Making the 'Next Billion' Demand Access*

The Local-Content Effect of `google.co.za` in Setswana

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Abstract

The introduction of the Setwana language interface on the South African Google Search website was a spillover of the development of that interface in accessibility of local language content leads to an increase in demand for Internet connectivity among native speakers. Internet connectivity provides enormous improvements in quality of life such as reduced racism, as well as many opportunities for the newly connected, yet recent attempts to connect the current 'next billion' in places such as sub-Saharan Africa have not met expectations. In places where infrastructure has come online and prices have gone down, the expected consequent increase in usage was not observed. The introduction of the Setswana language in the South-African Google Search website was a spillover of the Botswana Google search website being translated from English to Setswana. This exogenous improvement in the accessibility of Setswana-language content has resulted in a substantial increase in the number of native Setswana speakers coming online and owning personal computers. It has also led to increased usage of the Setswana language online.

1 Introduction

Internet uptake is a two-sided market, with users on one side and content on the other side. This market exists separately for each language and for many indigenous languages fails to take off properly.

With this study I seek to answer the question whether an increase in local language content, indeed leads to an increase in uptake of Internet usage among native speakers.

Because of the cross-side network effects in a two-sided market, any changes are inherently endogenous. I remedy this by using an exogenous shock in accessibility of Setswana language content in South Africa, with the introduction of the Google interface. I find that this leads to a strong increase in both the proportion of households reporting to have spent on Internet access in the last 30 days, as well as individuals owning a computer. This in turn has led to a large increase in the usage of the Setswana language online (using Google

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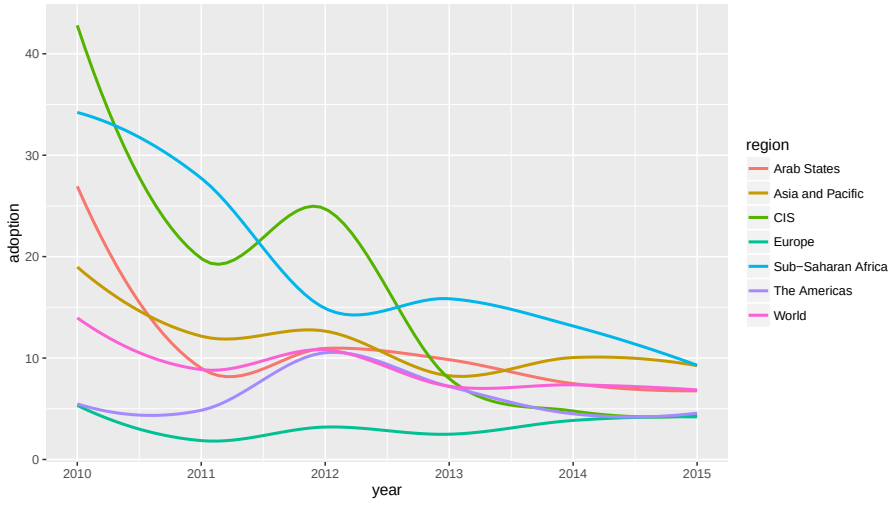
search queries). There is a strong increase in employment among individuals who spend on Internet or own a computer after the introdution. Suggesting that the expanded demographic of Setswana Internet users is benefiting from increased Internet adoption in terms of employability.

The term 'Connecting the Next Billion' was introduced in The Economist's 2006 'End of Year Report' (Standage, 2006), discussing the infrastructural requirements for connecting the second billion individuals to the Internet. Since then, close to 2 billion people are estimated to have been connected to the Internet, up from the just over one billion at the time of writing (Sanou, 2015). However, it seems increasingly unlikely that the current 'Next Billion' will be connected as easily as the previous ones.

In the period 2010-2014 the average annual growth of Internet bandwidth in sub-Saharan Africa was over fifty percent. This increased bandwidth also causes downward pressure on the cost of Internet access, which brought the sub-Saharan average cost of a 500MB prepaid Internet bundle down to around $10, increasingly putting it within range of the emerging middle classes. Yet, despite increased range and improved affordability, sub-Saharan Africa is showing stagnation in the growth of Internet connected individuals.

As is shown in Figure 1, growth of Internet usage in Sub-Saharan Africa is rapidly decreasing. Unlike in other regions in the figure, this observed stagnation is not a consequence of market saturation, as adoption levels are still very low.

Figure 1: Internet Adoption



A crucial determinant of Internet adoption is the interplay with content creation, the two-sided market, wherein the two sides benefit from cross-side network effects. These sides are content creators, such as news websites, and content consumers, the users. Ideally, adoption should follow a virtuous circle, whereby the content offering encourages more users to come online, which in turn incentivices more content creation. Unfortunately this virtuous circle sometimes fails to properly start for certain languages. Herein also lies the difficulty with finding empirical evidence of these dynamics, since the process of adoption by users and content creation is inherently endogenous. This paper

seeks to empirically address the question if increased accessabilty of content does indeed lead to an increase in Internet adoption.

Much research has been done on Internet and language with respect to the preservation of smaller languages, in particular indigenous languages. The focus here is often the preservation of the language, such as the below comment by Wikipedia founder Jimmy Wales (Forbes, 2010).

> The Web is a powerful tool for preserving languages that would otherwise be lost. We see this in a lot of the smaller European languages that have very active Wikipedia projects. For example, the Welsh Wikipedia is quite an active community and they have 27,000 articles and this is true even though virtually everyone who speaks Welsh also speaks English.

Unfortunately, this is less true for many indigenous languages outside of Europe. Increasingly language availability is also being concidered as a method for improving demand for connectivity (Gandal, 2006; Pena-Lopez, 1999). More recently,Viard and Economides (2014) use macro level connectivity data and a model whereby countries that share languages are used to isolate the effect of content on demand for connectivity, which they find to be positive and significant.

There are good reasons for striving for increased connectivity of remote populations. Jensen and Oster (2009) find that the introduction of cable television in Indian states has a pronounced positive effect on attitudes towards the oppression of women, violence against women, son preference, and as well as decreased fertility. Internet access can provide an in some ways similar window on the outside world, we might expect some of these things to also follow more widespread Internet adoption. Sinai and Waldfogel (2004) show that expanded Internet usage in cities can lead to less racism, an issue that can be of particular relevance to South Africa.

As mentioned above, Internet connectivity is a two-sided market, which makes it difficult to empirically isolate a causal effect of content availability on demand for Internet connectivity. This paper exploits an exogenous increase in the accessibility of content in the Setswana language in South Africa, in order to isolate the increase of Internet usage among native speakers. In 2010 Google collaborated with a team of Botswanan linguists (Otlogetswe, 2010) to make its Botswanan website (`google.co.bw`) available in the local language: 'Setswana'. In addition to being spoken in Botswana, there is also a sizable population of Setswana speakers across the border in South Africa, where it is also one of the official state languages. This led to the Setswana-language interface also being introduced on the South-African Google website (`google.co.za`), as a spillover of the translation work originally performed for Google's Botswanan website. This introduction led to a large increase in the number of native Setswana speakers reporting to have spent some amount of money in the past 30 days on Internet access as well as increased computer ownership.

The Google Search interface represents a very small number of words on the Internet and it is not required to use a certain interface language in order to search for content in this language. Yet, the search page is in many cases the first website viewed by users and thereby has a substantial impact on the decision to further engage or not. Asides from being able to understand the interface of

the website, having this interface be in a local language also encourages usage of this local language, which in turn reveals more local language content.

In short, we can identify two main channels through which this promotes increased online engagement, which together constitute the theory of change. Firstly, the ability to read and understand the words of the interface increases the chance that a user continues using the website and the Internet at large. Secondly, the visibility of local language content increases the likelihood of the user entering search queries in the local language and thereby finding more content in the local language.

The data used for this study comes from the South African National Income Dynamics Survey, provided by Southern Africa Labour and Development Research Unit (2008, 2012, 2013), the data is further discussed in section 2. After which section 3 discusses the methods employed in this study, specifically, the discussion of the identification strategy can be found is subsection 3.1 and the use of the Difference-in-Differences estimator in subsection 3.2. Further, we present the results of the estimation in section 4. Finally, we conclude in section 5.

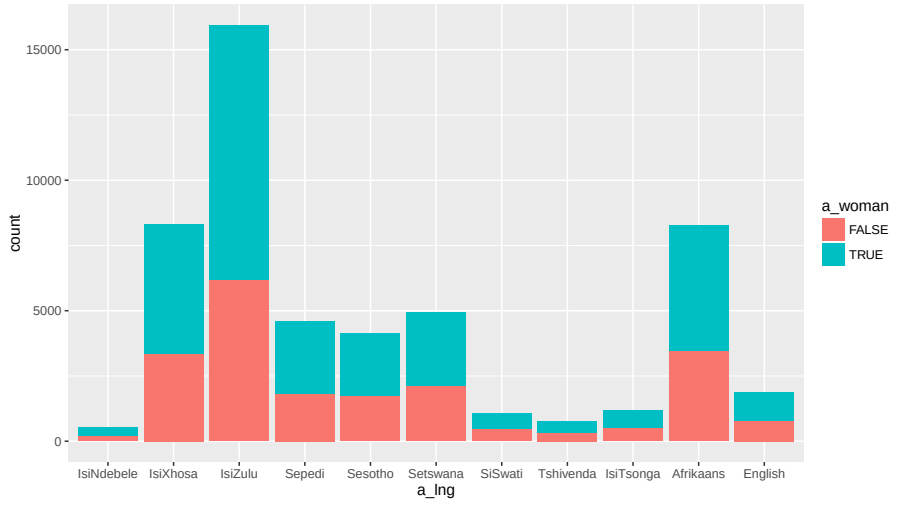
2 Data

South Africa's National Income Dynamics Survey collects data on a representative set of around ten thousand households across several time periods. The first wave was gathered in 2008, the second wave in late 2010 and early 2011, and the third wave was gathered in 2012 (Southern Africa Labour and Development Research Unit, 2008, 2012, 2013). The dataset contains an extensive household questionnaire, which breaks household expenditure down into many forms of food and non-food expenditure. In addition to this, the household income is calculated and imputed with other income such as home ownership. The individual (adult) questionnaires also contain information on linguistic skill in English and in the native language, as well as a series of variables relating to communication technology ownership and utilisation. In Figure 2 we can see the number of native speakers of each in the dataset, coloured by the sex of the individual. The dataset contains 51,612 observations (adult individuals), of which 2,806 are female native Setswana speakers and 2,140 are male native Setswana speakers.

A detailed breakdown of the mean number of households that spend on Internet access and cellphone usage, as well as cellphone and computer ownership by language and time period (wave) is presented in Table 4 of section 7.

Figure 2: Native Language and Sex

```
ggplot(data=NIDS, aes(x=a_lng, fill=a_woman)) + geom_bar()
```



3 Empirical Methodology

With this paper I aim to provide empirical evidence that increased content or accessibility of content leads to an increase in demand. This section begins with a discussion of the identification strategy employed, followed by a explanation of the estimator used to operationalise this, and finally a description of the software used for the implementation.

3.1 Identification Strategy

This paper exploits the introduction of the Setswana interface language to Google Search in South Africa as a spillover of the development of that interface for the Botswanan Google Search website. By comparing the number of native Setswana speakers in South Africa being Internet users, with the number of South Africans with a different native language around the same time, I isolate the effect of this introduction.

The Setswana language was first developed for the Botswanan Google Search website (`google.co.bw`). As such, the introduction of Setswana to the South African Google Search (`google.co.za`) was a spillover effect of that development. This allows me to rule out any possible endogeneity issues that might otherwise arise in contexts such as these. For instance, the Afrikaans language is almost solely spoken in South Africa. When we observe that the introduction of the Afrikaans Google Search interface occurs around the same time as a growth in the number of native Afrikaans Internet users, it will be hard to isolate the effect from the introduction from its cause (since an increase in native Afrikaans Internet users would be a good reason to introduce it as an interface language).

Substantial numbers of Setswana speakers exist in Botswana, South Africa,

Zimbabwe, and to some extend Namibia. However, the language is most important in Botswana, where it is spoken by approximately 80% of all people, and where it is the only official language other than English. As such, it is also the place where most linguistic work on the Setswana language takes place. The Setswana Google Search interface was also developed at the University of Botswana by prof. Otlogetswe.

It is worth noting that it is very common to not personally own a computer, therefore 'paying for Internet access' also includes a lot of people who use the Internet in other locations such as Internet cafe's.

In addition to using the propensity to spend on Internet (in the last thirty days), we also use the propensity to own a computer as a dependent variable.

3.2 Regression Specification

As mentioned in the above section, we compare the change in the level of Internet users among native Setswana speakers in South Africa, with that of native speakers of other language in South Africa around the introduction of the Setswana interface to the South-African Google Search. For this we use a Difference-in-Differences estimator (Abadie, 2005; Imbens and Wooldridge, 2009) using a native-Setswana speaker dummy variable (`setswana_logical`), interacted with an event dummy variable (`interface_intro`). The former is `TRUE` when the native language of the individual (`a_lng`) is `Setswana` and `FALSE` otherwise. The latter is `FALSE` for data collected prior to the introduction of the Setswana interface language (late 2010, here wave 1 and 2) and `TRUE` after this introduction (here wave 3). The model than takes the form as described in equation (1).

$$y_{it} = \alpha_i + \lambda_t + \delta D_{it} + \beta X_{it} + \epsilon_{it} \tag{1}$$

Where α_i represents the individual fixed effects, λ_t represent the time fixed effects, and X_{it} are the time varying covariates. The ϵ_{it} is the error term. Finally the term of interest is D_{it} which represents the treatment effect.

In addition to this estimation, we use an alternative specification whereby a factor variable of native language is interacted with the event dummy variable. In a linear regression context, factor variables are estimated as dummy variables for all levels (here: all languages) except for one 'base' level, which is where all language dummies are `FALSE` (i.e. `0`) and the level (native language) thus has to be the first one (here `IsiNdebele`).

The `h_nfnet` variable is recorded at a household level, as such a standard error correction needs to be applied, the model with standard error corrections is reported in the appendix.

Lastly, the dependent variables are both logical or binary variables, as such, normally a model such as logit should be used. However, since I am using Difference-in-Differences, this model would be undefined.

4 Results

In the base model, we use an interaction of the `event` dummy and `setswana` dummy in order to isolate the effect on the explanandum, a dummy variable describing household expenditure on Internet in the last thirty days or not

(Internet_expenditure, household non-food Internet). The results of this estimation are presented in Table 1.

We find that the interaction term of the event dummy (event) and the native Setswana speaker dummy (setswana) is positive and highly significant, with a p-value around 0.0018. Both the individual dummy variables (event and setswana) yield significant negative parameter estimates.

In addition to this, the covariates included in the estimation are also highly significant. The highest education level of the individual (best_edu) and the household income (hhincome) are both positive and significant. The parameter estimate of woman here is negative but not at all significant, this is unsurprising as we use Internet expenditure at a household level. Most women live in a household which includes men and vise versa, suggesting that this effect cannot be isolated in this estimation. We further investigate this issue in a separate estimation discussed below. The variables describing linguistic skills in reading and writing in both English and the native language do yield many significant results, though lower levels of English writing skill seems to be correlated with a lower propensity to use the Internet (a_edlitwrten for levels 2 and 3, but not the very lowest: 4).

In an alternative formulation, we include the native language variable as a categorical variable (language), interacted with the event dummy. In this estimation we only find significantly positive results for Setswana and Venda (as small language from the region bordering Zimbabwe), and a significantly negative effect for the language Afrikaans.

Table 1: Living in Household that Spent on Internet (last 30 days)

```
lm(h_nfnet ~  interface_intro*setswana_logical +
              factor(a_edlitrden)                      +
              factor(a_edlitwrten)                     +
              factor(a_edlitrdhm)                      +
              factor(a_edlitwrthm)                     +
              a_woman                                  +
              hhincome                                 +
              best_edu)
```

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	-0.0008565	0.0018351	-0.4667340	0.6406924
interface_introTRUE	-0.0117376	0.0012170	-9.6449716	0.0000000
setswana_logicalTRUE	-0.0135286	0.0024255	-5.5777454	0.0000000
factor(a_edlitrden)2	0.0015879	0.0040272	0.3942904	0.6933684
factor(a_edlitrden)3	0.0002543	0.0052755	0.0481963	0.9615600
factor(a_edlitrden)4	-0.0036574	0.0068160	-0.5365861	0.5915561
factor(a_edlitwrten)2	-0.0101933	0.0040178	-2.5369998	0.0111839
factor(a_edlitwrten)3	-0.0107676	0.0052214	-2.0621916	0.0391951
factor(a_edlitwrten)4	-0.0071685	0.0066937	-1.0709421	0.2842010
factor(a_edlitrdhm)2	-0.0025418	0.0036848	-0.6898084	0.4903181
factor(a_edlitrdhm)3	-0.0028899	0.0051291	-0.5634293	0.5731453
factor(a_edlitrdhm)4	-0.0079926	0.0069070	-1.1571655	0.2472107
factor(a_edlitwrthm)2	0.0008117	0.0037229	0.2180373	0.8274010
factor(a_edlitwrthm)3	0.0013993	0.0051372	0.2723915	0.7853222
factor(a_edlitwrthm)4	-0.0069174	0.0069137	-1.0005354	0.3170567
a_womanTRUE	-0.0013881	0.0011452	-1.2121278	0.2254696
hhincome	0.0000027	0.0000001	46.2987087	0.0000000
best_edu	0.0013582	0.0001164	11.6710813	0.0000000
interface_introTRUE:setswana_logicalTRUE	0.0119717	0.0038666	3.0961443	0.0019617

Furthermore, we also use a variant of the base model, in which the propensity of adults (`own_computer`) to own a computer is used as an explanandum. This is of particular relevance, as the explanandum here (`own_computer`) differs from the base model's explanandum in two ways. Firstly, it does not include expenditure on Internet in ways such as Internet cafes, but focusses on actual ownership, signaling a more long-term investment and interest. Secondly, the `Internet_expenditure` variable is at a household level, whereas the `own_computer` variable is at the level of an individual adult. The results from this estimation are included in Table 2. This form of the estimation yields similar results to those estimated in the base model. Firstly we find that the variable of interest, the interaction term between the event and the language dummy (`eventTRUE:setswanaTRUE`) is positive and highly significant, with a p-value smaller than `0.001`. The individual dummy variables (`event` and `setswana`) again are significant and negative with the former's p-value smaller than `0.01` and the latter's smaller than `0.001`. In terms of the linguistic skill, we find that the lower levels of English reading as well as English writing are correlated

with lower propensities of computer ownership. Similar to Internet expenditure model, household income (`hhincome`) and highest level of education (`best_edu`) are both positive and highly significant (p-value: `~0`). However, unlike in the household Internet expenditure model, the sex of the individual here is highly significant, specifically, parameter estimate of `woman` is negative and highly significant (p-value: `~0`). As mentioned above, this variable is difficult to interpret when using a household-level variable as an explanandum, however, here, the computer ownership variable is at an individual level, which makes the coefficient more interpretable.

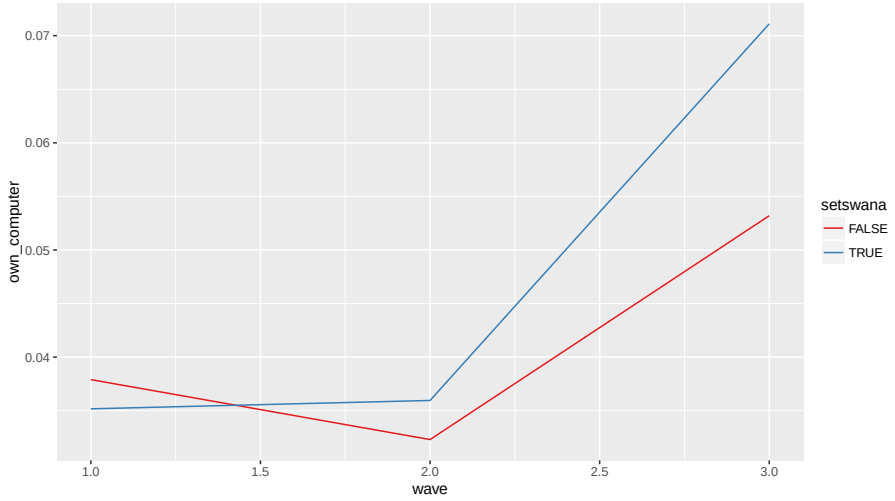
Table 2: Computer Ownership

```
lm(a_owncom ~ interface_intro*setswana_logical +
              factor(a_edlitrden)                    +
              factor(a_edlitwrten)                   +
              factor(a_edlitrdhm)                    +
              factor(a_edlitwrthm)                   +
              a_woman                                +
              hhincome                               +
              best_edu)
```

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	0.0075393	0.0031352	2.4047103	0.0161891
interface_introTRUE	-0.0053820	0.0020917	-2.5729824	0.0100856
setswana_logicalTRUE	-0.0147502	0.0041653	-3.5411916	0.0003987
factor(a_edlitrden)2	-0.0306749	0.0069077	-4.4406931	0.0000090
factor(a_edlitrden)3	-0.0310090	0.0090330	-3.4328617	0.0005978
factor(a_edlitrden)4	-0.0389174	0.0116674	-3.3355679	0.0008519
factor(a_edlitwrten)2	-0.0173238	0.0068925	-2.5134122	0.0119602
factor(a_edlitwrten)3	-0.0210640	0.0089384	-2.3565895	0.0184476
factor(a_edlitwrten)4	-0.0187291	0.0114540	-1.6351572	0.1020227
factor(a_edlitrdhm)2	-0.0017925	0.0063219	-0.2835349	0.7767681
factor(a_edlitrdhm)3	-0.0041655	0.0088001	-0.4733526	0.6359638
factor(a_edlitrdhm)4	-0.0267964	0.0118797	-2.2556443	0.0240974
factor(a_edlitwrthm)2	0.0010896	0.0063817	0.1707311	0.8644360
factor(a_edlitwrthm)3	-0.0020020	0.0088176	-0.2270503	0.8203856
factor(a_edlitwrthm)4	-0.0357886	0.0118921	-3.0094517	0.0026186
a_womanTRUE	-0.0230335	0.0019598	-11.7530143	0.0000000
hhincome	0.0000058	0.0000001	56.8794124	0.0000000
best_edu	0.0058419	0.0002002	29.1761771	0.0000000
interface_introTRUE:setswana_logicalTRUE	0.0238052	0.0066799	3.5637169	0.0003660

Figure 3: Computer Ownership Setswana

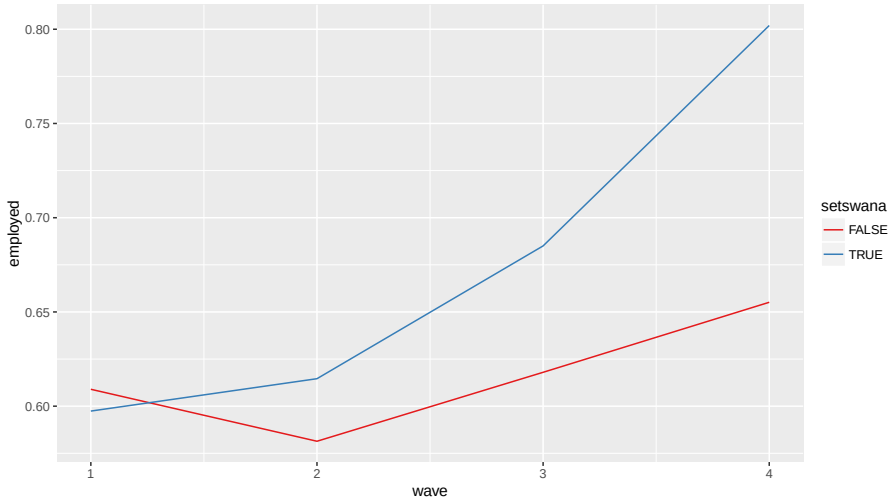
```
NIDS %>%
        group_by(setswana, wave)                                    %>%
        filter(language != 'Afrikaans')                             %>%
        summarise(own_computer = mean(own_computer, na.rm=TRUE)) %>%
        ggplot(aes(x=wave, y=own_computer, colour=setswana))        %+%
        geom_line()                                                 %+%
        scale_colour_brewer(palette='Set1')
```



In the below figure, I plot the employment status of individuals dat own a computer in the first wave after the introduction of the Setswana-language interface (wave 3). We can see that there is a sharp uptick in the proportion of employed individuals among Setswana speakers.

Figure 4: Employment for Individuals who Own a Computer in Wave 3

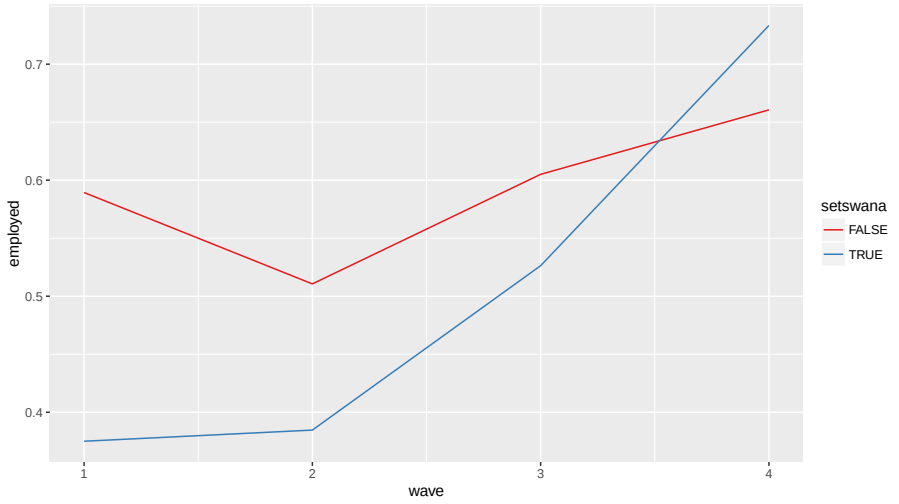
```
pids <- adulthh[which(adulthh$wave==3 &
                      adulthh$a_owncom==TRUE),]$pid

adulthh %>%
  filter(pid %in% pids) %>%
  group_by(setswana, wave) %>%
  summarise(employed = mean(employed, na.rm=TRUE)) %>%
  ggplot(aes(x=wave, y=employed, colour=setswana)) %+%
  geom_line() %+%
  scale_colour_brewer(palette='Set1')
```



Similarly, the individuals that lived in a household that spent on Internet access in the last 30 days also saw a strong increase in the proportion of employed individuals, overtaking the proportion for the rest of the population.

Figure 5: Employment for Individuals with Internet Expenditure in Wave 3

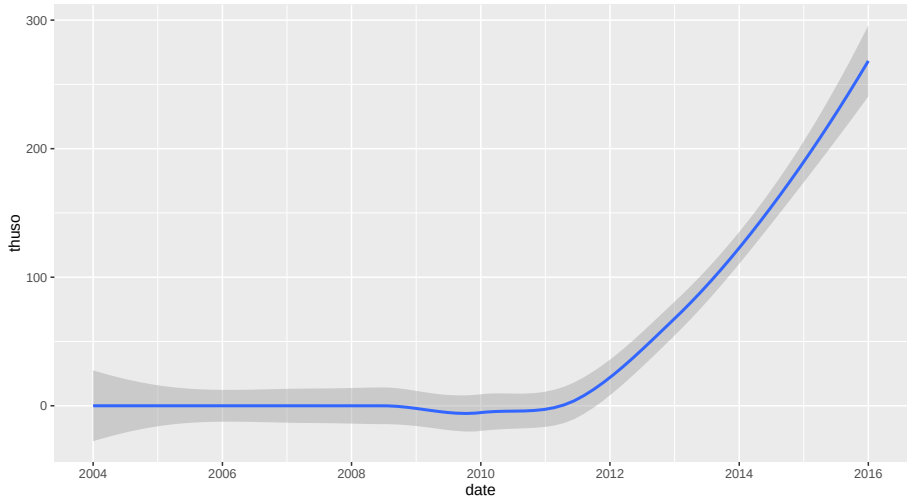
```
pids <- adulthh[which(adulthh$wave==3 &
                      adulthh$h_nfnet==TRUE),]$pid

adulthh %>%
  filter(pid %in% pids) %>%
  group_by(setswana, wave) %>%
  summarise(employed = mean(employed, na.rm=TRUE)) %>%
  ggplot(aes(x=wave, y=employed, colour=setswana)) %+%
  geom_line() %+%
  scale_colour_brewer(palette='Set1')
```



This last effect is also visible in Figure 6, which illustrates how usage of the Setswana word 'thuso', meaning 'help' in search queries, was zero prior to the introduction of the Setswana search interface and became widespread thereafter.

Figure 6: Usage of Setswana Words on Google.co.za

```
ggplot(thuso) + geom_smooth(aes(x = date, y = thuso))
```



5 Conclusions and Limitations

In conclusion, despite recent advances in the reach, speed, and afordability of Internet connectivity in sub-Saharan Africa, actual uptake has been stagnant. Internet adoption is a two-sided market, as a result, one aspect of this is that users benefit from cross-side network effects from content. Unfortuntely, in certain langauges, a sufficient amount of content is not always created, as a result, Internet adoption among native speakers of these languages can lag behind.

This paper demonstrates that this failure can in part be attributed to the dynamics of a two-sided market, whereby the vicious circle of few users and little content perpetuates a situation of low levels of adoption. Due to the endogenous nature of two-sided markets, there are few methods of isolating a causal effect.

I exploit the introduction of the Setswana-language interface on `google.co.za`, as a spillover of the development of this interface for `google.co.bw`, I find that it leads to a substantial increase in Internet usage and computer ownership among native Setswana speakers.

Furthermore, when comparing the Setswana speakers that own a computer or spend on Internet access after the event, with non Setswana speakers, we see a marked increase in the proporotion of employed individuals over that among the rest of the population. This increase is even stronger in wave 4 of the data, suggesting that it takes some time for the effect to fully materialise and that it is persistent.

This increase of Internet usage among the Setswana speaking population as a result of the newly introduced interface language on `google.co.za`, suggests that there is a serious lack in the availability of local content in many indigenous African languages, which serves as an impediment to further Internet adoption.

This suggests that the effect is unlikely to be ephemeral in nature, since

computer ownership constitutes a more long-term investment in Internet access.

As I discussed in the results section, the increase in computer ownership for Setswana speakers between wave 2 and wave 3, was 115%, compared to 70% for the rest of the population, or a 50% greater increase. The effect on Internet expenditure in the household, which includes expenditure in Internet cafes etc. is even greater. The proportion of Setswana households that spent on Internet in the last 30 days increased by 217%, whereas for the rest of the population it fell be 22%.

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6 Clustering

Table 3: Clustering

```
library(plm)     # panel linear model estimation
library(pglm)    # panel generalized linear model estimation
library(lmtest) # Standard Error corrections
library(broom)   # output formatting using tidy()

# specify panel model
plm4_3 <- formula(as.numeric(h_nfnet)  ~ post_event*setswana  +
                                         factor(a_edlitrden)  +
                                         factor(a_edlitwrten) +
                                         factor(a_edlitrdhm)  +
                                         factor(a_edlitwrthm) +
                                         a_woman              +
                                         hhincome             +
                                         best_edu              )

# estimate
plm4_3e <- plm(plm4_3, data=pNIDS, model='within')

# correct errors
tidy( coeftest(plm4_3e, vcov=vcovHC(plm4_3e,
                                    type="HC0",
                                    cluster="group")) )
```

term	estimate	std.error	statistic	p.value
post_eventTRUE	-0.0019402	0.0012392	-1.5657830	0.1174144
setswanaTRUE	0.0027958	0.0137038	0.2040204	0.8383396
factor(a_edlitrden)2	0.0061294	0.0039180	1.5643993	0.1177388
factor(a_edlitrden)3	0.0028083	0.0042618	0.6589578	0.5099301
factor(a_edlitrden)4	0.0001637	0.0044802	0.0365363	0.9708551
factor(a_edlitwrten)2	-0.0088583	0.0039162	-2.2619681	0.0237095
factor(a_edlitwrten)3	-0.0080226	0.0042172	-1.9023800	0.0571351
factor(a_edlitwrten)4	-0.0060115	0.0046454	-1.2940715	0.1956549
factor(a_edlitrdhm)2	-0.0029617	0.0043786	-0.6764141	0.4987852
factor(a_edlitrdhm)3	-0.0035411	0.0061579	-0.5750552	0.5652601
factor(a_edlitrdhm)4	-0.0056185	0.0068075	-0.8253295	0.4091939
factor(a_edlitwrthm)2	0.0020764	0.0043717	0.4749531	0.6348253
factor(a_edlitwrthm)3	0.0045419	0.0063446	0.7158756	0.4740761
factor(a_edlitwrthm)4	0.0077089	0.0074611	1.0332094	0.3015178
a_womanTRUE	-0.0012994	0.0012422	-1.0461001	0.2955268
hhincome	0.0000007	0.0000003	2.4693445	0.0135439
best_edu	0.0001411	0.0003131	0.4507013	0.6522095
post_eventTRUE:setswanaTRUE	0.0070425	0.0034066	2.0673056	0.0387175

7 Dependent Variables Descriptive Statistics

The below table breaks down computer and cellphone ownership as well as Internet and cellphone expenditure by linguistic group.

Table 4: Descriptive statistics on Ownership and Expenditure

```
adulthh %>%
  group_by(a_lng, wave) %>%
  summarise(a_owncel   = mean(a_owncel,   na.rm = TRUE),
            a_owncom   = mean(a_owncom,   na.rm = TRUE),
            h_nfcel    = mean(h_nfcel,    na.rm = TRUE),
            h_nfnet    = mean(h_nfnet,    na.rm = TRUE))
```

a_lng	wave	a_owncel	a_owncom	h_nfcel	h_nfnet
IsiNdebele	1	0.6026490	0.0331126	0.6533333	0.0000000
IsiNdebele	2	0.6864865	0.0270270	0.6800000	0.0284091
IsiNdebele	3	0.7611111	0.0333333	0.8722222	0.0000000
IsiXhosa	1	0.4631115	0.0112269	0.4352518	0.0012043
IsiXhosa	2	0.6065066	0.0186335	0.5996664	0.0054517
IsiXhosa	3	0.7564988	0.0345508	0.7041694	0.0019756
IsiZulu	1	0.5610984	0.0132693	0.5756053	0.0013730
IsiZulu	2	0.5169004	0.0127744	0.4721318	0.0086366
IsiZulu	3	0.7662405	0.0252420	0.7247881	0.0044928
Sepedi	1	0.6127214	0.0265273	0.5772947	0.0048309
Sepedi	2	0.7029372	0.0226818	0.5933485	0.0021994
Sepedi	3	0.7936063	0.0718697	0.7863152	0.0050477
Sesotho	1	0.6562986	0.0366044	0.5507812	0.0062598
Sesotho	2	0.6973684	0.0457010	0.5411671	0.0213640
Sesotho	3	0.8114210	0.0949535	0.8147901	0.0113032
Setswana	1	0.5796003	0.0351724	0.5281593	0.0068681
Setswana	2	0.6004872	0.0359537	0.6494778	0.0037783
Setswana	3	0.7728036	0.0711086	0.7684564	0.0106264
SiSwati	1	0.6593060	0.0441640	0.7823344	0.0000000
SiSwati	2	0.7598870	0.0612813	0.6693227	0.0091185
SiSwati	3	0.8247978	0.0458221	0.7816712	0.0134771
Tshivenda	1	0.5980861	0.0334928	0.5645933	0.0000000
Tshivenda	2	0.7804878	0.0000000	0.9621212	0.5441176
Tshivenda	3	0.8617363	0.0225080	0.8456592	0.0000000
IsiTsonga	1	0.6411765	0.0235294	0.4408284	0.0000000
IsiTsonga	2	0.7375887	0.0118203	0.7163636	0.0929368
IsiTsonga	3	0.8621495	0.0397196	0.8691589	0.0023529
Afrikaans	1	0.5392884	0.1345441	0.6227876	0.0465116
Afrikaans	2	0.5422477	0.0904605	0.6258591	0.0424710
Afrikaans	3	0.6686971	0.1106225	0.7645862	0.0399458
English	1	0.7266667	0.2969374	0.7449933	0.1016043
English	2	0.7976190	0.3234127	0.8728814	0.1070707
English	3	0.8608059	0.3156934	0.8811700	0.1023766

8 General Descriptive Statistics

Figure 7: Household Income

```
ggplot(adulthh, aes(x=hhincome, fill=a_lng )) +
    stat_bin(bins=50)
```

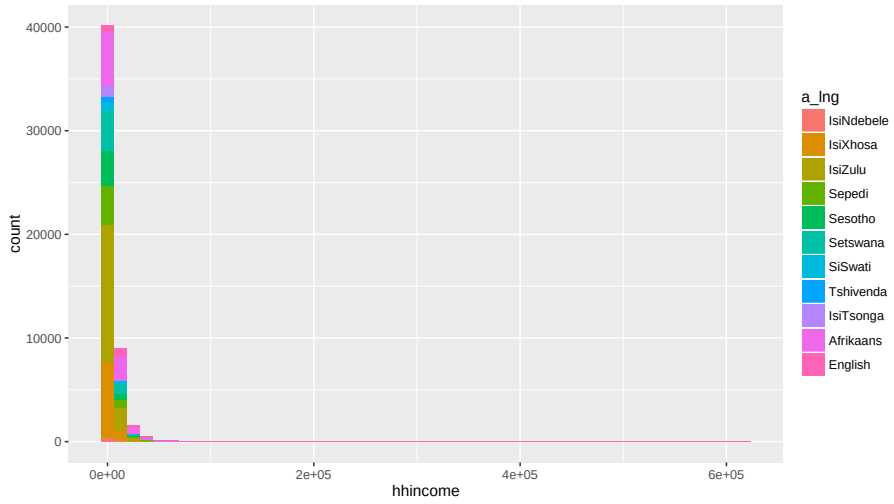
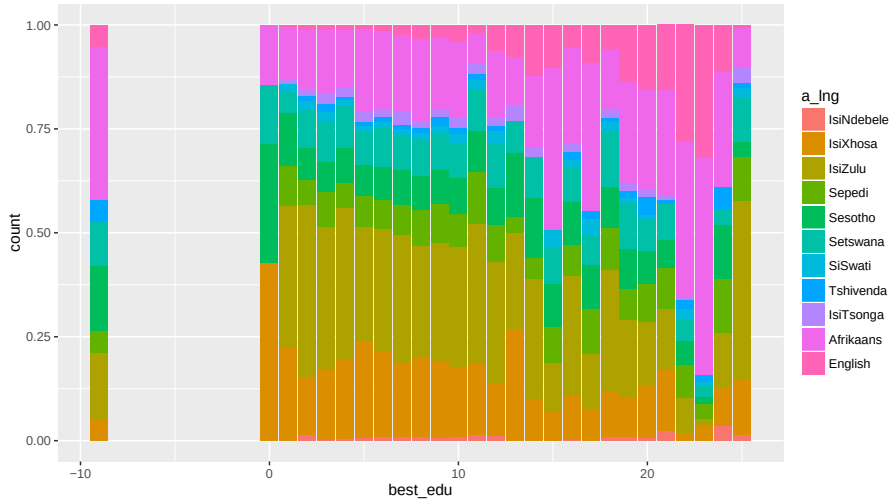


Figure 8: Years of Education

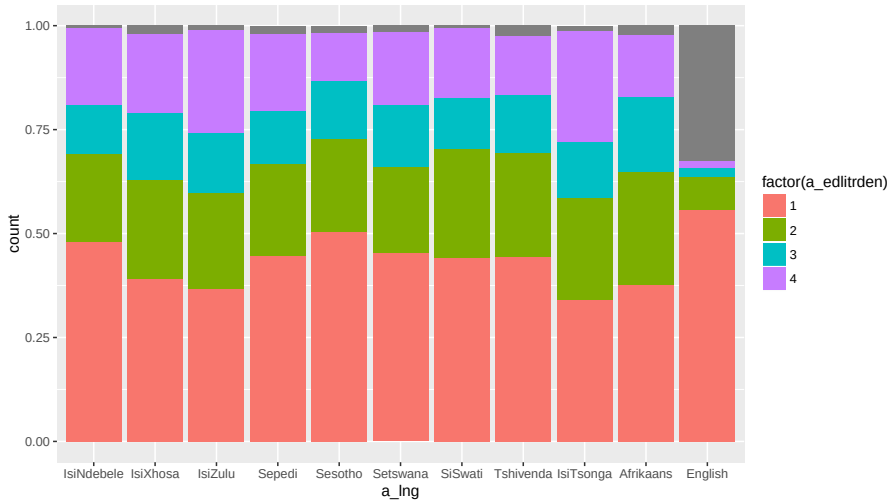
```
ggplot(adulthh, aes(x=best_edu, fill=a_lng )) +
    geom_bar(position = 'fill')
```



The Figure 9 describes the skill of individuals in reading the English language, where 1 the best and 4 is the worst, grey values are `NA`.

Figure 9: English Language Reading Skills

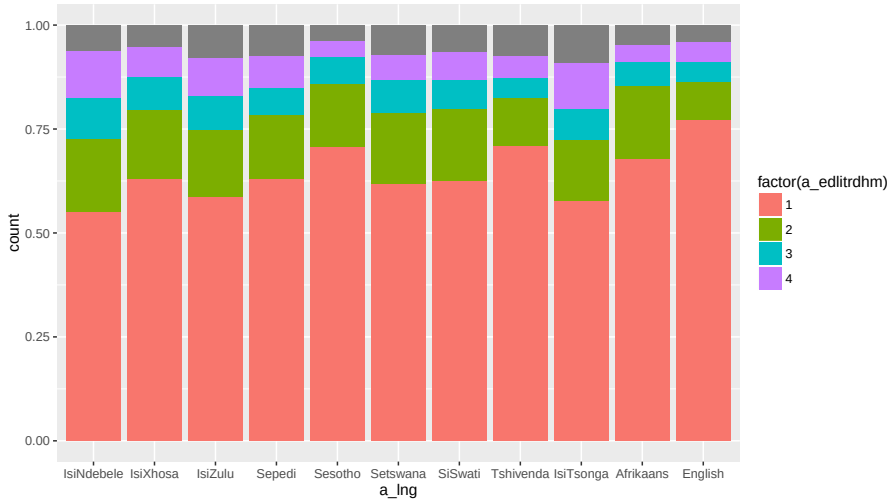
```
ggplot(adulthh, aes(x = a_lng, fill = factor(a_edlitrden)) ) +
        geom_bar(position = 'fill')
```



The Figure 10 does the same but with regards to the native language.

Figure 10: Native Language Reading Skills

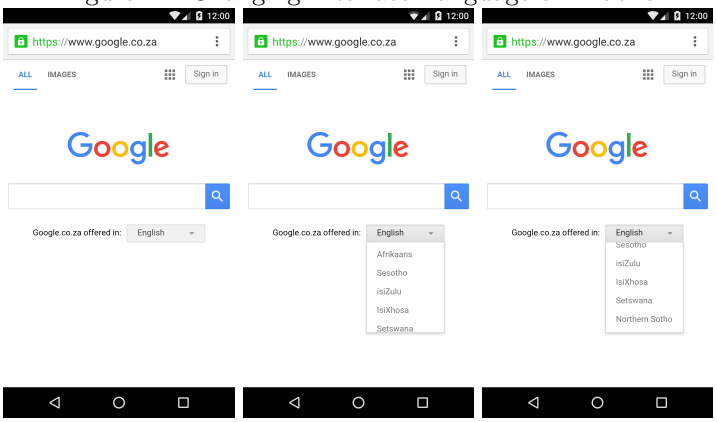
```
ggplot(adulthh, aes(x = a_lng, fill = factor(a_edlitrdhm)) ) +
        geom_bar(position = 'fill')
```



9 Language Switching on Mobile

The graphics in Figure 11 illustrate the process of switching the mobile `google.co.za` interface language to Setswana, from the default English. The mobile interface language can automatically be changed based on the system language of the operation system (in most cases Android), however, as Setswana and many African languages are not available as system languages in Android, the website interface on `google.co.za` will default to English.

Figure 11: Changing Interface Language on Mobile



10 Software

The estimation is primarily performed using R (R Core Team, 2016), specifically using `lm()` and `glm()` functions included in the `stats` package (Venables and Ripley, 2013). Additionally, I make the of the `plm()` and `pglm()` functions which are available in packages by the same names (Croissant, 2013; Croissant and Millo, 2008). Standard error corrections are computed using the `lmtest` and `sandwich` packages Zeileis (2004, 2006); Zeileis and Hothorn (2002).

In order to make the result as easily reproducible as possible, this research and writing in the article has been done exclusively using open-source software such as R (R Core Team, 2016). This document is written and LyX (LyX Team, 2016) in the LaTeX(Lamport, 1985) language and compiled using the LuaTeX implementation(Hoekwater et al., 2016). The integration of R code and output in the document is performed using a process call literate programming Knuth (1984) using the knitr implementation Xie (2015) of the Sweave framework (Leisch, 2002).

All changes are logged using the version control system Git (Git Team, 2016) and publicly available on GitHub at https://github.com/bquast/Making-Next-Billion-Demand-Access/[1]

[1]The repository can by cloned to a local computer by entering in following command in a terminal (with Git installed):
`git clone https://github.com/bquast/Making-Next-Billion-Demand-Access.git`