS sample since 3G coverage data is available for South Africa. The coefficient on the treatment variable for access to fast Internet falls only slightly, and remains significant. It is thus clear that Internet affects employment rates whether or not the area is covered by the 3G network.

In columns 2 and 5, we include country×year controls. This is possible when (1) is estimated on the multi-country DHS and Afrobarometer samples, where the arrival of submarine cables is staggered and country×year can be included in addition to location fixed effects and the treatment indicator. With this additional control included, the change in the probability of employment for individuals in connected locations when fast Internet arrives is estimated in comparison only to the corresponding change for unconnected individuals in the same country and at the same point in time.[45] The results are essentially unchanged. In column 8, we approximate the same control in the South Africa- only QLFS sample by including province×quarter fixed effects, again with little impact on the estimated treatment effect of interest.

We next control for a "non-linear trend" in employment that is specific to the connected locations. Specifically, we include interactions between the Connected indicator and the time fixed effects in columns 3 and 6 of Table VI. This is possible for the multi-country DHS and Afrobarometer samples, where the arrival of fast Internet is staggered across time. Estimating the treatment effect of interest while controlling for Connected×Time FEs is unusually demanding on the data. Remarkably, the estimated coefficient on $\text{SubmarineCables}_{it} \times \text{Connected}_i$ is essentially unchanged, in both the DHS and the Afrobarometer sample.[46] In column 9, we again approximate the multi-country specification in the South Africa sample, now by including linear grid-cell specific trends. The estimated coefficient on the access-to-fast-Internet indicator

[44]The GIS shapefile for African electricity grids comes from The Africa Infrastructure Country Diagnostic (AICD), and that for African road networks from the Socioeconomic Data and Applications Center (SEDAC) at the Center for International Earth Science Information Network at Columbia University.

[45]Similarly to excluding observations far from the backbone network from the analysis sample, including country×year controls has the likely benefit of making the treatment and control groups compared more similar, but comes at a cost. The cost is that, when including country×year, we exclude groups of individuals who are comparatively unlikely to be indirectly affected by the arrival of fast Internet in the relevant country from the comparison group.

[46]In the latter, the estimate is no longer statistically significant as we lose precision with non-linear trends included.

is essentially unchanged.

Finally, in columns 10 and 11, we include a lead and a lag of SubmarineCables$_{it}$. This is possible in the QLFS dataset, wherein data is collected every quarter. Most of the effect of SubmarineCables$_{it}$ $\times$ Connected$_i$ loads on the lag, indicating that it takes time for the full impact of fast Internet on employment to arise, as we would expect. More importantly, the estimated coefficient on the lead is near zero and insignificant, supporting the identifying assumption of parallel trends.

Bertrand *et al.* (2004) pointed out that serial correlation can bias standard errors in difference-in-differences analysis. To address this concern, we follow Chetty *et al.* (2009) and conduct a non-parametric permutation test of $\beta = 0$. We can do so in the QLFS dataset, where data is collected every quarter. We sample from the set of possible submarine cable arrival times, assigning a randomly chosen "fake" arrival time to each location while maintaining each observation's backbone connectivity status. Figure III depicts the empirical cdf of estimates resulting from permuting arrival times 500 times and running (1) on the fake datasets. The vertical line represent the true estimate: where it falls in the empirical cdf of estimates from datasets with permuted arrival times implies its p-value. As seen in the figure, the true estimate is near the top of the empirical cdf, with an implied p-value of 0.09.

Conley (1999) pointed out that *spatial* correlation may also require corrections to standard errors, and developed a method for implementing such corrections. In Panel A of Appendix Table A3, we present the estimates from Table III and standard errors that are calculated using Conley's method. In Panel B of the same table, we cluster the standard errors by administrative unit, rather than grid-cells. In both cases, the estimated effect of fast Internet on employment rates remains highly statistically significant.

Finally, in Figure IV, we again take advantage of the "high(er)-t" panel structure of the South Africa QLFS dataset to display the path of the employment rate in connected and unconnected areas before and after the arrival of the first submarine cable in South Africa. This allows us to inspect how the gap between the two areas evolves after fast Internet arrives, and, more importantly, to check if the identifying assumption of parallel pre-trends appears to hold. Indeed, while the employment rate in both areas declines between 2008 and 2011, in part due to the financial crisis that hit South Africa during that period, the shape of the graph is virtually identical for connected and unconnected areas before the submarine cable arrives in mid-2009. The gap in the employment rate between the connected and unconnected areas starts to increase soon after submarine cable arrival and widens further over time, illustrating the treatment effect estimated in Table III.

We conclude that the evidence suggests that the estimated effect of access to fast Internet on employment rates in Africa is robust and likely represents a causal response.

5.4 Fast Internet and employment rates across space

We have established that the arrival of fast Internet in Africa led to a large increase in employment rates in connected areas relative to unconnected areas. This finding would hold even if the SUTVA assumption is violated, but it is possible that we either underestimate or overestimate the "direct" effect of fast Internet access in treated areas in sub-section 5.2 because of mismeasurement or shifting of (existing or newly created) jobs across space. (Underestimates could be due e.g. to surveyed individuals commuting to work in or migrating to connected areas, whereas overestimates could be due e.g. to employment in untreated areas suffering from fast Internet arriving in neighboring treated areas). We now investigate this possibility.

First, note that we find no effect of access to fast Internet on migration in South Africa and Tanzania (for which the required data is available).[47]

[47]None of the surveys we use elicited respondents' migration status or place of birth in both "pre" and "post" survey rounds

Second, recall that we confirmed in Table IV that the estimated effect of fast Internet is not sensitive to the radius around the backbone network used to define connection status. This finding implies that our results are unlikely to be driven by a simultaneous decrease (or increase) in employment in areas neighboring connected locations.

Finally, we investigate more directly in Table VII. Recall that we consider individuals and areas located within 500 meters of the backbone network connected. We now divide those located outside of this connection radius into two groups: those 500 meters to 5 kilometers from the backbone and those further away than 5 kilometers from the backbone. We compare the two groups closest to the backbone to those further than 5 kilometers away, before and after the arrival of submarine cables on the coast. In the DHS countries and South Africa, there is no evidence of shifting of employment across space after the arrival of fast Internet: in those samples, the estimated coefficient on $\text{SubmarineCables}_{it} \times \text{I}[0.5 \text{ km} < \text{Distance} < 5 \text{ km}]_i$ is near zero and statistically insignificant. In the Afrobarometer sample, the estimates in Table VII indicate that the employment rate in areas located 500 meters to 5 kilometers from the backbone network may decrease somewhat after the arrival of fast Internet, however. In that sample, the estimated coefficient on $\text{SubmarineCables}_{it} \times \text{I}[0.5 \text{ km} < \text{Distance} < 5 \text{ km}]_i$ is -0.021, or 3.6 percent, but statistically insignificant. This raises the possibility that some of the relative increase in employment in connected areas in the Afrobarometer countries could be due to displacement of jobs in locations further from the backbone network. At 0.044, the estimated increase in connected areas in Afrobarometer countries is considerably larger than the estimated increase for connected areas in the DHS countries and South Africa; larger in absolute value also than the -0.021 estimated decrease in areas of intermediate distance from the backbone network in Afrobarometer countries; and significant also when $\text{SubmarineCables}_{it} \times \text{I}[0.5 \text{ km} < \text{Distance} < 5 \text{ km}]_i$ is included. We leave an investigation of the possibility of modest job displacement in areas of intermediate distance from the backbone network in Afrobarometer countries for future research. We now explore how fast Internet affects structural change as measured by occupational employment shares in Africa.

5.5 Fast Internet and employment in skilled and unskilled jobs

The overall response of employment to the arrival of fast Internet in Africa is made up of underlying changes in job creation and destruction across specific occupations and the sectors associated with those occupations. How technological change affects occupational and sectoral employment shares is particularly important in poor countries that have not (yet) industrialized, and in an age where countries' possible paths to prosperity may include more (or less) than the historically predominant agriculture-to-industry transition. To explore this question, it is important that we distinguish between *jobs* and *workers*. While none of our individual level datasets include (non-missing) information on workers' past occupation(s), two of them do record employed individuals' current occupation. Therefore, for example "the employment rate in occupation X" will here mean the probability of holding a job in occupation X (not the overall employment rate of workers who ("permanently") belong to occupation X). We believe that the changes in occupational employment rates we document mostly reflect changes in the size of different sectors.[48] But readers can alternatively

conducted during our data period. (QLFS contains a question about migration, but the variable is missing for the majority of the sample). But in South Africa and Tanzania, it is possible to run (1) with migration status on the left-hand side by using another data source (South Africa) or adding a later survey round conducted by DHS (Tanzania). Results available from the authors upon request.

[48] In addition to our expectation that low rates of tertiary education make African workers comparatively likely to switch sectors, this is because we in Section 6 find that when fast Internet arrives, there are noteworthy changes in firm entry across sectors in South Africa and an expansion of the manufacturing sector in Ethiopia. On the other hand, most studies find that another form of globalization—trade liberalization—in poor regions of the world mainly shifts workers across jobs within sectors (see e.g. Harrison & Hanson, 1999; Currie & Harrison, 1997; Attanasio *et al.* , 2004; Topalova, 2010). The literature has focused mostly on India and Latin America.

interpret the results in this sub-section as reflecting a combination of within- and across-sector changes in employment in skilled and unskilled occupations.

In Table VIII we use the DHS and QLFS datasets, where occupations are recorded and can thus be categorized. In the first two columns of Panel A, we define skilled and unskilled employment categories following the ILO's ISCO categorization of occupations' skill level (ILO, 2012).[49] In the DHS countries—Benin, D.R. Congo, Ghana, Kenya, Namibia, Nigeria, Togo, and Tanzania—the arrival of fast Internet increases the probability that an individual holds a skilled job by nine percent, and decreases the probability of unskilled employment by 12 percent. In South Africa, fast Internet increases the probability of skilled employment by seven percent and decreases the probability of unskilled employment by seven percent. Our findings thus imply a *positional* skill bias of fast Internet in Africa that is directionally similar to what has been found for computerization and fast Internet in the U.S. and Europe. The magnitude of the increase in employment in skilled occupations is particularly noteworthy.

In columns 3-6 of Panel A in Table VIII, we break the skilled category (ISCO levels 2-4) into its subcategories as defined by the ILO.[50] There is an increase in the probability of "highly" skilled (ISCO level 4) employment in both the DHS countries and South Africa; an increase in "somewhat" skilled (ISCO level 3) employment in South Africa; and an increase in "moderately" skilled (ISCO level 2) employment in both the DHS countries and South Africa, when fast Internet becomes available.[51]

In Panel B of Table VIII, we consider specific types of occupations.[52] We find that fast Internet increases the probability that an individual holds a professional job by 40 percent; a clerical job by 25 percent; and a services job by 25 percent, in the DHS countries. There is also a one and a half percentage point increase in domestic employment that is statistically significant, though off of a tiny base. Finally, there is a 23 percent decrease in the probability of working in agriculture on the individual's own farm. In South Africa, we find a 23 percent increase in the probability that an individual holds a legislative job; a 15 percent increase in the probability that she holds a technical job; and a seven percent decrease in the probability that she holds an "elementary" job, when fast Internet becomes available.

McMillan & Rodrik (2014) and McMillan & Harttgen (2014) show that the overall trends in structural change in Africa improved after 2000. While the low base rates must be kept in mind when interpreting the large magnitude of some of the estimates in Table VIII in percent terms, they suggest that greater and cheaper access to information and communication may be among the changes in the economic environment that helped shift workers out of small-scale farming and "elementary" work towards occupations that usually display higher productivity. We return to this question in sections 6 and 7, where we investigate whether firms whose productivity increased, or which started exporting more, also hired more workers when fast Internet became available, and how the technology affects living standards in Africa. In the next sub-section we explore how job inequality in Africa responds to the arrival of fast Internet.

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[49] Unskilled jobs (ISCO level 1) "typically involve performance of simple and routine physical or manual tasks" (ILO, 2012, p. 12).

[50] Moderately skilled jobs (ISCO level 2) "typically involve performance of tasks such as operating machinery and electronic equipment; driving vehicles; maintenance and repair of electrical and mechanical equipment; and manipulation, ordering and storage of information". Somewhat skilled jobs (ISCO level 3) "typically involve performance of complex technical and practical tasks that require an extensive body of factual, technical and procedural knowledge in a specialized field". Highly skilled jobs (ISCO level 4) "typically involve performance of tasks that require complex problem-solving, decision-making and creativity based on an extensive body of theoretical and factual knowledge in a specialized field" (ILO, 2012, pp. 12-13).

[51] There are no observations in the ISCO level 3 categories in the DHS sample.

[52] The occupational categories observed in the two datasets are: professional, clerical, sales, self-employed agriculture, employed agriculture, domestic, services, skilled manual, and unskilled manual (DHS), and legislate, professional, technical, clerical, services, skilled agriculture, craft, plant and machinery, elementary, and domestic (QLFS). In both Tables VIII and IX, we show results for all categories for which we find a significant effect of fast Internet in at least one of the two datasets in at least one of the two analyses.

5.6 Fast Internet and job inequality

Given the lack of direct evidence on the factor bias of ICT in poor countries, it is a priori unclear if fast Internet affects job inequality across the educational attainment range in Africa in the same way that "computerization" has been shown to do in rich countries (Katz & Autor, 1999; Bond & Van Reenen, 2007; Goldin & Katz, 2007; Akerman *et al.* , 2015). We investigate this question in Table IX. The initial employment rates that the estimates shown can be compared to are in Appendix Table A4. That table reports employment rates—overall, in skilled and unskilled jobs, and in specific occupational categories—for individuals with a completed tertiary degree, secondary school, primary school, or less than primary school, before the arrival of fast Internet. It shows that the probability of being employed in a skilled occupation rises with educational attainment, and the probability of unskilled employment falls with educational attainment, in both the DHS countries and South Africa (more so in South Africa). Appendix Table A4 also shows that individuals with less than secondary school do hold skilled jobs in Africa, for example in retail, commercial agriculture, and technical occupations; and that those with tertiary or secondary education also hold unskilled jobs, for example in "elementary" occupations.

In Table IX we report results from interacting $\text{SubmarineCables}_{it} \times \text{Connected}_i$ with educational attainment. In the DHS countries, the estimated rise in the employment rate is driven by those with primary school or more. The increase in employment is somewhat greater among those with secondary or tertiary education than among those with only primary school. In the Afrobarometer countries, the increase in employment is largest and significant only for those with primary school.[53] In South Africa, the increase in employment is driven by, and of similar magnitude for, those with primary or secondary school.

In the DHS countries, those with secondary or tertiary education see an increase in skilled employment. The increase is especially large for those with tertiary education. Unskilled employment decreases both for those with less than primary school and those with tertiary education. In South Africa, skilled employment increases for individuals with primary school and especially those with secondary school.

The results in Table IX in combination with those in Table VIII illuminate important similarities and differences in the way modern ICT technologies affect job inequality in Africa versus rich countries. We saw in Table VIII that the skill complementarity of fast Internet as defined by its relative impact on net creation (and/or saving) of high and low skill *jobs* in Africa resembles the skill-bias documented in the West. The results in Table IX show that, in the eight DHS countries in our sample, those with almost no education are the only group of *individuals* whose employment outcomes do not benefit from fast Internet. In these countries, while the technology increases *skilled* employment among more educated workers the most, fast Internet thus reduces (un)employment inequality across the majority of the adult population. In South Africa, even skilled employment increases more for individuals with primary or secondary school than for those with tertiary education. These results partially contrast both with existing findings on computers and fast Internet as SBTC in rich countries, and with the adverse effect of another important form of globalization—trade liberalization—on (income and wage) inequality in developing countries (Goldberg & Pavcnik, 2007; Harrison *et al.* , 2011; Goldberg, 2015).

For the DHS countries, these overall impacts can be understood in more detail by looking at the results for specific occupational categories, which we also show in Table IX (for South Africa, we lack the power to learn much from the occupation specific results when interacting the treatment with educational attainment,

[53]Note that we have less power in the Afrobarometer sample than in the bigger DHS and QLFS samples. The estimated coefficient on $\text{SubmarineCables}_{it} \times \text{Connected}_i$ is of similar magnitude for the other educational attainment groups in the Afrobarometer sample, but not significant.

but we display the results for completeness). For example, the increase in the overall employment rate for individuals with primary school is primarily due to an increase in employment in services and domestic occupations. Jobs in commercial agriculture shift from less to more educated individuals, probably reflecting technological upgrading in the sector. Workers with tertiary education are less likely to work in unskilled manual jobs and more likely to work in services, when fast Internet arrives.

The overall pattern that emerges in the DHS countries is arguably not surprising. The especially large increase in skilled employment for workers with tertiary education suggests that fast Internet is in one sense a high education-biased technology in these countries. The stock of workers with tertiary education is low in Sub-Saharan Africa, however. This may help explain why we observe a considerable increase in skilled employment also for workers with "only" secondary education in the DHS countries. The productivity of such workers may benefit from fast Internet only moderately less than that of tertiary education workers, and/or such workers may receive targeted on-the-job training (Green *et al.* , 2001; Frías *et al.* , 2009).[54] The increase in employment for workers with primary school in the DHS countries may be due, for example, to the emergence of new types of positions that are complementary to skilled jobs wherein highly educated workers make more direct use of Internet technology (see Acemoglu & Autor, 2011; Michaels *et al.* , 2014). The pattern in South Africa—where the employment rate of workers with primary and secondary school increases more than that of workers with tertiary education both overall and in skilled jobs—is more distinct. It could be, for example, that the "self-correcting" forces embedded in the evolution of group-specific wage levels and other factor prices (as in Acemoglu & Restrepo, 2015) are strong in South Africa; that workers there sort into new types of jobs during technological transitions based not only on educational attainment, but also ability (Galor & Moav, 2000); or that fast Internet is in fact a "middle education-biased technology" in South Africa in a production function sense. We leave a deeper exploration of these possibilities for future research, and in the next Section investigate *how* fast Internet affects employment in Africa.

6 Understanding how Fast Internet Affects Employment in Africa

6.1 Firm entry

The observed changes in average speeds and use of the Internet after the arrival of the submarine cables suggest that new, and new forms of, employment may occur both through extensive margin (new Internet users) and intensive margin (different use of the Internet by existing users) responses. In this sub-section, we analyze how fast Internet affects firm entry and exit; in the next two sub-sections we explore possible changes in the productivity and exports of existing firms.

We first use a dataset from South Africa's CIPC, which records the names, addresses (including zip-codes) of firms that register or de-register, and the date of registration/de-registration. We run (1) at the zip-code$\times$quarter level. As seen in Table X, we find a significant 5.6 percent increase in overall net firm entry per quarter when fast Internet arrives in South Africa. This increase is due to greater entry—the estimated change in firm exit is near zero and insignificant—and likely helps explain the increase in employment when fast Internet arrives in South Africa.

The specific sectors in which we see a significant increase in net firm entry and firm entry—commercial agriculture and the financial sector—are ones that use ICT extensively (World Bank, 2006). The point estimates are fairly large but not significant for several other sectors, including retail/sales and services.

[54] Such a scenario could increase incentives for educational attainment (Franck & Galor, 2017), but it takes time for the stock of educated workers to "catch up" (Goldin & Katz, 2008). In Section 6, we explore how access to fast Internet affects on-the-job training.

These sectoral responses in firm entry reinforce the view that fast Internet's impact on structural change was at least partly favorable insofar as productivity in the financial and agribusiness sectors is likely high relative to other sectors in South Africa (see e.g. Collier & Dercon, 2013).

6.2 Firm and labor productivity in existing firms

6.2.1 OLS results

We have seen that access to fast Internet increases firm entry, which appears to contribute to its impact on employment rates. Does the new technology also affect employment within existing firms, and, if so, why? To investigate these questions, we first use Ethiopia's LMMIS dataset of large and medium- sized manufacturing firms, which is to our knowledge the only African dataset with detailed enough information and the geographical and time coverage needed to estimate changes in firms' production function with the arrival of fast Internet. We restrict the sample to firms that are observed both before and after the submarine cable that gets connected to Ethiopia's backbone network arrives on the coast.

In columns 1-6 of Table XI, we continue to use a similar specification and definition of right hand-side variables as in (1), but i now represents a firm and observations are at the firm$\times$year level. The estimated increase in total employment per firm when fast Internet arrives is about 15 percent in column 1, where we control for firm and year fixed effects, and about 38 percent in column 2, where we control instead for grid-cell and industry$\times$year fixed effects. The estimated increase in skilled and unskilled positions per firm (as discussed in Section 3, these are proxied using salary bins) is respectively about six and eight percent (but not statistically significant) when we control for firm and year fixed effects, and (each) about 26 percent (and significant) when we control instead for grid-cell and industry$\times$year fixed effects. The firm level estimates of changes in employment when fast Internet arrives in Ethiopia are thus qualitatively comparable to the individual level employment results for the broader samples of African countries and South Africa in Section 5. The relative increase in unskilled positions appears larger in Ethiopian manufacturing firms.

In the last three columns of Table XI, we explore whether the increase in employment in Ethiopian manufacturing firms may be explained by an increase in the output elasticity of labor and/or firm level productivity with the arrival of fast Internet. We start with the following OLS regression:

$$\text{va}_{ijt} = x'_{ijt}\alpha + \text{SubmarineCablesConnected}_{ijt}x'_{ijt}\beta + \delta_{\mathbf{j}(i)} + \psi_{jt} + \epsilon_{ijt} \tag{2}$$

where va_{ijt} is the value added of firm i, in grid-cell $\mathbf{j}(i)$, industry j, and year t; x'_{ijt} is a set of inputs (labor, capital) used by the firm and a constant term; ψ_{jt} is an industry$\times$year fixed effect, and the other variables are as defined previously.[55] Results from this specification are in column 7 in Table XI. The coefficients on capital and labor are of similar magnitude to what other studies have found for comparable contexts. The estimated change in the output elasticity of labor in skilled positions increases significantly, from 0.473 to 0.531, with the arrival of fast Internet, but that of labor in unskilled positions falls. If accurate, these changes in the output elasticity of labor may help to explain the changes in employment seen in Section 5 and columns 1-6 of Table XI.

[55] To ease comparison with the structural results in columns 8 and 9 of Table XI, we interact only labor and the constant term with $\text{SubmarineCablesConnected}_{i\mathbf{j}(i)jt}$.

6.2.2 Structural estimation

OLS estimates of the share of variation in output attributable to different input factors may partly reflect the fact that some input factors—such as labor—are chosen after a firm's productivity (unobserved to the researcher) is fully or partially known to the firm. Olley & Pakes (1996) (OP) and Levinsohn & Petrin (2003) (LP) developed practical methods that help overcome such simultaneity bias. The commonly used LP method involves using intermediate inputs to proxy for a firm's unobserved productivity in the production function (see LP for details). Suppose we now posit the following "structural" model:

$$\text{va}_{ijt} = l_{ijt}\theta + \text{SubmarineCablesConnected}_{ijt} l_{ijt}\phi + \kappa k_{ijt} + \omega_{ijt} + \epsilon_{ijt} \tag{3}$$

where l_{ijt} are labor inputs and the productivity term ω_{ijt} subsumes the constant term and the fixed effects. ϵ_{ijt} represents a standard i.i.d. error term capturing unanticipated shocks to productivity and measurement error. We present LP estimates in column 8 of Table XI. As expected, the coefficient on capital is now bigger than the OLS estimate, while both $\hat{\theta}$ and $\hat{\phi}$ are now smaller in magnitude, and the $\hat{\phi}$ from the interaction of SubmarineCablesConnected$_{ijt}$ and workers in skilled positions is no longer significant.

De Loecker (2011) points out a methodological tension when using the OP/LP methods to investigate how a change in the operating environment affects output elasticities. Suppose that a firm's productivity *itself* is influenced by the change in the operating environment. If the productivity response in turn influences hiring, investment, and value added—as conventional models of firm behavior predict, and consistent with the results we have seen so far in Table XI—then changes in the coefficients on labor and capital estimated using methods that do not account for the firm level productivity response will be incorrect.

Inspired by De Loecker (2011), we assume the following law-of-motion for firm productivity:

$$\omega_{ij,t+1} = \alpha\omega_{ijt} + \tau \text{SubmarineCablesConnected}_{ijt+1} + \delta_{\mathbf{j}(i)} + \psi_{jt} + \xi_{ij,t+1} \tag{4}$$

where grid-cell and industry×year fixed effects control for differences across space in, and industry-wide shocks to, productivity. We continue to use the LP estimation procedure, but adjust the method to allow both the output elasticity of labor and firm level productivity itself to change. We first estimate ϕ while controlling for a possible response in firm level productivity to fast Internet. As in the conventional LP method, we use a flexible polynomial in the other input factors—including intermediate inputs—to proxy for ω_{ijt}. The adjustment we make in this first step is that we include SubmarineCablesConnected$_{ijt}$ among the factors included in the polynomial. We run:

$$\text{va}_{ijt} = l_{ijt}\theta + \text{SubmarineCablesConnected}_{ijt} l_{ijt}\phi + \Psi\left[m_{ijt}, k_{ijt}, \text{SubmarineCablesConnected}_{ijt}, \delta_{\mathbf{j}(i)}, \psi_{jt}\right] + \epsilon_{ijt} \tag{5}$$

where $\Psi\left[m_{ijt}, k_{ijt}, \text{SubmarineCablesConnected}_{ijt}, \delta_{\mathbf{j}(i)}, \psi_{jt}\right]$ is a polynomial of inputs used (m_{ijt}), capital (k_{ijt}), access to fast Internet, and grid-cell and industry×year fixed effects.

The estimated effect of fast Internet on the output elasticity of labor estimated through this procedure is reported in column 9 of Table XI. The estimated decrease in the output elasticity of labor in unskilled positions increases in absolute magnitude to -0.051 and remains significant. The estimated increase in the output elasticity of labor in skilled positions is very similar to the estimate from the conventional LP method—0.027.

In the second step of the procedure, we estimate the coefficient on capital by GMM using the moment condition $\mathbb{E}\left[\xi_{ijt}(\kappa)\, k_{ijt}\right] = 0$, which is motivated by the assumption that capital cannot be adjusted in response to unobserved shocks to productivity.[56] $\hat{\xi}_{ij,t+1}$ is obtained by taking the OLS residual from (4), where ω_{ijt} and ω_{ijt-1} come from applying (3), that is, by subtracting the labor coefficients estimated in (5) and the coefficient for capital from the predicted value added obtained from (5).

For our purposes the coefficient on capital is needed only as an input into the procedure for estimating how fast Internet affects firm level productivity. With estimates of the coefficients on labor, capital, and the interaction between labor and SubmarineCablesConnected$_{ijt}$ in hand, we can construct $\hat{\omega}_{ijt}$ using (3) and then estimate the law-of-motion for productivity in the third step. The results are reported in column 9 of the bottom panel of Table XI. The estimated increase in firm level productivity when fast Internet becomes available is around 12 percent and statistically significant.

We conclude that an increase in firm level productivity likely contributes to increased hiring in existing Ethiopian manufacturing firms after the arrival of fast Internet, and that changes in the output elasticity of skilled labor may also play a role. Ethiopian firms not only employ more workers in skilled positions after the arrival of fast Internet, but also more workers in unskilled positions. This is noteworthy because the output elasticity of such positions falls, and probably explained by the increase in firm level productivity.

6.3 Firms' exports, on-the-job training, and Internet communication

In Table XII, we use data from the World Bank Enterprise Surveys to explore how the arrival of the submarine Internet cables changed the behavior and performance of firms in Ghana, Kenya, Mauritania, Nigeria, Senegal, and Tanzania. The statistical power to detect changes in behavior and performance with precision is more limited in this dataset, in part because WBES firms are relatively concentrated geographically.[57] Nevertheless, informative patterns emerge. We include location fixed effects throughout. In panel A, we additionally include industry fixed effects; in panel B, industry$\times$year fixed effects; and in panel C, country$\times$year fixed effects.

As seen in columns 1 and 2, access to fast Internet has no significant effect on WBES firms' total number of employees, nor employees in unskilled positions (as proxied by production positions), although the point estimates are positive and fairly large. We find a significant 24-33 percent increase in the number of employees in skilled positions per firm (as proxied by non-production positions). The firm level estimates of changes in employment when fast Internet arrives in the WBES countries are thus comparable to the individual level employment results in Section 5.

In column 4, we show that firms are 118-142 percent more likely to provide on-the-job training to their employees when fast Internet becomes available. This finding may help explain why the technology boosts employment not only for highly educated workers, but also less educated workers, in Africa.

In columns 5 to 7, we explore how firms' sales responds to the arrival of fast Internet. We find a small and insignificant increase in in-country sales in column 5, and a large (30-58 percent) but insignificant increase in indirect exports in column 6. Most importantly, the estimated change in exports is positive, very large—167-178 percent—and significant, as seen in column 7. In light of the existing literature documenting the benefits to firms and employment consequences of exporting (see e.g. Verhoogen, 2008; Frías *et al.* , 2009; Goldberg *et al.* , 2010b; Atkin *et al.* , 2015), this finding suggest that one way in which fast Internet increases

[56] We use the OLS estimates as starting values, and bootstrapped standard errors.

[57] Because almost all firms in WBES are located in large cities and sub-city information on their location is not reported, a within-500-meters-of-the-backbone indicator incorrectly classifies many connected WBES firms/cities as unconnected (for example those in Abuja, Accra, Dar es Salaam, and Kano. That these cities are in fact connected to the backbone is clear: the maps show backbone cables whose route was clearly chosen to connect them). In WBES we thus classify firms/cities as connected if they are within the sample median distance of the network, which is about 3.5 kilometers. This issue is not relevant to our other datasets, where we have much more fine-grained information on individuals' and firms' location.

employment is by making it easier for firms to sell to customers abroad. The increase in exports is also evidence of an interaction between technological change and trade that differs from the trade-induced SBTC analyzed by an existing literature (Wood, 1995; Acemoglu, 2003; Attanasio *et al.* , 2004; Burstein *et al.* , 2013; Koren & Csillag, 2016; Raveh & Reshef, 2016). Here, causality runs from technological change to trade, rather than the other way around.

Unlike our other firm datasets, WBES contains information on firms' use of the Internet. As seen in columns 8 and 9, we find a large (18-23 percent) but statistically insignificant increase in firms' probability of communicating with clients through email, and a significant 56-68 percent increase in firms' probability of communicating with clients through a website, when fast Internet arrives. Easier website communication with clients may be part of the reason why African firms' ability to export increased when submarine Internet cables reached the continent.

In sum, we have seen evidence in this section indicating that the increase in employment when fast Internet arrived in Africa was driven in part by greater firm entry in South Africa; by higher firm level productivity in existing Ethiopian manufacturing firms; and by an increase in exports, on-the-job training, and use of website communication among firms in the six WBES countries in our sample. While the large magnitudes of these economic responses is important in their own right, data limitations prevent us from investigating what *share* of the changes in employment patterns they account for. Additional mechanisms likely also played a role.[58]

7 Fast Internet, Employment, and Living Standards

Some would consider employment a means to an end more than an end in itself. In Table XIII, we explore how the arrival of fast Internet ultimately affects living standards in Africa. We focus on individual level wealth and average incomes at location level. Increasing access to, and lowering the cost of, information and communication may affect living standards also through other channels than employment outcomes. But to the extent that fast Internet affects overall and skilled net job creation, we would a priori also expect such an employment response to ultimately translate into higher incomes and wealth.

In the DHS survey, enumerators calculate and record a 1-5 wealth index based on the respondent's ownership of selected assets (such as televisions, bicycles, high quality housing, etc). In column 1, we show that the arrival of fast Internet lead to an increase in households' wealth index score of about nine percent on average in Benin, D.R. Congo, Ghana, Kenya, Namibia, Nigeria, Togo, and Tanzania. In columns 2 and 3, we show that this estimate is essentially unchanged when we control for year fixed effects interacted with respectively country indicators and backbone connectivity.

In columns 3-6, we follow a growing literature and proxy for average incomes at location level with light density at night as measured by satellites (see e.g. Henderson *et al.* , 2012; Bleakley & Lin, 2012; Michalopoulos & Papaioannou, 2013; Lowe, 2014). In addition to capturing the *aggregate* economic benefits of fast Internet, an advantage of this income proxy is that it is available for all 12 countries in our sample. The National Oceanic and Atmospheric Administration (NOAA) provides pixel-level measures of average night light density from satellite images. We thus construct a grid of such pixels that are 0.1 degree apart[59], in the spirit of Michalopoulos & Papaioannou (2013). The estimating equation we use is (1) as throughout the paper; the i subscript now indexes the pixels. In column 3, we see that night light density rises by about 17

[58] For example, Hardy & McCasland (2015) show that small firms in Ghana are labor constrained. Fast Internet may ease information frictions and make it easier for employers and job-seekers to find each other through online job boards or work platforms.

[59] There are thus several of these pixels within each of the 0.25×0.25 degree grid-cells we use for location fixed effects.

percent when fast Internet becomes available. The sign and significance of the estimate is unchanged when we control for country×year fixed effects and connected×year fixed effects in columns 4 and 5; in the latter regression, the estimated effect of fast Internet on our proxy for average incomes falls to seven and a half percent.

The night lights data is available for every location, every year of our data period. This enables us to include a lead and a lag of $\text{SubmarineCables}_{it} \times \text{Connected}_i$, in column 7. As the impact on employment, the full effect of fast Internet on average incomes does not arise immediately: the estimated effect now loads on the lag. More importantly, the coefficient on the lead is near zero and insignificant, supporting the identifying assumption of parallel trends and a causal interpretation of the estimated effect of fast Internet on average incomes.

The balanced panel, "high(er)-T" format of the night lights data also allows us to trace out how fast Internet affects economic activity over time better than the household surveys we use allow. We do so in Appendix Figure A3 by interacting a location's connectivity status with years-to/since-cable-arrival-dummies, as in an event study. First, we see that year-to-year changes in average incomes in connected locations relative to unconnected locations hover around zero prior to the arrival of submarine cables. Second, relative average incomes in connected locations start to slowly rise the year fast Internet arrives. Third, the rise continues in each of the two following years, before relative average incomes in connected locations level off in the third "post" year. It thus appears that the impact of fast Internet on incomes in Africa persist over time, but that the *growth* effect may be especially large in the first few years after the submarine cables arrive.

8 Conclusion

This paper provides evidence on how fast Internet affects employment in Africa. We exploit the gradual arrival of 10 submarine Internet cables from Europe in cities on Africa's coast in the late 2000s and early 2010s and interact landing points and -times with an indicator for whether a given location is on the terrestrial cable network that connects users with the coast. We first show that both average speeds and use of the technology increase when the submarine cables arrive. We then compare the changes in employment patterns in cities and towns with a bigger versus a smaller increase in access to fast Internet, controlling for location and time fixed effects. In each of three different datasets that together cover 12 African countries with a combined population of roughly half a billion people, we find a significant relative increase—of 4.2 to 10 percent—in the employment rate in connected areas when fast Internet becomes available. Extensive prodding of the identifying assumptions that underlie our "dynamic" difference-in-differences approach suggests that these estimates reflect a causal effect of access to fast Internet on employment rates. Employment responses of the magnitude we document indicate that building fast Internet infrastructure may be among the currently feasible policy options with the greatest employment-creating potential in Africa. We also show that the technology reduces employment in unskilled jobs, but enables a bigger increase in employment in higher-skill occupations. Finally, fast Internet moderately lowers (un)employment inequality across the educational attainment range in Africa.

The observed changes in average speeds and use of the Internet after the arrival of the submarine cables suggest that new and new types of jobs may have been (net) created both via "extensive margin" (new Internet users) and "intensive margin" (different use of the Internet by existing users) responses. We explore these possibilities with more detailed firm level data available for some countries. In South Africa, firm entry increases—especially in sectors that benefit from ICT—as does the productivity of existing manufacturing firms in Ethiopia, when fast Internet becomes available. We also show that fast Internet enables firms in Ghana, Kenya, Mauritania, Nigeria, Senegal, and Tanzania to export (much) more, perhaps in part because website communication with clients became easier.

The impact on job inequality we document indicates that the “skill bias” of fast Internet in Africa is much more nuanced than what has been found for “computerization” and fast Internet in rich countries. This in turn suggests that the primary explanation for the slow economic progress of poor workers in Africa and other similar contexts during the last few decades is unlikely to be the factor bias of recent technological change. The sectors that ex ante appear to have been most constrained by lack of access to ICT, and that create more “good” jobs when fast Internet becomes available, are generally sectors associated with high relative productivity in Africa. In at least some of these sectors in some parts of the continent, fast Internet further increases productivity, and enables exporting. This suggests that the technology contributed positively to structural change in Africa during our data period.

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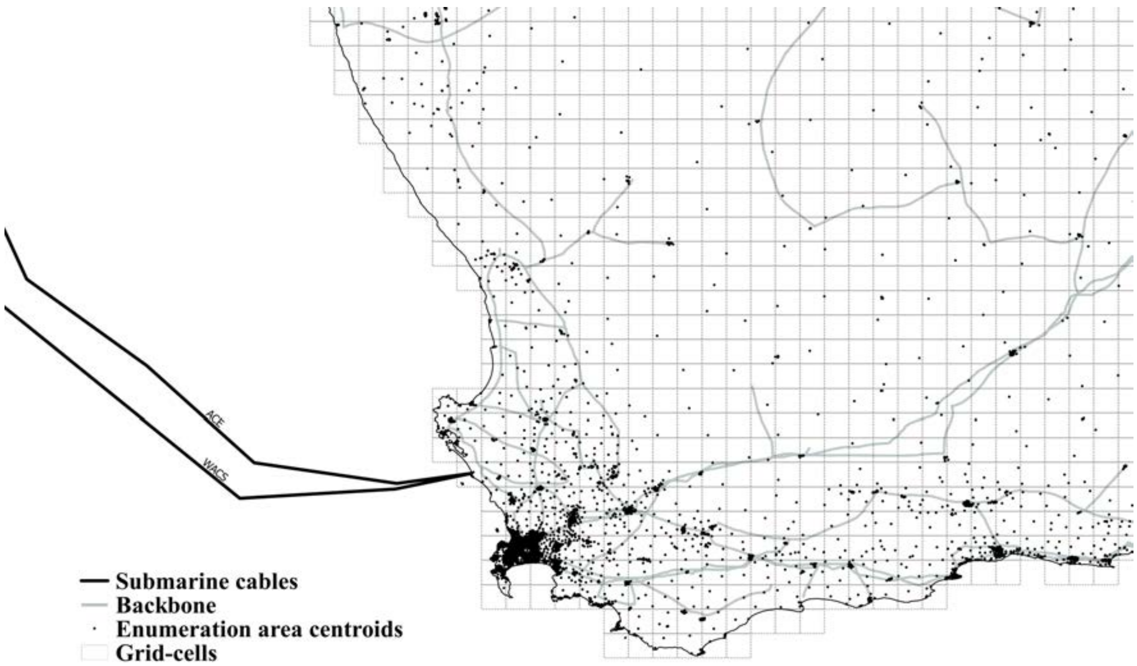
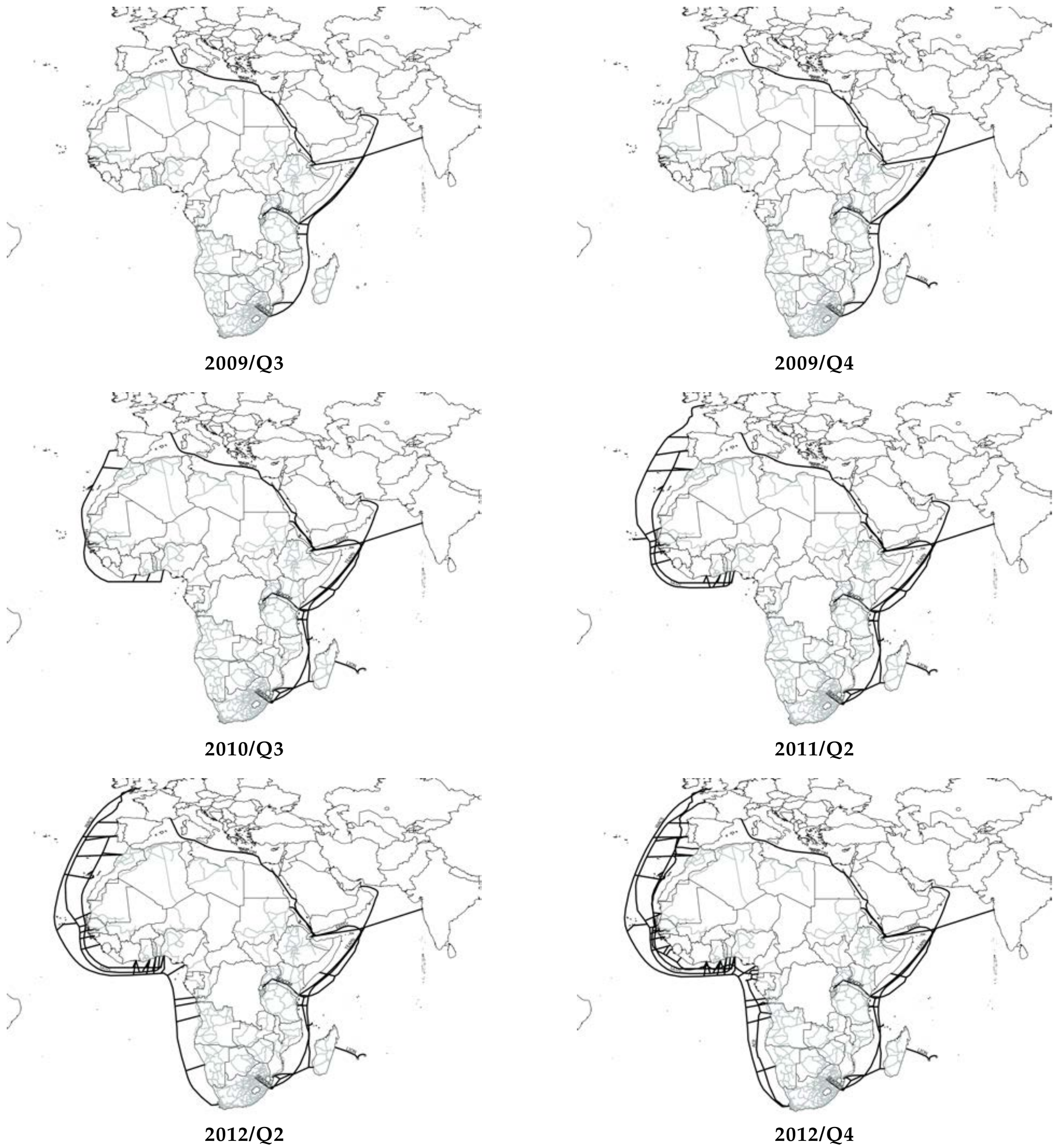
Figures

FIGURE I: THE TERRESTRIAL BACKBONE NETWORK, GRID-CELLS USED FOR LOCATION FIXED EFFECTS, AND SAMPLING CLUSTERS (SOUTHWESTERN SOUTH AFRICA AND SA-QLFS DATASET AS EXAMPLE)



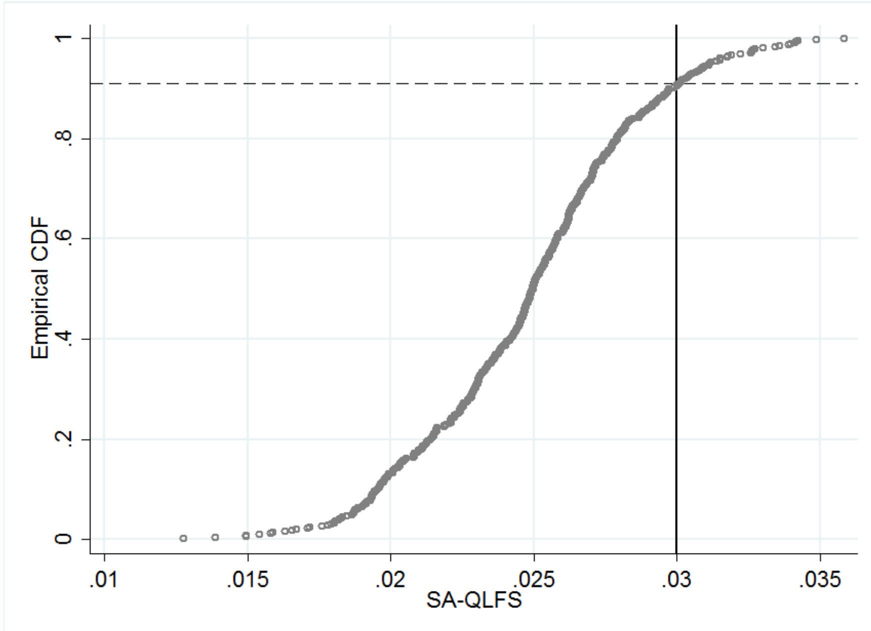
This figure shows submarine Internet cables arriving to Yzerfontein, just north of Cape Town in South Africa, the country's terrestrial backbone network, and centroids of the SA-QLFS enumeration areas. Grid-cells are 0.25×0.25 decimal degrees, which is roughly 25×25 km.

Figure II: Submarine Internet cable arrival in Africa



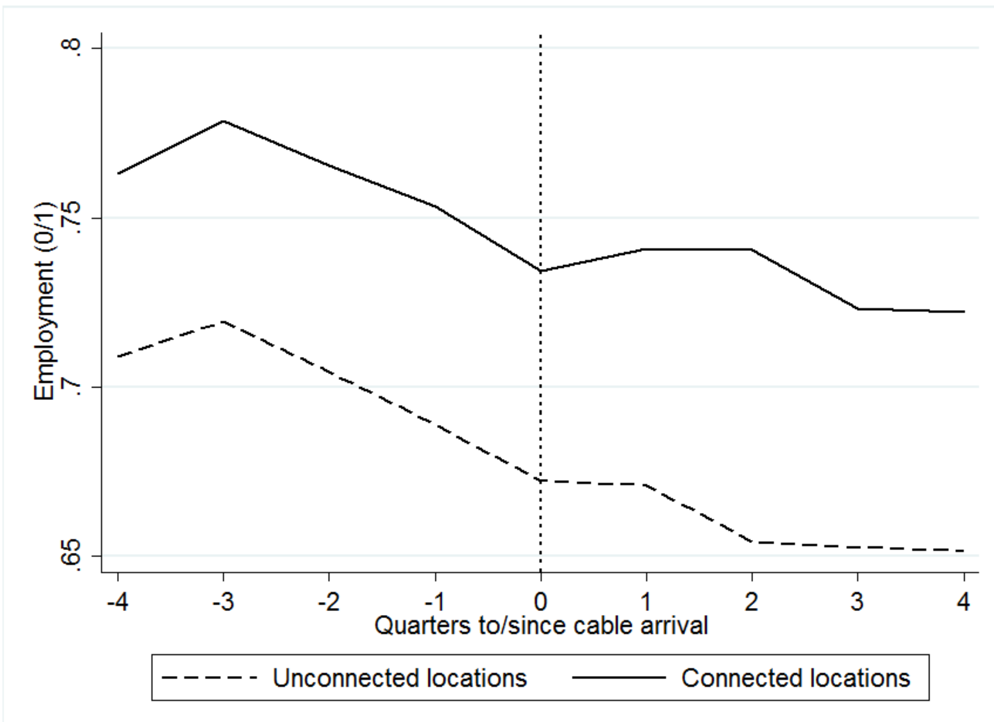
This figure shows the arrival of submarine Internet cables in Africa over time. The first two cables during our analysis period arrived in 2009/Q3 and the last in 2012/Q4. The submarine cables are Seacom and Teams (2009/Q3), Lion (2009/Q4), Eassy and MainOne (2010/Q3), Glo1 (2011/Q2), WACS (2012/Q2), and ACE (2012/Q4).

FIGURE III: DISTRIBUTION OF PLACEBO ESTIMATES: FAST INTERNET AND EMPLOYMENT IN SOUTH AFRICA



This figure shows a non-parametric permutation test of $\beta = 0$. We sample from all possible submarine cable arrival times, assigning a randomly chosen "fake" arrival time to each location while maintaining each observation's backbone connectivity status. There are as many possible arrival times as there are quarters in the SA-QLFS sample. The figure depicts the empirical cdf of estimates resulting from permuting arrival times 500 times and running (1) on each fake dataset. The vertical line represents the true estimate; where it falls in the empirical cdf of estimates from the dataset with permuted arrival times implies its p-value, which is 0.09.

Figure IV: Employment rate in connected and unconnected locations in South Africa before and after fast Internet arrival



This figure plots the employment rate in connected and unconnected locations in South Africa before and after the first submarine cable during our data period arrived in the country (2009/Q3).

Tables

TABLE I: INTERNET SPEED AND USE, AND EMPLOYMENT OUTCOMES, BEFORE SUBMARINE CABLE ARRIVAL

	Connected	Un-connected	All
INTERNET			
Internet speed (kbps)	304.7	307.2	306.9
	[246.5]	[369.0]	[353.4]
Daily Internet use	0.08	0.09	0.09
	[0.27]	[0.29]	[0.28]
Weekly Internet use	0.16	0.18	0.17
	[0.37]	[0.38]	[0.38]
EMPLOYMENT OUTCOMES – WORKER LEVEL			
Benin, D.R. Congo, Ghana, Kenya, Namibia, Nigeria, Togo, Tanzania (DHS)			
Employment	0.67	0.70	0.70
	[0.47]	[0.46]	[0.46]
Skilled	0.57	0.52	0.53
	[0.49]	[0.50]	[0.50]
Benin, Ghana, Kenya, Madagascar, Mozambique, Nigeria, Senegal, South Africa, Tanzania (Afrobarometer)			
Employment	0.56	0.58	0.58
	[0.50]	[0.49]	[0.49]
South Africa (QLFS)			
Employment	0.77	0.70	0.71
	[0.42]	[0.46]	[0.45]
Skilled	0.56	0.48	0.49
	[0.50]	[0.50]	[0.50]
EMPLOYMENT OUTCOMES – FIRM LEVEL			
Ghana, Kenya, Mauritania, Nigeria, Senegal, Tanzania (WBES)			
# employees	39.2	20.6	30.9
	[123.7]	[32.5]	[95.0]
# skilled positions	13.7	5.4	10.2
	[52.9]	[18.5]	[42.1]
Ethiopia (LMMIS)			
# employees	83.8	83.8	83.8
	[176.2]	[322.9]	[231.4]
# skilled positions	25.1	20.2	23.6
	[86.6]	[126.3]	[100.5]

All measures displayed are from the period before submarine cable arrival. Internet speed data come from Akamai. They provided us with quarterly data on average connection speeds for ∼900 African locations during the 2007-2013 period. These locations are shown in Appendix Figure A1. Akamai averages the speeds recorded for residential users, educational institutions, government offices, and firms in a given location×quarter, excluding those who connect via mobile networks. We restrict to location×quarters for which the speed measure is based on more than 10 unique IP addresses. (We also exclude the four biggest cities in each country from the speed data sample in this table; see Table II). Internet use rates come from Afrobarometer (survey countries and years are listed in Table A1). We restrict the (individual level) Afrobarometer sample to observations near (<20 km) Akamai locations for comparability. Employment rates are from Demographic Health Surveys (DHS), Afrobarometer, and South African Quarterly Labor Force Surveys (QLFS), and firm data are from the Ethiopia Large and Medium Scale Manufacturing Industries Survey (LMMIS), and the World Bank Enterprise Survey (WBES). Occupational skill levels in DHS and QLFS are defined according to ILO ISCO standards. In WBES, skilled positions are proxied by the number of non-production employees. In LMMIS, skilled positions are defined as those where earnings are more than 800 Birr per year (roughly the sample salary median). Individuals (locations) are considered connected if they are closer than 0.5 km to the backbone network. Standard deviations are shown in square brackets.

TABLE II: SUBMARINE CABLE ARRIVAL AND INTERNET SPEED AND USE

						Internet use					
Outcome:	**Internet speed (asinh)**					**Daily (0/1)**			**Weekly (0/1)**		
Unit of analysis:	Location					Individual					
Sample:	**Akamai**					**Afrobarometer**					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
SubmarineCables × Connected	0.245**	0.252**	0.409***	0.366**	0.452**	0.054**	0.068**	0.103*	0.093***	0.103***	0.104**
	(0.105)	(0.126)	(0.149)	(0.167)	(0.206)	(0.025)	(0.028)	(0.052)	(0.029)	(0.032)	(0.049)
Observations	8562	7293	2373	2373	2373	4928	4928	4928	4928	4928	4928
Mean of Outcome						0.087	0.087	0.087	0.172	0.172	0.172
Time FE	Yes	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes
Location FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
# unique IP's > 10	No	No	Yes	Yes	Yes	No	No	No	No	No	No
Country×Time FE	No	No	No	Yes	No	No	Yes	No	No	Yes	No
Connected×Time FE	No	No	No	No	Yes	No	No	Yes	No	No	Yes
Including biggest cities	Yes	No	No	No	No	No	No	No	No	No	No

Internet speed (kbps) and use (0/1) data come from Akamai and Afrobarometer respectively (more details in Table I). Akamai data is for 2007-2014 and the locations shown in Appendix Figure A1. Afrobarometer survey countries and years are listed in Table A1. Akamai recommends focusing on location×quarters for which the speed measure is based on more than 1000 unique IP addresses, but this dramatically reduces the sample size. We thus restrict to #unique IP>10 after column 2. Individuals (locations) are considered connected if they are closer than 0.5 km to the backbone network. This indicator may incorrectly classify large, connected cities as unconnected when the city is considered as one geographical unit. Since the Akamai data is at location/city×quarter level (e.g., Cape Town×2009/Q1), we exclude each country's four largest cities (as defined by UNData) from the Akamai sample (if they are present in the sample to begin with). As seen in column 1, the estimated effect of fast Internet is of similar magnitude and significant also in the full sample. (Note that this issue is not relevant to our other datasets, where we have much more fine-grained information on individuals and firms' location). We restrict the (individual level) Afrobarometer sample to observations near (<20 km) Akamai locations for comparability. Time FEs are quarters in Akamai and years in Afrobarometer. Location FEs are the reported location (a town or city) in Akamai and 0.25×0.25 decimal degree grid-cells, which is roughly 25×25 km, in Afrobarometer. Robust standard errors clustered at the level of location FEs in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

TABLE III: FAST INTERNET AND EMPLOYMENT

Panel A: Employment			
Outcome:	**Employment (0/1)**		
Unit of analysis:	Individual		
Sample:	**DHS**	**Afro-barometer**	**SA-QLFS**
	(1)	(2)	(3)
SubmarineCables × Connected	0.031***	0.058***	0.030***
	(0.010)	(0.021)	(0.010)
Observations	186434	13176	322944
Mean of Outcome	0.697	0.580	0.711
Time FE	Yes	Yes	Yes
Grid-cell FE	Yes	Yes	Yes

Panel B: Work-related outcomes from SA-QLFS				
Outcome:	**Hours worked (asinh)**	**Wants to work more (0/1)**	**Formal employment (0/1)**	**Informal employment (0/1)**
Unit of analysis:	Individual			
	(1)	(2)	(3)	(4)
SubmarineCables × Connected	0.141***	-0.022***	0.040***	0.001
	(0.043)	(0.008)	(0.012)	(0.005)
Observations	321556	547476	322944	322944
Mean of Outcome		0.666	0.476	0.121
Time FE	Yes	Yes	Yes	Yes
Grid-cell FE	Yes	Yes	Yes	Yes

The DHS sample includes Benin, D.R. Congo, Ghana, Kenya, Namibia, Nigeria, Tanzania, and Togo. The Afrobarometer sample includes Benin, Ghana, Kenya, Madagascar, Mozambique, Nigeria, Senegal, South Africa, and Tanzania. The QLFS survey is from South Africa. Survey years for each DHS and Afrobarometer country are reported in Table A1. QLFS data are 2008/Q1-2010/Q2. Grid-cells are 0.25×0.25 decimal degrees, which is roughly 25×25 km. Time FEs are quarters in QLFS and years in DHS and Afrobarometer. Individuals (locations) are considered connected if they are closer than 0.5 km to the backbone network. Hours worked is defined as zero for unemployed individuals. Robust standard errors clustered at the level of location FEs in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

TABLE IV: FAST INTERNET AND EMPLOYMENT, VARYING CONNECTION RADIUS

Outcome:	**Employment (0/1)**		
Unit of analysis:	Individual		
Sample:	**DHS**	**Afro-barometer**	**SA-QLFS**
	(1)	(2)	(3)
Connected radius:			
SubmarineCables × Connected, baseline × 0.5	0.0215*	0.0618***	0.0249**
	(0.0121)	(0.0233)	(0.0122)
SubmarineCables × Connected, baseline × 0.7	0.0287***	0.0768***	0.0327***
	(0.00999)	(0.0217)	(0.0107)
SubmarineCables × Connected, baseline × 0.9	0.0321***	0.0558**	0.0285***
	(0.00980)	(0.0221)	(0.0104)
SubmarineCables × Connected, baseline × 0.95	0.0303***	0.0537**	0.0311***
	(0.00970)	(0.0216)	(0.0103)
SubmarineCables × Connected, baseline × 0.97	0.0312***	0.0594***	0.0294***
	(0.00973)	(0.0213)	(0.0102)
SubmarineCables × Connected, baseline × 0.99	0.0311***	0.0585***	0.0295***
	(0.00980)	(0.0212)	(0.0102)
SubmarineCables × Connected, baseline radius	0.0309***	0.0584***	0.0300***
	(0.00973)	(0.0212)	(0.00985)
SubmarineCables × Connected, baseline × 1.01	0.0282**	0.0580***	0.0297***
	(0.0114)	(0.0211)	(0.00986)
SubmarineCables × Connected, baseline × 1.03	0.0278***	0.0583***	0.0293***
	(0.0101)	(0.0210)	(0.00966)
SubmarineCables × Connected, baseline × 1.05	0.0277***	0.0638***	0.0280***
	(0.0101)	(0.0207)	(0.00951)
SubmarineCables × Connected, baseline × 1.1	0.0246**	0.0627***	0.0266***
	(0.00988)	(0.0204)	(0.00940)
SubmarineCables × Connected, baseline × 1.3	0.0158*	0.0621***	0.0311***
	(0.00919)	(0.0211)	(0.00952)
SubmarineCables × Connected, baseline × 1.5	0.0134	0.0680***	0.0322***
	(0.0101)	(0.0201)	(0.00913)
Observations	186434	13176	322944
Mean of Outcome	0.697	0.580	0.711
Time FE	Yes	Yes	Yes
Grid-cell FE	Yes	Yes	Yes

The DHS sample includes Benin, D.R. Congo, Ghana, Kenya, Namibia, Nigeria, Tanzania, and Togo. The Afrobarometer sample includes Benin, Ghana, Kenya, Madagascar, Mozambique, Nigeria, Senegal, South Africa, and Tanzania. The QLFS survey is from South Africa. Survey years for each DHS and Afrobarometer country are reported in Table A1. QLFS data are 2008/Q1-2010/Q2. Grid-cells are 0.25×0.25 decimal degrees, which is roughly 25×25 km. Time FEs are quarters in QLFS and years in DHS and Afrobarometer. For the baseline radius, individuals (locations) are considered connected if they are closer than 0.5 km to the backbone network. Robust standard errors clustered at the level of location FEs in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table V: Fast Internet and Employment, Varying the Sample and Terrestrial Cables Considered

Panel A: Employment			
Outcome:	**Employment (0/1)**		
Unit of analysis:	Individual		
Sample:	**DHS**	**Afro-barometer**	**SA-QLFS**
	(1)	(2)	(3)
Panel A: Backbone cables reported in 2 maps			
SubmarineCables × Connected	0.035***	0.055**	0.030**
	(0.010)	(0.023)	(0.011)
Observations	186434	13154	322944
Mean of Outcome	0.683	0.583	0.696
Panel B: Excluding obs. close to landing station			
SubmarineCables × Connected	0.031***	0.066***	0.030***
	(0.010)	(0.025)	(0.010)
Observations	176233	11002	301430
Mean of Outcome	0.682	0.579	0.690
Panel C: Excluding obs. with distance to backbone >10 km			
SubmarineCables × Connected	0.029***	0.067***	0.031***
	(0.010)	(0.022)	(0.010)
Observations	79574	9610	291131
Mean of Outcome	0.674	0.583	0.710
Panel D: Excluding obs. with distance to backbone >5 km			
SubmarineCables × Connected	0.027***	0.064***	0.032***
	(0.009)	(0.023)	(0.010)
Observations	62488	8352	259015
Mean of Outcome	0.670	0.582	0.719
Time FE	Yes	Yes	Yes
Grid-cell FE	Yes	Yes	Yes

The DHS sample includes Benin, D.R. Congo, Ghana, Kenya, Namibia, Nigeria, Tanzania, and Togo. The Afrobarometer sample includes Benin, Ghana, Kenya, Madagascar, Mozambique, Nigeria, Senegal, South Africa, and Tanzania. The QLFS survey is from South Africa. Survey years for each DHS and Afrobarometer country are reported in Table A1. QLFS data are 2008/Q1-2010/Q2. Grid-cells are 0.25×0.25 decimal degrees, which is roughly 25×25 km. Time FEs are quarters in QLFS and years in DHS and Afrobarometer. Individuals (locations) are considered connected if they are closer than 0.5 km to the backbone network. Panel A defines the backbone network as the intersection of AfTerFibre (2014)'s map and www.africabandwidthmaps.com map from 2013/Q2. Panel B excludes observations that are closer than 20 km to a landing station. Robust standard errors clustered at the level of location FEs in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

TABLE VI: FAST INTERNET AND EMPLOYMENT, INCLUDING PLACEBO "TREATMENTS", AND CONTROLLING FOR TRENDS

Outcome:	**Employment (0/1)**										
Unit of analysis:	Individual										
Sample:	**DHS**			**Afrobarometer**			**SA-QLFS**				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
SubmarineCables × Connected	0.032***	0.030***	0.030***	0.059***	0.046**	0.058	0.021**	0.029***	0.027**	0.013	0.027**
	(0.009)	(0.010)	(0.011)	(0.022)	(0.021)	(0.060)	(0.010)	(0.010)	(0.011)	(0.009)	(0.012)
SubmarineCables × Connected to road network	-0.006			-0.010			0.004				
	(0.006)			(0.017)			(0.006)				
SubmarineCables × Connected to electricity grid	0.004			0.017			-0.004				
	(0.010)			(0.020)			(0.014)				
SubmarineCables × Connected to 3G							-0.001				
							(0.006)				
SubmarineCables × Connected, t-1										0.018*	
										(0.010)	
SubmarineCables × Connected, t+1											0.005
											(0.007)
Observations	186434	186434	186434	13154	13154	13154	322944	322944	322944	322944	322944
Mean of Outcome	0.697	0.697	0.697	0.580	0.580	0.580	0.711	0.711	0.711	0.711	0.711
Time FE	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	Yes
Grid-cell FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country×Time FE	No	Yes	No	No	Yes	No	No	No	No	No	No
Province×Time FE	No	No	No	No	No	No	No	Yes	No	No	No
Linear grid-cell trend	No	No	No	No	No	No	No	No	Yes	No	No
Connected×Time FE	No	No	Yes	No	No	Yes	No	No	No	No	No

The DHS sample includes Benin, D.R. Congo, Ghana, Kenya, Namibia, Nigeria, Tanzania, and Togo. The Afrobarometer sample includes Benin, Ghana, Kenya, Madagascar, Mozambique, Nigeria, Senegal, South Africa, and Tanzania. The QLFS survey is from South Africa. Survey years for each DHS and Afrobarometer country are reported in Table A1. QLFS data are 2008/Q1-2010/Q2. Grid-cells are 0.25×0.25 decimal degrees, which is roughly 25×25 km. Time FEs are quarters in QLFS and years in DHS and Afrobarometer. Individuals (locations) are considered connected to the backbone, roads, and electricity if they are closer than 0.5 km to the backbone network, the road network, and the electricity grid respectively; and to 3G if the individual (location) is within 3G coverage. Road data comes from SEDAC, electricity data from AICD, and 3G data from Collins Bartholomew. Robust standard errors clustered at the level of location FEs in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

TABLE VII: FAST INTERNET AND EMPLOYMENT ACROSS SPACE

Outcome:	**Employment (0/1)**		
Unit of analysis:	Individual		
Sample:	**DHS**	**Afro-barometer**	**SA-QLFS**
	(1)	(2)	(3)
SubmarineCables × Connected	0.031***	0.044*	0.035***
	(0.012)	(0.026)	(0.013)
SubmarineCables × I[0.5 km < Distance < 5 km]	0.001	-0.021	0.007
	(0.008)	(0.022)	(0.009)
Observations	186434	13176	322944
Mean of Outcome	0.697	0.580	0.711
Time FE	Yes	Yes	Yes
Grid-cell FE	Yes	Yes	Yes

The DHS sample includes Benin, D.R. Congo, Ghana, Kenya, Namibia, Nigeria, Tanzania, and Togo. The Afrobarometer sample includes Benin, Ghana, Kenya, Madagascar, Mozambique, Nigeria, Senegal, South Africa, and Tanzania. The QLFS survey is from South Africa. Survey years for each DHS and Afrobarometer country are reported in Table A1. QLFS data are 2008/Q1-2010/Q2. Grid-cells are 0.25×0.25 decimal degrees, which is roughly 25×25 km. Time FEs are quarters in QLFS and years in DHS and Afrobarometer. Individuals (locations) are considered connected if they are closer than 0.5 km to the backbone network. Robust standard errors clustered at the level of location FEs in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

TABLE VIII: FAST INTERNET AND EMPLOYMENT IN SKILLED AND UNSKILLED POSITIONS

Panel A: ILO ISCO skill levels

Outcome:	**Skilled (0/1)**	**Un-skilled (0/1)**	**Highly skilled (0/1)**	**Somewhat skilled (0/1)**	**Moderately skilled (0/1)**	**Un-skilled (0/1)**
Unit of analysis:	Individual					
	(1)	(2)	(3)	(4)	(5)	(6)
DHS:						
SubmarineCables × Connected	0.049***	-0.024**	0.025***		0.023*	-0.024**
	(0.013)	(0.012)	(0.007)		(0.012)	(0.012)
Observations	186616	186588	186452		186598	186588
Mean of Outcome	0.526	0.193	0.063		0.464	0.193
Time FE	Yes	Yes	Yes		Yes	Yes
Grid-cell FE	Yes	Yes	Yes		Yes	Yes
SA-QLFS:						
SubmarineCables × Connected	0.044***	-0.014*	0.016**	0.012**	0.016**	-0.014*
	(0.014)	(0.008)	(0.008)	(0.006)	(0.008)	(0.008)
Observations	322944	322944	322944	322944	322944	322944
Mean of Outcome	0.489	0.222	0.084	0.079	0.326	0.222
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Grid-cell FE	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Occupations

Outcome:	**Legisl-ative (0/1)**	**Profes-sional (0/1)**	**Cler-ical (0/1)**	**Serv-ices (0/1)**	**Dom-estic (0/1)**	**Retail/ sales (0/1)**	**Empl. agri. (0/1)**	**Self-empl. agri. (0/1)**	**Unskilled manual (0/1)**	**Tech-nical (0/1)**	**Elem-entary (0/1)**
Unit of analysis:	Individual										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
DHS:											
SubmarineCables × Connected		0.025***	0.004**	0.016***	0.015***	0.006	-0.005	-0.035***	-0.005		
		(0.007)	(0.002)	(0.006)	(0.005)	(0.008)	(0.005)	(0.011)	(0.004)		
Observations		187537	187535	187537	187535	187560	187542	187540	187538		
Mean of Outcome		0.062	0.016	0.063	0.004	0.183	0.090	0.154	0.033		
Time FE		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes		
Grid-cell FE		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes		
SA-QLFS:											
SubmarineCables × Connected	0.011**	0.006	0.008	0.005	-0.002					0.012**	-0.012**
	(0.005)	(0.004)	(0.005)	(0.004)	(0.004)					(0.006)	(0.006)
Observations	322944	322944	322944	322944	322944					322944	322944
Mean of Outcome	0.048	0.036	0.074	0.092	0.058					0.079	0.164
Time FE	Yes	Yes	Yes	Yes	Yes					Yes	Yes
Grid-cell FE	Yes	Yes	Yes	Yes	Yes					Yes	Yes

The DHS sample includes Benin, D.R. Congo, Ghana, Kenya, Namibia, Nigeria, Tanzania, and Togo. The QLFS survey is from South Africa. Survey years for each DHS country are reported in Table A1. QLFS data are 2008/Q1-2010/Q2. Grid-cells are 0.25×0.25 decimal degrees, which is roughly 25×25 km. Time FEs are quarters in QLFS and years in DHS. Individuals (locations) are considered connected if they are closer than 0.5 km to the backbone network. We categorize occupations' skill level following the ILO's ISCO categorization (ILO, 2012), and display results for the occupational categories for which we find a significant effect of fast Internet in either DHS or QLFS and in either the regressions for Table VIII or those for Table IX. For DHS, the Highly skilled occupation group includes professional; the Moderately skilled group clerical, skilled manufacturing, retail and sales, services, and employed agriculture; and the Unskilled group unskilled manufacturing, self-employed agriculture, and domestic work. There are no observations in the Somewhat skilled occupation group in the DHS sample. For QLFS, the Highly skilled occupation group includes legislative work and professional; the Somewhat skilled group technical work; the Moderately skilled group clerical, skilled agriculture, crafts workers, services, and plant workers; and the Unskilled group elementary work and domestic work. The Skilled category in Panel A column 1 corresponds to the Highly, Somewhat, and Moderate skilled occupation groups. Robust standard errors clustered at the level of location FEs in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

TABLE IX: FAST INTERNET, EMPLOYMENT, AND EMPLOYMENT IN SKILLED AND UNSKILLED POSITIONS, BY EDUCATIONAL ATTAINMENT

Outcome:	Empl-oyed (0/1)	Skilled (0/1)	Unskil-led (0/1)	Legisl-ative (0/1)	Profes-sional (0/1)	Cler-ical (0/1)	Serv-ices (0/1)	Dom-estic (0/1)	Retail/ sales (0/1)	Empl. agri. (0/1)	Self-empl. agri. (0/1)	Unskilled manual (0/1)	Tech-nical (0/1)	Elem-entary (0/1)
Unit of analysis:	Individual													
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
DHS:														
SubmarineCables × Connected														
× Not primary	-0.017	0.044	-0.067***		0.007	-0.002	0.017	0.008	0.061**	-0.030***	-0.083***	0.006		
	(0.029)	(0.037)	(0.021)		(0.009)	(0.003)	(0.024)	(0.007)	(0.024)	(0.005)	(0.020)	(0.007)		
× Primary	0.033*	0.004	0.022		-0.001	-0.004*	0.024**	0.054***	0.006	-0.034***	-0.037	0.005		
	(0.018)	(0.022)	(0.024)		(0.008)	(0.002)	(0.011)	(0.015)	(0.015)	(0.004)	(0.023)	(0.011)		
× Secondary	0.042***	0.050***	-0.015		0.006	0.003	0.010	0.009	0.014	0.012***	-0.019**	-0.006		
	(0.012)	(0.012)	(0.011)		(0.006)	(0.003)	(0.007)	(0.005)	(0.010)	(0.004)	(0.009)	(0.004)		
× Higher	0.041*	0.091***	-0.049***		0.023	0.013	0.030***	-0.014	-0.007	0.029**	-0.016	-0.020***		
	(0.024)	(0.030)	(0.018)		(0.025)	(0.009)	(0.011)	(0.010)	(0.010)	(0.011)	(0.013)	(0.006)		
Observations	186434	186616	186588		187537	187535	187537	187535	187560	187542	187540	187538		
Time FE	Yes	Yes	Yes		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes		
Grid-cell FE	Yes	Yes	Yes		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes		
Afrobarometer:														
SubmarineCables × Connected														
× Not primary	0.051													
	(0.039)													
× Primary	0.064**													
	(0.028)													
× Secondary	0.056													
	(0.034)													
× Higher	0.059													
	(0.038)													
Observations	13154													
Time FE	Yes													
Grid-cell FE	Yes													
SA-QLFS:														
SubmarineCables × Connected														
× Not primary	0.003	0.012	-0.009	0.007	0.001	-0.002	0.001	0.009					0.004	-0.018
	(0.017)	(0.017)	(0.020)	(0.006)	(0.002)	(0.004)	(0.009)	(0.013)					(0.006)	(0.016)
× Primary	0.031***	0.021*	0.010	0.004	-0.000	0.003	0.004	0.009					0.004	0.000
	(0.012)	(0.011)	(0.010)	(0.004)	(0.002)	(0.005)	(0.005)	(0.006)					(0.004)	(0.009)
× Secondary	0.033**	0.043**	-0.010	0.018**	-0.003	0.006	0.000	-0.005					0.010	-0.005
	(0.015)	(0.017)	(0.007)	(0.008)	(0.004)	(0.007)	(0.008)	(0.003)					(0.007)	(0.007)
× Higher	0.010	0.019	-0.009	-0.005	0.009	0.006	0.014	-0.005*					-0.013	-0.004
	(0.010)	(0.012)	(0.005)	(0.011)	(0.015)	(0.010)	(0.009)	(0.003)					(0.015)	(0.005)
Observations	319579	319579	319579	319579	319579	319579	319579	319579					319579	319579
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes					Yes	Yes
Grid-cell FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes					Yes	Yes

The DHS sample includes Benin, D.R. Congo, Ghana, Kenya, Namibia, Nigeria, Tanzania, and Togo. The Afrobarometer sample includes Benin, Ghana, Kenya, Madagascar, Mozambique, Nigeria, Senegal, South Africa, and Tanzania. The QLFS survey is from South Africa. Survey years for each Afrobarometer and DHS country are reported in Table A1. QLFS data are 2008/Q1-2010/Q2. Grid-cells are 0.25×0.25 decimal degrees, which is roughly 25×25 km. Time FEs are quarters in QLFS and years in Afrobarometer and DHS. Individuals (locations) are considered connected if they are closer than 0.5 km to the backbone network. We categorize occupations' skill level following the ILO's ISCO categorization (ILO, 2012) (more details in Table VIII). Afrobarometer does not record respondents' occupation. Controls for educational attainment (primary school not completed, primary school completed, secondary school completed, and higher education) are included. Robust standard errors clustered at the level of location FEs in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

TABLE X: FAST INTERNET AND FIRM ENTRY IN SOUTH AFRICA

Outcome:	**All firms (asinh)**	**Agri-culture (asinh)**	**Retail/ sales (asinh)**	**Tech-nology (asinh)**	**Manu-facturing (asinh)**	**Services (asinh)**	**Finan-cial (asinh)**	**White-collar (asinh)**	**Blue-collar (asinh)**
Unit of analysis:	Location								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Net firm entry									
SubmarineCables × Connected	0.056*	0.011**	0.018	0.005	-0.000	0.026	0.056**	0.013	0.016
	(0.032)	(0.005)	(0.014)	(0.008)	(0.004)	(0.019)	(0.024)	(0.010)	(0.011)
Observations	58542	58542	58542	58542	58542	58542	58542	58542	58542
Panel B: Firm entry									
SubmarineCables × Connected	0.054**	0.007*	0.022	0.008	0.001	0.028	0.062***	0.013	0.013
	(0.026)	(0.004)	(0.014)	(0.008)	(0.003)	(0.017)	(0.023)	(0.010)	(0.010)
Observations	58542	58542	58542	58542	58542	58542	58542	58542	58542
Panel C: Firm exit									
SubmarineCables × Connected	0.007	-0.003	0.003	0.003	0.001	0.004	0.011	-0.001	-0.003
	(0.020)	(0.003)	(0.007)	(0.004)	(0.003)	(0.012)	(0.013)	(0.006)	(0.006)
Observations	58542	58542	58542	58542	58542	58542	58542	58542	58542
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Location FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Data at location×quarter level, 2007-2014. Location FEs are zip-codes. Time FEs are quarters. See Table A5 for information on how firms are categorized into sectors. Sectors not shown are mining and tourism. The point estimate is positive and insignificant for these sectors. Firms are considered connected if they are closer than 0.5 km to the backbone network. Robust standard errors clustered at the level of location FEs in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table XI: Fast Internet, Employment, Output Elasticity of Labor, and Productivity in Ethiopian Firms

Outcome:	Employees (asinh)		Skilled employees (asinh)		Unskilled employees (asinh)		Value added (asinh)	Value added (asinh)	Value added (asinh)
Unit of analysis:	Firm								
Method:	OLS		OLS		OLS		OLS	Reg LP	Adj LP
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Submarine Cables × Connected	0.147**	0.377***	0.0.056	0.260***	0.081	0.255***			
	(0.066)	(0.079)	(0.068)	(0.102)	(0.071)	(0.066)			
Capital							0.204***	0.298***	0.296***
							(0.010)	(0.019)	(0.019)
Unskilled							0.288***	0.107***	0.103***
							(0.061)	(0.028)	(0.032)
Skilled							0.473***	0.187***	0.187***
							(0.029)	(0.017)	(0.017)
Submarine Cables × Connected ×									
Unskilled							-0.133***	-0.040**	-0.051**
							(0.048)	(0.018)	(0.022)
Skilled							0.058*	0.029	0.027
							(0.029)	(0.021)	(0.021)
Control for Productivity							No	Yes	Yes
Control for Submarine Cables × Connected × Productivity							No	No	Yes
Outcome									**Productivity**
Submarine Cables × Connected									0.123**
									(0.057)
Time FE	Yes	No	Yes	No	Yes	No	No	No	No
Grid-cell FE	No	Yes	No	Yes	No	Yes	Yes	Yes	Yes
Industry×Time FE	No	Yes	No	Yes	No	Yes	Yes	Yes	Yes
Firm FE	Yes	No	Yes	No	Yes	No	No	No	No
Observations	7829	7829	7829	7829	7829	7829	6279	6279	6279

Data from the Ethiopian LMMIS manufacturing firm census. 2006-2013. Grid-cells (for location FEs) are 0.25×0.25 decimal degrees, which is roughly 25×25 km. Time FEs are years. Firms are considered connected if they are closer than 0.5 km to the backbone network. The sample is restricted to firms observed both before and after submarine cable arrival and includes 1,974 firms. Skilled (unskilled) positions are defined as those earning more (less) than 800 Birr per year, approximately the sample salary median. Capital is the average of start-of-year and end-of-year book value. The production function specifications allow fast Internet to directly affect value added via a change in the intercept (not shown). Robust standard errors clustered at grid-cell level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

TABLE XII: FAST INTERNET, EMPLOYMENT, EXPORTING, ON-THE-JOB TRAINING, AND FIRM COMMUNICATION

	Employment				Trade			Internet use	
Outcome:	**Emplo-yees (asinh)**	**Prod-uction emp-loyees (asinh)**	**Non-prod-uction emp-loyees (asinh)**	**On-the-job train-ing (0/1)**	**National sales (asinh)**	**Indirect exports (asinh)**	**Direct exports (asinh)**	**Email commu-nica-tion (0/1)**	**Website use (0/1)**
Unit of analysis:					Firm				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A:									
SubmarineCables × Connected	0.040	0.082	0.330**	0.391***	0.058	0.397	1.724***	0.086	0.077*
	(0.068)	(0.102)	(0.118)	(0.096)	(0.552)	(0.443)	(0.566)	(0.057)	(0.041)
Observations	5542	3586	3576	4528	4517	4520	4522	5777	5771
Mean of Outcome				0.279				0.381	0.123
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry×Time FE	No	No	No	No	No	No	No	No	No
Country×Time FE	No	No	No	No	No	No	No	No	No
Panel B:									
SubmarineCables × Connected	0.043	0.085	0.316***	0.396***	0.051	0.295	1.671***	0.079	0.084**
	(0.058)	(0.094)	(0.112)	(0.098)	(0.542)	(0.469)	(0.540)	(0.053)	(0.037)
Observations	5542	3586	3576	4528	4517	4520	4522	5777	5771
Mean of Outcome				0.279				0.381	0.123
Time FE	No	No	No	No	No	No	No	No	No
City FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry×Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country×Time FE	No	No	No	No	No	No	No	No	No
Panel C:									
SubmarineCables × Connected	0.035	0.080	0.237*	0.333**	0.182	0.577	1.782***	0.070	0.069
	(0.085)	(0.129)	(0.120)	(0.126)	(0.381)	(0.474)	(0.572)	(0.050)	(0.043)
Observations	5542	3586	3576	4528	4517	4520	4522	5777	5771
Mean of Outcome				0.279				0.381	0.123
Time FE	No	No	No	No	No	No	No	No	No
City FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry×Time FE	No	No	No	No	No	No	No	No	No
Country×Time FE	Yes	Yes	Yes	Yes	Yes	Yes			

Data from World Bank Enterprise Surveys. The sample includes firms from Ghana, Kenya, Mauritania, Nigeria, Senegal, and Tanzania. 2006-2014. Time FEs are years. We use the number of production employees as a proxy for unskilled labor, and the number of non-production employees as a proxy for skilled labor. The trade outcomes are defined (by WBES) as shares of annual sales, and we interact that variable with annual sales to get, e.g., the value of exports in 2009 USD. Indirect exports are defined as going through a third party. The Internet use variables are equal to one if the firm states that it uses email or a website to communicate with clients. Because almost all firms in WBES are located in large cities and sub-city information on their location is not reported, a within-500-meters-of-the-backbone indicator incorrectly classifies many connected WBES firms/cities as unconnected (for example those in Abuja, Accra, Dar es Salaam, and Kano. That these cities are in fact connected to the backbone is clear: the maps show backbone cables whose route was clearly chosen to connect them). In WBES we thus classify firms/cities as connected if they are within the sample median distance of the network, which is about 3.5 km. (This issue is not relevant to our other datasets, where we have much more fine-grained information on individuals and firms' location). The results are robust to using smaller and larger radii than 3.5 km to define connectivity. Robust standard errors clustered at city level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

TABLE XIII: FAST INTERNET, INCOMES, AND WEALTH

Outcome:	**Wealth index (1-5)**			**Light density at night (asinh)**			
Unit of analysis:	Individual			Point			
Sample:	DHS			NOAA			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
SubmarineCables × Connected	0.293*	0.292*	0.271	0.172***	0.171***	0.075**	-0.017
	(0.165)	(0.165)	(0.182)	(0.019)	(0.019)	(0.035)	(0.013)
SubmarineCables × Connected, t-1							0.192***
							(0.024)
SubmarineCables × Connected, t+1							-0.021
							(0.015)
Observations	67178	67178	67178	520205	520205	520205	520205
Mean of Outcome	3.356	3.356	3.356				
Time FE	Yes	No	Yes	Yes	No	Yes	Yes
Grid-cell FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country×Time FE	No	Yes	No	No	Yes	No	No
Connected×Time FE	No	No	Yes	No	No	Yes	No

The DHS sample includes Benin, D.R. Congo, Ghana, Kenya, Namibia, Nigeria, Tanzania, and Togo. The light density at night sample includes Benin, D.R. Congo, Ghana, Kenya, Madagascar, Mozambique, Namibia, Nigeria, Senegal, South Africa, Tanzania, and Togo. Survey years for each DHS country are reported in Table A1, the light density at night is yearly and for 2007-2013. Grid-cells are 0.25×0.25 decimal degrees, which is roughly 25×25 km. Time is years. Individuals (locations) are considered connected if they are closer than 0.5 km to the backbone network. Light density at night proxies for average income at location level. Robust standard errors clustered at grid-cell level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

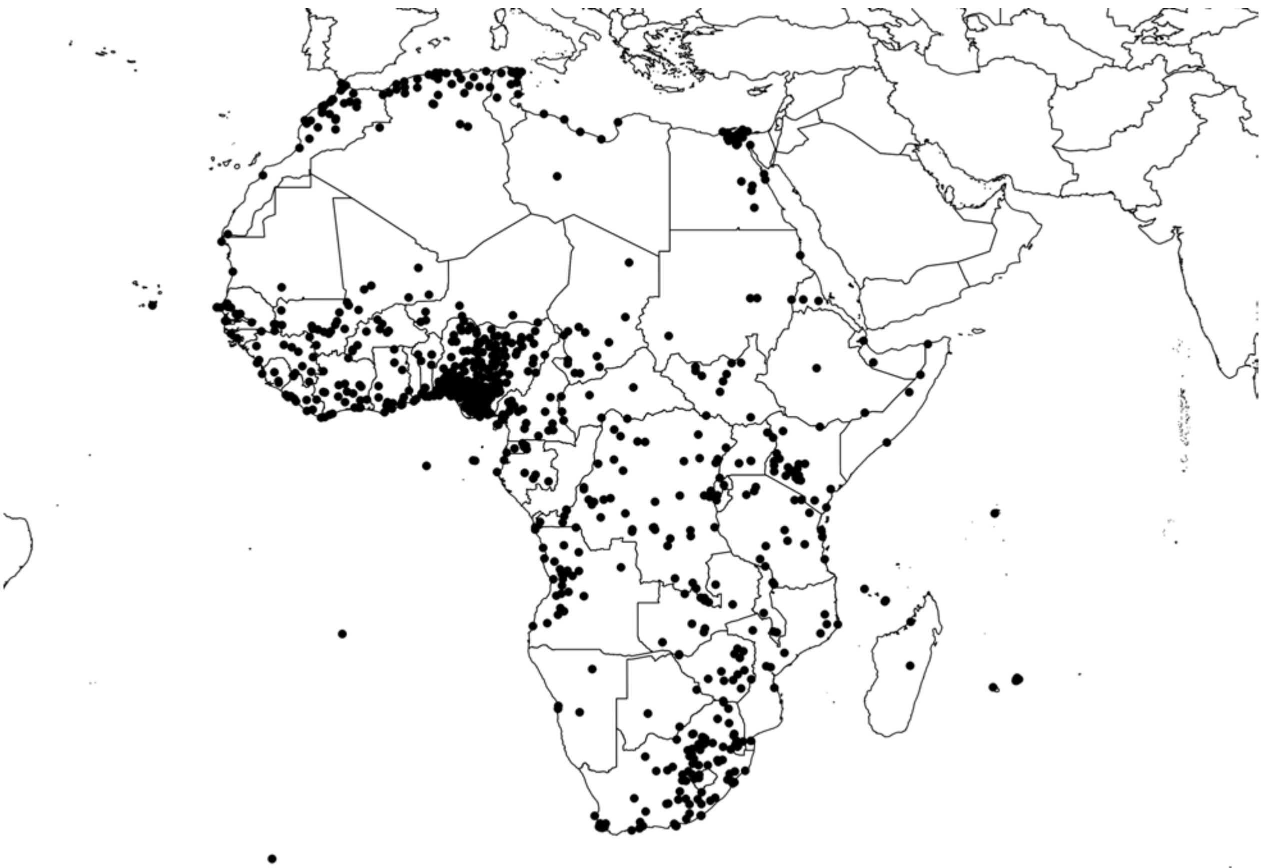
Appendix

The South Africa Companies and Intellectual Property Commission's administrative dataset of firm registrations categorizes firms only as public, private or NGO. To estimate the effect of fast Internet on sector specific firm creation, we thus need to categorize the firms based on their names. We choose a set of sectors that, as far as possible, correspond to the categories of occupations reported in the DHS and QLFS datasets: services, white collar firms, blue collar firms, retail and sales, technology, manufacturing, finance, agriculture, mining, and tourism and foods.

We start by splitting all firm names on the space between the words. For example, "The South African Mining Company" would render five new variables. The first one would be called "name1" and would have the value "The", the second one would be called "name2" and would have the value "South", and so on.

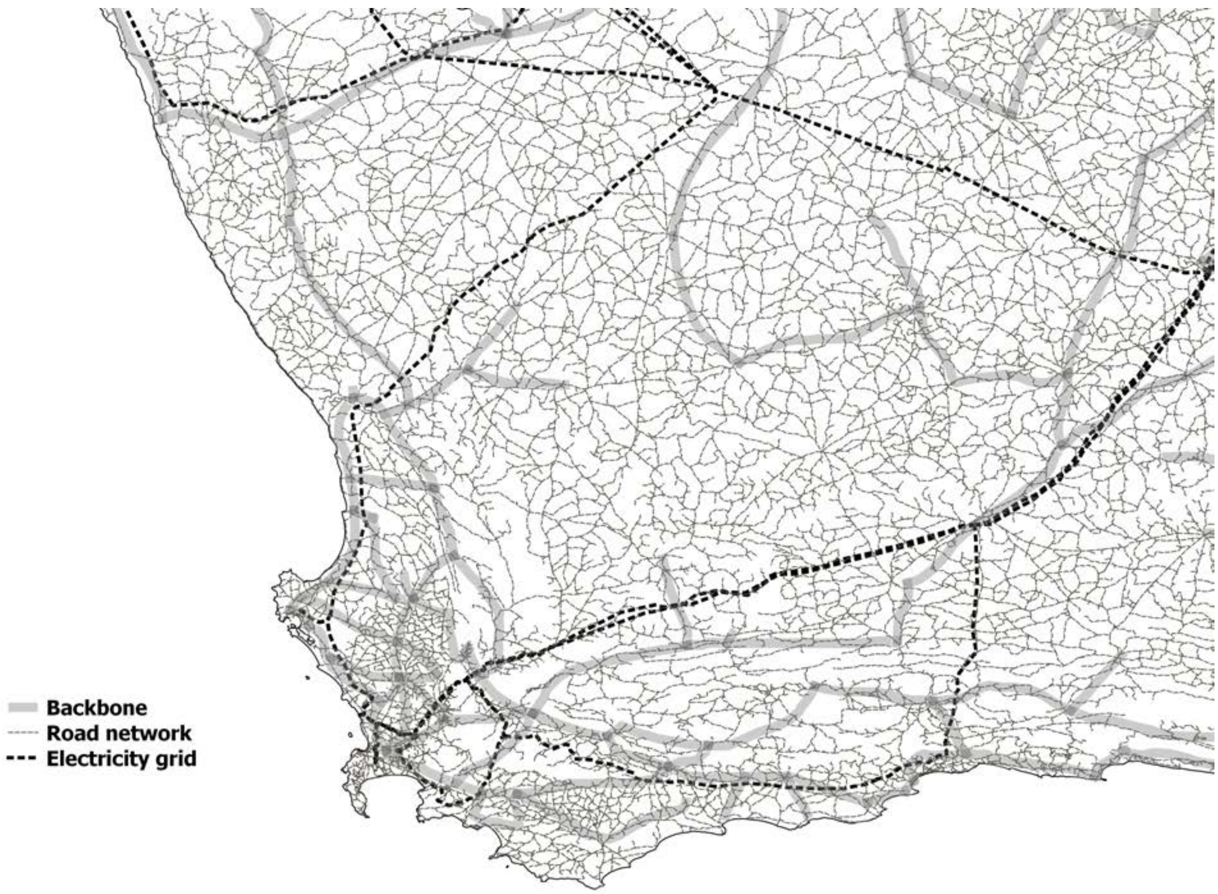
name2, as specified above, usually contains the important key word that makes it possible to categorize a firm, such as "accounting", "trading", "properties", or "catering". We therefore use name2 to manually match key words to the sectors listed above. For example, we categorize firm X as belonging to the technological sector if name2 contains the words "computer", "tech", "telecommunications", and so on. The mapping of words to sectors is provided in Appendix Table A5. Of course, the key words could have ended up in any of the other name variables. We thus run the exact same iteration for all of those, up to name10. With this method, we are able to categorize 67 percent of the firms in the CIPC sample.

FIGURE A1: LOCATIONS INCLUDED IN DATASET ON INTERNET SPEEDS



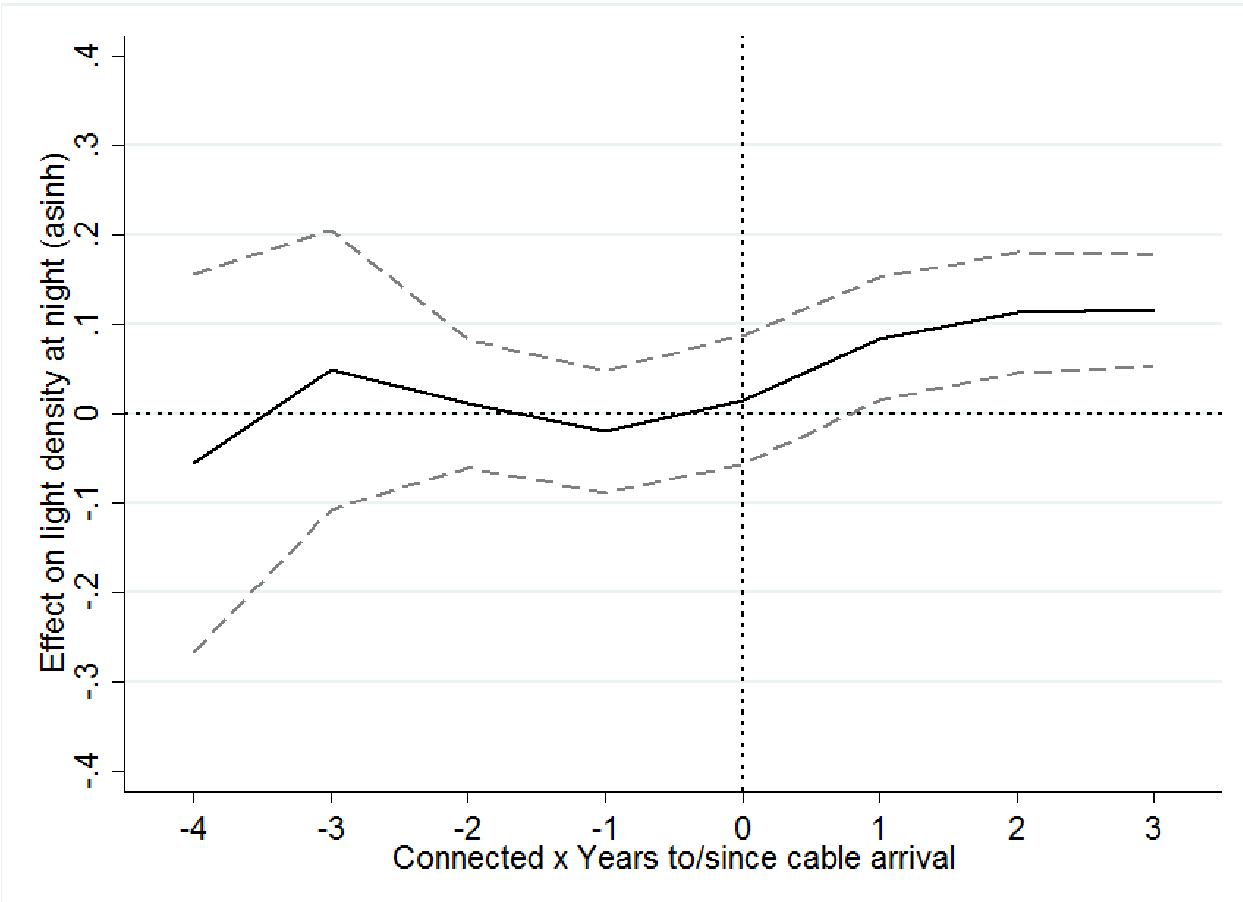
This graph plots the locations for which Akamai has information on Internet speed between 2007 and 2014. There are around 920 locations in this sample. We use data for the countries listed in Table A1.

FIGURE A2: ROAD NETWORKS AND ELECTRICITY GRID (SOUTHWESTERN SOUTH AFRICA AS EXAMPLE)



This graph plots the road networks and electricity grid used in the placebo "treatment" estimations. Road data comes from SEDAC and electricity data from AICD.

FIGURE A3: FAST INTERNET AND INCOMES OVER TIME



This graph plots the coefficients from the interaction terms between the connected status and event-time indicators. The event time is calculated as the year of light measurement net the year of first cable connection. A dummy variable is created for each event time and is subsequently interacted with the connected indicator. Country×year FE's are included in the regression, but the results are virtually unchanged using year FE's solely.

TABLE A1: INCLUDED COUNTRIES, SURVEY ROUNDS, AND CABLE CONNECTION

Country	Survey	First connected
Benin	Afrobarometer (2008, 2011); DHS (2001, 2012)	2010/Q3
D.R. Congo	DHS (2007, 2013)	2012/Q2
Ghana	Afrobarometer (2008, 2012); DHS (2008, 2014)	2010/Q3
Kenya	Afrobarometer (2008, 2011); DHS (2008, 2014)	2009/Q3
Madagascar	Afrobarometer (2008, 2013)	2010/Q3
Mozambique	Afrobarometer (2008, 2012)	2009/Q3
Namibia	DHS (2006, 2013)	2012/Q2
Nigeria	Afrobarometer (2008, 2012); DHS (2008, 2013)	2010/Q3
Senegal	Afrobarometer (2008, 2013)	2010/Q3
South Africa	Afrobarometer (2008, 2011); SA-QLFS (2008/Q1 - 2010/Q2)	2009/Q3
Tanzania	Afrobarometer (2008, 2012); DHS (1999, 2010)	2009/Q3
Togo	DHS (1998, 2013)	2010/Q3

This table shows the survey rounds and connection quarters for countries included in our main analysis. Included countries (1) have surveys conducted both before and after cable arrival; (2) have detailed geographical markers; (3) have employment status for individuals; and (4) are not landlocked. We only make use of *Standard DHS* surveys.

Table A2: Fast internet and employment, Varying Grid-Cell Size

Outcome:	**Employment (0/1)**						
Unit of analysis:	Individual						
Grid-cell size:	**10 km**	**15 km**	**20 km**	**25 km**	**30 km**	**35 km**	**40 km**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
DHS:							
SubmarineCables × Connected	0.024***	0.026***	0.030***	0.031***	0.027***	0.024**	0.029***
	(0.009)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Observations	186434	186434	186434	186434	186434	186434	186434
Mean of Outcome	0.697	0.697	0.697	0.697	0.697	0.697	0.697
Afrobarometer:							
SubmarineCables × Connected	0.055**	0.063***	0.076***	0.058***	0.057**	0.054**	0.061**
	(0.025)	(0.024)	(0.023)	(0.021)	(0.024)	(0.021)	(0.024)
Observations	13176	13176	13176	13176	13176	13176	13176
Mean of Outcome	0.580	0.580	0.580	0.580	0.580	0.580	0.580
SA-QLFS:							
SubmarineCables × Connected	0.026***	0.023***	0.028***	0.030***	0.039***	0.037***	0.045***
	(0.009)	(0.008)	(0.009)	(0.010)	(0.008)	(0.009)	(0.009)
Observations	322944	322944	322944	322944	322944	322944	322944
Mean of Outcome	0.711	0.711	0.711	0.711	0.711	0.711	0.711
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Grid-cell FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

The DHS sample includes Benin, D.R. Congo, Ghana, Kenya, Namibia, Nigeria, Tanzania, and Togo. The Afrobarometer sample includes Benin, Ghana, Kenya, Madagascar, Mozambique, Nigeria, Senegal, South Africa, and Tanzania. The QLFS survey is from South Africa. Survey years for each DHS and Afrobarometer country are reported in Table A1. QLFS data are 2008/Q1-2010/Q2. Grid-cells range from 10×10 km to 40×40 km. Time is quarters in QLFS and years in DHS and Afrobarometer. Individuals (locations) are considered connected if they are closer than 0.5 km to the backbone network. Robust standard errors clustered at grid-cell level in parentheses, using the same grid-cell size as stated in the column headers. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

TABLE A3: FAST INTERNET AND EMPLOYMENT, ALTERNATIVE STANDARD ERRORS

Outcome:	**Employment (0/1)**		
Unit of analysis:	Individual		
Sample:	**DHS**	**Afro-barometer**	**SA-QLFS**
	(1)	(2)	(3)
Panel A: Standard errors accounting for spatial correlation			
SubmarineCables × Connected	0.031***	0.058***	0.030***
	[0.011]	[0.021]	[0.005]
Observations	186434	13176	322944
Mean of Outcome	0.697	0.580	0.711
Panel B: Standard errors clustered on administrative area			
SubmarineCables × Connected	0.033***	0.058**	0.030***
	[0.012]	[0.024]	[0.009]
Observations	126960	13176	322785
Mean of Outcome	0.643	0.580	0.711
Time FE	Yes	Yes	Yes
Grid-cell FE	Yes	Yes	Yes

The DHS sample includes Benin, D.R. Congo, Ghana, Kenya, Namibia, Nigeria, Tanzania, and Togo. The Afrobarometer sample includes Benin, Ghana, Kenya, Madagascar, Mozambique, Nigeria, Senegal, South Africa, and Tanzania. The QLFS survey is from South Africa. Survey years for each DHS and Afrobarometer country are reported in Table A1. QLFS data are 2008/Q1-2010/Q2. Grid-cells are 0.25×0.25 decimal degrees, which is roughly 25×25 km. Time is quarters in QLFS and years in DHS and Afrobarometer. Individuals (locations) are considered connected if they are closer than 0.5 km to the backbone network. This table presents the precision of our main results using Conley standard errors that accounts for spatial auto-correlation in Panel A (Conley, 1999).The cut-off window is 100 km, but the results are virtually unchanged for 50 km, 500 km, and 1,000 km. Panel B clusters the standard errors on a region (DHS and Afrobarometer) and municipality (SA-QLFS, since South Africa does not formally have regions, and there are only nine provinces) level. The estimates and number of observations differ somewhat due to missing information on regions and municipalities in the DHS and SA-QLFS data. There are 95 distinct regions in the DHS sample, 154 distinct regions in the Afrobarometer sample, and 341 distinct municipalities in the SA-QLFS sample. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

Table A4: Employment in skilled and unskilled occupations by Educational Attainment before fast Internet arrival

Outcome:	**Empl-oyed (0/1)**	**All skilled (0/1)**	**Unskil-led (0/1)**	**Legisl-ative (0/1)**	**Profes-sional (0/1)**	**Cler-ical (0/1)**	**Serv-ices (0/1)**	**Dom-estic (0/1)**	**Retail/ sales (0/1)**	**Empl. agri. (0/1)**	**Self-empl. agri. (0/1)**	**Unskilled manual (0/1)**	**Tech-nical (0/1)**	**Elem-entary (0/1)**
Unit of analysis:	Individual													
DHS														
Not primary	0.78	0.50	0.30		0.01	0.002	0.02	0.002	0.25	0.12	0.28	0.01		
Primary	0.74	0.50	0.27		0.03	0.006	0.06	0.007	0.17	0.11	0.20	0.06		
Secondary	0.61	0.53	0.10		0.06	0.03	0.010	0.003	0.16	0.06	0.06	0.03		
Higher	0.71	0.69	0.09		0.38	0.05	0.04	0.002	0.14	0.03	0.007	0.02		
Afrobarometer														
Not primary	0.47													
Primary	0.55													
Secondary	0.66													
Higher	0.78													
SA-QLFS														
Not primary	0.72	0.28	0.44	0.01	0.002	0.007	0.06	0.14					0.014	0.31
Primary	0.65	0.38	0.27	0.02	0.009	0.04	0.09	0.07					0.03	0.20
Secondary	0.70	0.59	0.11	0.07	0.03	0.15	0.13	0.02					0.08	0.010
Higher	0.91	0.89	0.02	0.15	0.18	0.12	0.06	0.002					0.32	0.02

This table displays the probability of employment in different occupations for individuals of varying educational attainment prior to fast Internet arrival.

TABLE A5: CATEGORIZATION OF SOUTH AFRICAN FIRMS' SECTOR BASED ON KEYWORDS FROM FIRM NAMES

Services:									
abbatoir	accommodation	acquisitions	advertising	air-conditioning	aircon	airconditioning	airlines	airport	answers
apartments	art	arts	assessing	assessment	assessments	assist	assistance	aviation	baby
bakery	bar	bars	bay	bistro	block	booking	boxing	burial	cafe
care	carriers	carwash	caterers	catering	caterings	chauffeur	child	children	childrens
christian	church	clinic	clinical	clinics	club	coaches	coaching	coffee	coffees
college	commercial	communication	communications	compliance	concerts	conditioning	conference	conferences	consultation
cooking	cosmetics	cottages	council	counsellors	courier	couriers	couture	creche	cuisine
cure	dance	daycare	deliveries	design	designs	destination	destinations	dienste	driver
driving	drycleaners	eatery	eats	educare	education	empowerment	entertainment	estate	estates
event	events	exhibitions	export	exporters	exporting	exports	facilitators	fashion	fast
feed	fellowship	fencing	fitness	flats	food	football	franchising	funeral	funerals
games	gaming	gardening	god	gourmet	guest	guesthouse	gym	habitat	hair
hairdresser	haven	healing	health	healthcare	hire	hiring	homecare	homecleaners	homes
homestead	hospital	hospitality	host	hosting	hotel	hotels	house	housing	immobiliare
implementation	import	importers	imports	information	innovations	inspections	installations	intelligence	islam
kafee	karate	kontrakteurs	laundry	leadership	learning	leasing	leisure	living	lodge
logistic	logistics	logistix	mail	makelaars	mansions	meals	memorials	migration	ministries
ministry	mission	missions	monitoring	motel	networking	nominees	nursery	nursing	orchards
outsource	paintball	park	parking	payment	payments	pet	planning	pools	pre-school
procurement	promotions	properties	property	protection	realty	recruit	recruiting	recruitment	recruits
recycling	rent	rental	rentals	residence	residential	residentials	resourcing	restaurant	restaurants
resturant	resturants	retirement	retreat	rugby	safety	salon	sanctuary	school	security
seminars	service	services	servicing	shaving	shipping	shuttle	shuttles	spa	sport
sports	sportsbar	staffing	storage	strategies	strategy	supervision	surgical	swimming	tavern
tax	taxi	theatre	theatres	tourism	tours	training	tranport	transformation	transformers
transport	transportation	transporters	transporting	travel	traveling	travelling	travels	treats	trucking
tutoring	undertakers	venue	villa	village	villages	villas	wash	waste	wedding
weddings	wellbeing	wellness							
White collar:									
academy	admin	administrasie	administration	administrators	advisors	advisory	akademie	analytics	architechts
architects	architectura	architectural	architecture	assurance	attorneys	biometrics	branding	chemical	chemicals
consult	consultancies	consultancy	consultant	consultants	consulting	data	decor	dental	designers
directors	editing	entrepreneurs	fashions	forensic	forensics	geoconsultants	ideas	institute	insurance
interior	interiors	konsultante	landscaping	legal	management	managers	managing	marketing	media
optometrist	optometrists	petrochemicals	publication	publishers	publishing	publishings	radiology	research	risk
translation									
Blue collar:									
autobody	automobile	baking	blocks	brick	brickforce	bricks	build	builders	building
butchery	car	carpenter	carpentry	clean	cleaners	cleaning	coaters	coating	coatings
concrete	construction	constructions	constructors	contracting	contractors	deco	distribution	distributions	distributor
distributors	drilling	equipment	fabrics	filtration	fishing	flooring	forestry	foundry	freight
fuel	gas	hunters	hunting	installation	installations	irrigation	knitting	konstruksie	laminations
lawns	maintenance	mechanics	metal	metals	movers	packaging	packing	paint	painters
painting	paints	pavers	paving	plastering	plumbers	plumbing	recyclers	refrigiration	refurbishing
renovations	repair	repairs	roofing	scaffolding	textiles	towing	truck	woodwork	
Retail and sales:									
accessories	aesthetics	affairs	alarms	apparel	appliances	auction	auctioneers	auctions	auto
bags	bathrooms	beads	beautique	beauty	bedding	beverages	books	booksellers	bookshop
boutique	brand	brands	bread	canopies	cement	ceramics	cheese	clothing	commerce
commodities	components	condoms	confectionary	confectionery	consumables	cooling	cosmetic	cosmetics	covers
crafts	creations	cupboards	curtain	curtains	dealer	dealers	deals	delights	detailing
diary	discounters	elegance	enterprise	enterprises	fertilisers	films	flowers	foods	footwear
fuels	furnishers	furniture	furnitures	garden	garments	gift	gifting	gifts	glass
goodies	goods	groceries	grocery	handelaars	hardware	heating	herbs	hygiene	images
ingredients	instruments	jewellers	jewellery	juice	kiosk	kitchen	kitchens	kitchenware	leather
lifestyle	lighting	lights	linen	liquor	liquors	lubricants	machinery	machines	mall
market	markets	mart	materials	meat	meats	medical	medicine	merchandise	merchandising
merchant	mini-supermarket	motor	motorcycles	motors	movies	music	newspaper	noodles	nutrition
oil	oils	optical	opticals	outdoor	outfitter	outfitters	parts	patisserie	pawn
pearls	perfumes	petroleum	pharmaceutica	pharmaceutical	pharmaceuticals	pharmacy	photography	photos	pictures
plant	plants	plates	print	printers	printing	printings	prints	produce	pumps
refrigeration	remedies	resale	retail	retailers	retailing	sales	sewing	shoes	shop
shopfitters	shopping	signs	snacks	spices	sportswear	stationary	stationers	stationery	store
style	suit	superette	supermarket	superstore	supplements	supplier	suppliers	supplies	supply
sweets	telesales	things	timber	timbers	toiletries	tools	towels	toys	trailers
tyre	tyres	upholsterers	upholstery	vehicle	vehicles	vending	wear	wholesailers	wholesale
wholesaler	wholesalers	windscreen	windscreens	wine	wines				
Technology:									
3d	apps	audio	cable	cables	cabling	cellular	computer	computers	computing
digital	electrical	electricals	electrician	electricians	electronics	energy	engeneering	engineering	engineers
fibre	hydraulics	infrastructure	internet	it	mechanical	mobile	multimedia	online	software
solar	tech	technical	technicians	technics	technik	technique	techniques	technological	technologies
technology	telecommunication	telecommunications	telecoms	web	website				
Manufacturing:									
brewery	brewing	fabrication	factory	manufacturer	manufacturers	manufactures	manufacturing	plastic	plastics
production	productions	products	refineries	refiners	refinery	refining			
Financial:									
accountant	accountants	accounting	asset	audit	auditors	beleggings	bonds	bookkeeping	brokers
capital	cash	clearing	credit	credits	debt	equities	equity	finance	finances
financial	finans	finansiele	fund	funding	futures	holding	holdings	invest	investements
investing	investment	investments	investors	lending	loan	loans	money	mortgage	mortgages
portfolio	portfolios	savings	securities	trade	traders	trading	tradings	trust	wealth
Agriculture:									
agri	agri-business	agribusiness	agricultural	agriculture	boerdery	boerderye	farm	farmers	farming
farms	fisheries	growers	horticultural	horticulture	livestock	poultry			
Mining:									
alu	aluminium	aluminum	coal	copper	diamond	diamonds	gold	iron	mine
mineral	minerals	mines	mining	platinum	steel	steelworks	uranium		
Tourism and foods:									
bagel	burgers	cakes	chicken	chickens	cookies	fish	fruit	fruits	pizza
resort	resorts	safari	safari's	safaris	tour	vacations			

This table displays the key words used when assigning firms observed in the CIPC data to a sector. See the Appendix for details on the procedure.