The Apple App Store - Mechanism of Technology Adoption

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Summer term 2013

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Economics

5th term

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1   Introduction

Since the foundation of economics during the Scottish Enlightenment, modern economics is deeply shaped by the century long search for an explanation of the differences in the Wealth of Nations. Both Adam Smith (1776) and David Ricardo (1817) concluded that differences in the adoption of free trade and advantages in labor productivity are the two main factors determining cross-country differences in GDP per capita. Thereby they already implicitly stated different total factor productivity and institutional differences to be the main factors for cross-country differences in income.

Among the first who put institutions at the center of a growth theory was Max Weber (1905). He argued that Northern Europe's capitalist institutions developed due to a specific protestant work ethic that was morally supportive to the acquisition of wealth. According to Weber, those capitalist institutions were responsible for Northern Europe's relatively higher wealth compared to its southern neighbors. Acemoglu (2005) and Weingast (1995) still stress the efficiency of institutions as one of the main causes for cross-country differences in income per capita.

Solow's Neoclassical Growth Theory (1956) offers capital intensity and total factor productivity as explaining factors for differences in GDP per capita and predicts long-term convergence. De Long (1988) demonstrates that using Solow's model there is little empirical evidence of convergence. Mankiw, Romer and Weil (1992) show that if human capital is included as a second investment opportunity next to physical capital, the model accurately predicts the actually recorded slope of convergence. In more recent empirical studies it was shown that only a small part of cross-country differences can be explained by different levels of capital-intensity. Accordingly differences in per capita output appear to be mostly caused by differences in total factor productivity (Hall and Jones (1999).

In this respect the two major sources for different total factor productivity levels are differences in the range of technologies used and non-technological factors that affect the efficiency of all technology and production factors (e.g. Human Capital).

As the range of available technologies changes consistently, the extent of technology adoption affects total factor productivity continuously. There are two measures for the level of technology adoption, the extensive margin and the intensive margin. While the extensive margin measures how long it takes a country to adopt a technology at all, the intensive margin measures the extent to which a technology is adopted by a nation as a whole. Comin and Hobijn (2010) explore the importance of the range of technologies used for cross-country differences in TFP by developing a model that combines one sector neoclassical growth model with Schumpeterian

elements. They estimate that technology adoption accounts for 70 percent of differences in cross-country per capita income, while differences in the intensive margin of technology adoption account for 45 percent of cross-country differences in per capita income (Comin and Mestieri (2010)). The rate of technology adoption is one of the driving forces shaping cross-country wealth differences. Thus it seems plausible that different rates of technology diffusion cause different levels of economic wealth.

The important question that remains is which factors cause the differences in the level of internal diffusion in different countries and thereby determine the underlying mechanisms of growth. Knowing the real causes of rising total factor productivity could help emerging economies to increase to catch up faster. According to Krugman (1994) even Western Asia's economic miracles have still not managed to catch up in terms of efficiency. He states that their rapid growth in recent times was mostly input driven and predicts, that although Asian emerging economies will become important economic powers, a significant gap in wealth levels will remain.

In this paper we use the case of the introduction of the Apple App Store, the iPhone and the whole iOS environment, whose innovations were quickly adopted all around the world to test whether and in which way internal diffusion of a new technology depends on country specific factors. Since its release in 2008 the iPhone has radically changed the way people communicate and consume information. Following the foundation of the Apple App Store a whole new ecosystem of apps developed, radically changing distribution channels in the gaming, the newspaper industry and advertisement methods. Smartphones of all kinds became one of the major factors shaping the information and telecommunications revolution.

For such a technological revolution in globalized times the time lags of the product's official introduction around the world were significant. Although it can be assumed, that iPhone's were theoretically available throughout the world directly after their US launch, there were high technical barriers such as the need to jailbreak your iPhone, which prevented a great majority user from using an iPhone in their home countries. Only after the product was officially introduced in a country, the product was distributed and easily available to everyone. After its US release on June 29, 2007 it took until November of the same year for the iPhone to become available in the big western European countries of France, Germany and the United Kingdom. It took until July 2008 for the iPhone to become available in other G7 states such as Japan, Spain, Italy and Canada. In the fall of 2008, it was officially released in the important emerging economies of Brazil, South Africa, Russia and Turkey but it took until October 2009 for the

iPhone to become available in China. More than two years after its official release the iPhone was finally available in all G7 and BRIC countries. Even today many new features of the iOS software system such as Siri are only available in a relatively small number of countries, thus increasing technological gaps around the world.

Although differences in external margins of technology adoption around the world already appear to be noticeable, the differences in internal margins are much more significant. In this paper we are interested in the importance of particular factors, which affect the intensive margin of technology adoption. We measure cross-country differences in the internal adoption of iOS technologies and try to find which country specific factors cause differences in the speed of internal diffusion of a new groundbreaking technology. Such country specific factors could then be made responsible for existing wealth gaps between countries. To estimate the intensive margin of technology adoption we use a measure for the Apple App Store's revenue per capita - the conversion ratio. The conversion ratio describes the percentage of user who downloaded a free app and then go on to purchase its full paid version. Therefore it is also a direct measure for the user's willingsness to pay for apps. We show that GDP per capita is the most important factor determining about half of the speed of technology adoption. We couldn't find significant institutional, technological and cultural factors causing differences in the cross-country adoption of the Apple App Store.

2 Modeling an App Purchase

The conversion ratio bases on a "Lite-Full-Strategy", in which a "lite" app is available for download for free to show off the apps functionality to potential buyers. To incentive users to buy the app's full version the functionality is usually limited. The "full" app is advertised inside the free app to encourage user wanting the app's full functionality to purchase it. The "full" paid app is also available for purchase on the app store. Usually users of the free app are transferred to the paid app via the paid apps' app store link, to purchase the full version. Therefore when the app developer uses a "Lite-Full-Strategy" customers can purchase the paid version of the app in two ways: They can download the free app and afterwards download the paid version via a link. Or they can purchase the paid version directly without trying the free version first. Both distribution channels lead to the same result, a purchase worth 0.99$ and we can't technically distinguish them. Therefore when speaking of the conversion rate, in fact we mean:

$$\frac{Indirect\ Purchases\ via\ "Lite\ Version"\ +\ Purchases\ via\ search}{Free\ Downloads} \tag{1}$$

It can easily be seen, that this conversion rate as we measure it, systematically overestimates the actual conversion rate of free app downloads, as downloads are included that weren't caused by the free app's advertising.

In the following paragraphs we propose a model to describe the app purchase decision in a lite-full-model. This app purchase decision model leads to the specification of country-independent factors and cultural factors that could influence the conversion rate. Such country-independent factors will be used throughout the rest of the paper to correct for differences in countries average preferences such as cultural differences. An app purchase will take place whenever the perceived expected utility of the app exceeds the opportunity costs of spending 0.99$. Given a high uncertainty about the app's quality, an app purchase decision is a typical example for adverse selection. The Lite-Full-strategy is a method to reduce this information asymmetry through reliable additional information of the app's functionality and features that is given to the customer in advance of his final purchase decision. The number of potential customers for a given quality and a given price increases as their expected utility rises when uncertainty is reduced.Therefore the Lite-Full strategy is a Pareto-improvement compared to offering only paid apps.

But there still remains a first barrier. The expected utility of the free app must still be

higher than the search costs of finding, downloading and trying the app. Hence, given a lite-full-strategy, we can split the purchase decision into two stages. At the first stage the customer decides whether to or not to download the Lite-version. She downloads the Lite-Version if and only if her expected utility exceeds her search costs. Afterwards she receives further information about the app by using its lite version. Based on this form of Bayesian learning she corrects her assumptions about the full version. If her new expected utility then exceeds the opportunity costs of 0.99$, a purchase will take place.

To formalize our verbal model at first we define consumer preferences. Apps - just as the iPhone - are superior goods with an income elasticity of demand > 1. Using Stone-Geary preferences we assume a market of two goods x_1 and x_2 and two subsistence levels leading to a minimum consumption of s_1 and s_2. Given x_1 represents the consumption of apps we set $s_1 = 0$, while x_2 can be seen as a numeraire good, with a given subsistence level s_2 representing the cost of living. We normalize the price of both goods to be one.

The resulting utility function is:

$$u(x_1, x_2) = \alpha ln(x_1) + (1 - \alpha) \, ln \, (x_2 - s_2) \tag{2}$$

Now we introduce the apps quality $\theta \in [\underline{\theta}, \bar{\theta}]$ into our model. To simplify the model assume that all apps are of the highest quality: $\theta = \bar{\theta}$. Every customer has different tastes for apps looking for different functionality and perceiving the same quality level differently. To acknowledge for that we define the customers perceived quality to be:

$$v_i(\bar{\theta}) = \begin{cases} 1 \; with \, probability & p_i(\bar{\theta}) \\ 0 \; with \, probability & 1 - p_i(\bar{\theta}) \end{cases} \tag{3}$$

Thus an app's perceived quality is individual but depends on the apps quality θ. For a given omega an app is perceived by an individual to be of high quality with probability $p_i(\theta)$. Given their preferences and consumption behavior the customers form rational expectations about their individual expected perceived quality: $E_i[v(\bar{\theta})] = p_i(v(\bar{\theta}))$.

We assume that $p_i(\bar{\theta})$ is linearly distributed on [0,1]. Therefore the apps average perceived quality by the whole audience is: $E[v(\bar{\theta})] = 1/2$

In the next step we will introduce the apps perceived quality into our utility function. We assume that an app's perceived quality positively affects the marginal utility of its consumption.

Therefore we add a quality index to the Stone-Geary's utility function:

$$\alpha v_i(\bar{\theta}) \ ln \ (x_1) + (1 - \alpha) \ ln \ (x_2 - s_2) \tag{4}$$

Lemma: *Unsecurity about the apps' perceived quality reduces the demand for the entirety of apps at a given price. Put differently the apps' demand function rises with higher expected perceived quality:*

Proof: *Given Stone-Geary preferences including perceived quality it follows that:*

$$\max \quad \alpha \ v_i(\bar{\theta}) \ ln \ (x_1) + (1 - \alpha) \ ln \ (x_2 - s_2) \quad \textbf{\textit{s.t.}} \quad x_1 + x_2 = m \tag{5}$$

$$\Rightarrow \quad x_1{}^* = \frac{\alpha \ v_i \ (\bar{\theta})[m - s_1]}{1 - \alpha + \alpha \ v \ (\bar{\theta})} \tag{6}$$

$$\frac{\delta \ x_1}{\delta \ v_i(\bar{\theta})} = [1 - \alpha] \ \alpha \ [m - s_1] > 0 \tag{7}$$

With the introduction of a two stages purchase model in the full-lite strategy the purchase decision is split up into two stages. At the first stages the individual decides to download the free version of an app whenever the opportunity costs $c_t \cdot t$ of doing so are smaller than the expected utility of using the free version of the app.

$$E[\ v \ (FreeApp)] > c_t \times t + e \tag{8}$$

At the second stage the customer can decide to purchase the app. To purchase the app she has to put in the effort e to evaluate the free app's quality. For every app this effort level needed is equal. This effort has already implicitely been done by using the free app.

Lemma: *The customers' total app demand is dependent only on her disposable income.*

Proof:

$$\max \quad \alpha \ ln \ (x_1) + (1 - \alpha) \ ln \ (x_2 - s_2) \quad \textbf{\textit{s.t.}} \quad x_1 + x_2 = m \tag{9}$$

$$\Rightarrow \quad x_1{}^* = \alpha \ (m - s_2) \tag{10}$$

$$with \quad \frac{\delta \ x_1{}^*}{\delta \ m} \times \frac{m}{x} = \frac{m}{m - s_2} > 1 \tag{11}$$

Let's further assume that every app's visibility in the market is symmetric and $n \in N$ apps constitute the whole app store. The function of perceived quality now differs between apps and

becomes:

$$v_{ij}(\bar{\theta}) = \begin{cases} 1 \ with \ probability & p_{ij}(\bar{\theta}) \\ 0 \ with \ probability & 1 - p_{ij}(\bar{\theta}) \end{cases} \tag{12}$$

But the apps' quality stays fixed at $\bar{\theta}$. Thus the total downloads of the free app is a fraction $1/n$ of total free downloads D. Then the median demand for the individual app amounts to :

$$E[x_{ij}] = \frac{1}{n} \times \alpha \ (m - s_2) \tag{13}$$

Given that apps differ in average perceived quality $E[p_{ij}(\bar{\theta})]$ the number of downloads must be multiplied by the ratio of perceived qualities $\frac{E[p_{ij}(\bar{\theta})]}{E[p(\bar{\theta})]}$

$$x_{ij} = \frac{1}{n} \times \frac{E[p_{ij}(\bar{\theta})]}{E[p(\bar{\theta})]} \times \alpha \ (m - s_2) \tag{14}$$

$$x_{ij} = \frac{1}{n} \times \frac{1}{2} \times E[p_{ij}(\bar{\theta})] \times \alpha \ (m - s_2) \tag{15}$$

Lemma: *The conversion ratio of an individual app is dependent of disposable household income and perceived quality.*

Proof: *Given equation (14) we can easily establish*

$$Conv \ x_{ij} = \frac{1}{D} \times \frac{1}{2} \times E[p_{ij} \ (\bar{\theta})] \times \alpha \ (m - s_2) \tag{16}$$

3   Data Sources

To analyze the internal margin of technology adoption we use data from a portfolio of thirteen apps published in the Apple App Store that only run on iPhone devices. They all explain how an iPhone in general and its specific functions are used, focusing on three different versions of Apple's mobile operating system iOS 5, iOS 6 and iOS 7 and Apple's cloud storage and cloud computing service iCloud. Being based on the Phonegap mobile development framework all apps can be broadly identified as e-book-type mobile applications. The period of study starts on 7th December 2011 and ends at 31th July 2013. During this time the chosen sample's combined number of downloads amounted to 7.28 million.

The observed portfolio follows a so-called "lite/full strategy, referring to the fact, that a paid ("full") app is advertised by a free ("lite") version with limited content and usability. Both apps are independently available for the iPhone on the Apple App Store. The free version links to the paid version to encourage buyers to purchase the app with full functionality. This strategy is typically used to reduce information asymmetries between customers and developers. In our case the paid apps are advertised via several links and textual explanations at crucial points inside the app, to make it obvious that a full, ad-free version with additional content is acquirable. The conversion rate describes the ratio between paid downloads of the "full versionänd free downloads of the "light-version". In our example the conversion ratio is a direct measure of the customers' willingness to pay for the additional content offered to him. Sales figures are delivered by iTunes Connect, an Apple service responsible for all payments to developers. Therefore iTunes Connect's monthly reports can be considered as official sales figures, which are split up by countries and days.

To maximize earnings, the free- versions of the offered apps are equipped with AdMob banner ads. AdMob sells advertisement space to every advertiser using an auction system thereby determining the cost per click - the sum that AdMob receives from the advertiser for every click. AdMob itself takes a fixed percental cut and pays out the rest to the developer, giving them a daily earning report. As a result AdMob banner advertisements pay a sum (usually 0.05$ - 0.15$) to the developer for every click by a customer on them. Daily earning reports can be split up on country levels and shows the number of impressions, clicks and revenue. Every 15 seconds an impression is delivered. Given a fill rate of 99%, the number of impressions and the complete usage time are almost identical, a relation that is important throughout the paper.

We analyzed extensive country specific data using publicly available data from the Federal Statistical Office of Germany and the World Bank. To measure institutional efficiency we used the index of economic freedom published by the Heritage Foundation in collaboration with the Wall Street Journal. According to Beach and Kane (2008) the creators of the index took an approach similar to Adam Smith's in The Wealth of Nations, that "basic institutions that protect the liberty of individuals to pursue their own economic interests result in greater prosperity for the larger society". Instead of total factor productivity for which only sporadic data exists we use labor productivity. Though total factor productivity at first sight seems to be very similar to labor productivity, it is noticeable that capital intensity positively influences labor productivity. This should severely reduce the significance of differentiating between GDP per capita and labor productivity per hour, since we can't hold capital intensity constant. Thus

we expect very similar results, using either of the two variables. In general the use of several highly correlated country specific variables, such as GDP per capita, productivity, or internet usage as predictor variables in a multiple regression model, poses threats of multicollinearity. Therefore we have to be very careful when choosing the selection of country specific variables used.

4 Empirical Model

Building on the app purchase model in equation (12) we start by assuming that the conversion ratio depends on the likeability of an app and on disposable income. Disposable income itself depends on GDP per capita, total factor productivity, the abundance of technologies and the efficiency of institutions. Our central goal is to find which variables influence the yearly conversion ratio by country.

Though the purchase of an app is a binary decision, we can't break aggregated daily data to the level of an individual app purchase decision. Thus we can't use a probit model. The conversion ratio can reach values > 1 but not < 0. Therefore in theory our data is truncated, but in fact no country in our sample had a zero conversion ratio and the difference when assuming a truncated normal distribution bound below at 0 seems to be negligible. Due to ongoing debates whether the maximum likelihood estimator in the probit model is consistent under heteroskedastic conditions (Maddala and Nelson (1975), Arabmazar and Schmidt (1982a,b)), we chose to estimate the causal effects of country specific factors on the conversion ratio with a multiple linear regression model. A panel data approach would allow us to automatically exclude fixed country specific effects and thus enabling a much more sensitive analysis of the effect of time-changing country specific variables such as GDP per capita, institutional efficiency or the percentage of internet users. We don't use a panel data approach due to the nature of our data. It only spans two years, and therefore country specific variables are at most available for 2 years or 8 quarters respectively.

The basic empirical model then amounts to:

$$Conversion\ Ratio\ =\ \beta_0\ +\ \beta_1\ \times\ Perceived\ Quality\ +\ \beta_2\ \times\ Country\ Specific\ Factors \tag{17}$$

We measure likeability by impressions per download. It seems plausible that - even more given all apps in the sample are content based - the longer a customer uses the app the higher

is its utility for him. The customers update the paid version's expected utility depending on the likeability of the free version. Then the time spent in the free version and the willingness to pay to upgrade to the full version should be strongly correlated.

It's much more difficult to measure the original level of perceived usefulness, as we don't have any valid evidence for it. We decided to use a proxy. It can be assumed with higher visibility, search and other opportunity costs of a free download decrease. Thus the average expected utility of people who downloaded the free version decreases with higher visibility. Another direct consequence of higher visibility is a higher number of downloads per capita. Hence we can use the average downloads per capita as a proxy for perceived usefulness before the lite-version was downloaded. We assume that the average downloads per capita and the perceived average usefulness are negatively correlated.

We only took countries with more than 1.000 total downloads in our sample. For small countries the Law of Large Numbers doesn't hold and a high variability in conversion ratios results. This high variability could distort the OLS-estimators due to outliers. The most obvious reason for a high technology adoption rate is a high GDP per capita and a high capital intensity, facilitating investment in new technologies. Following the same argumentation efficient institutions and strong investor and property rights are beneficial to technology diffusion. Technology adoption in technological advanced countries can take place faster ceteribus paribus due to lower barriers due to the general availability of the technological predecessor. For example it is often argued that countries with already very efficient data networks and a high proportion of daily internet users did adopt smartphones a lot faster due to lower technological barriers and higher usability. Expenses for research and development are another measure for technological development and show how technologically forward thinking a nation is.

The basic multiple regression model used in this paper thus amounts to:

$$Conv \ = \ \beta_0 \ + \ \beta_1 \ \times \ Impression \ per \ download \ + \ \beta_2 \ \times \ Downloads \ per \ capita$$

$$+ \ \beta_3 \ \times \ GDP \ per \ capita \ + \ \beta_4 \ \times \ (GDP \ per \ capita)^2 \ + \ \beta_5 \ \times \ Institutional \ Efficiency$$

$$+ \ \beta_6 \ \times \ Internet \ User \ + \ \beta_7 \ \times \ Expenses \ for \ R\&D$$

This basic multiple regression model could lead to inconsistent estimates due to two mechanisms of reverse causality. We are using instrumental variables in a two stages least squares method to correct for this bias. According to the Neoclassic Growth Model total output of an economy depends on the input factors of labor, capital and technology. Solow (1956) uses a

Cobb-Douglas-Production function homogenous of degree one.

$$Y \;=\; F(K(t), A(t)L(t)) \tag{18}$$

We use the conversion ratio to measure the internal margin of technology adoption. The internal margin of technology adoption and total factor productivity are strongly positively correlated: (10)

Thus it follows that:

$$Y \;=\; K(t)^{\alpha} \left[A(t)L(t) \right]^{\alpha} \tag{19}$$

$$\Leftrightarrow \left(\frac{K(t)}{L(t)} \right)^{\alpha} \times A(t)^{1-\alpha} = GDP\ per\ Capita \tag{20}$$

$$A\ (Internal\ margin\ of\ adoption) = A\ (conversion\ ratio) \tag{21}$$

To correct for reverse causality we use GDP per capita in 2008 as an IV-Variable. The Apple App Store was invented in 2008. Thus the technological advancement due to apps can't have an influence on the GDP per capita in 2008 such that IV-exogeneity is fulfilled.

Secondly in a Full-Lite Strategy we have two purchase channels, an indirect purchase channel via the Lite- version linking directly to the app store and a direct purchase channel via search. A higher search rank improves the app's visibility and leads to more purchases through the direct purchase channel. Officially, the search rank itself is influenced by the total numbers of downloads, recent trend in download numbers, keywords weight and average ratings. In practice the number of total downloads and recent downloads are dominating search ranks. Thus higher download numbers have a self-enforcing effect leading to a higher download rate.

We use the level of competition as an instrumental variable. To measure for competition it seems appropriate to measure the number of downloads the competition receives and to calculate the market share of our app portfolio. In lack of actual data for our competitors we estimate the market share by analyzing the number of ratings of our competitors. The number of ratings is directly related to the number of downloads but appears to be also dependent of the apps quality and possibly incentives provided to encourage the users to rate. Due to a lack

of reviews in many countries [1] we can't compare them with our own and thus we can't estimate our market share. But the number of ratings per capita can still be used to estimate per country download numbers of competing apps. The higher the competing apps' download numbers the lower is our search rank ceteribus paribus. Thus the number of the competing apps' ratings can be used as an instrumental variable.

5   Results

This section is divided into two subsections. In the first section we use a multiple regression model to estimate OLS coefficients of country specific factors. We test for heteroskedasticity, show that the app demand is in fact non-linear to the GDP per capita and choose our set of exogeneous variables to avoid multicollinearity as much as possible. In the second section we use GDP per capita in 2007 as an instrumental variable to account for possible reverse causality problems. We show that the instrument is highly relevant. Using Hausman's Test we test for the endogeneity of GDP per capita but can't reject the null hypothesis. Thus it is questionable whether using an IV-model is really necessary. We decide not to use an instrumental variable approach for the search rank of the paid version, due to its insignificance in the robust ordinary least squares model and due to the lack of availability of a suitable instrumental variable. We show that an IV model using the measure for competition described above suffers from weak instrumental variables. Given a very small cross-country variance of search ranks for the main keywords it doesn't seem as if any form of cross-country differences in the app's popularity would significantly influence search ranks (see Figure 1 for a boxplot of the search rank variable).

5.1   Ordinary Least Squares Model

Columns (1) - (5) of Table 1 report estimated parameters and their standard errors from a version of equation (15). In Column 1 the only country specific factor taken into the set of explaining variables is the gross domestic product per capita in US- Dollar. We also added GDP squared (Columns 2-5) to account for a possibly nonlinear relationship between app demand and GDP per capita. Surprisingly according to our results, the income elasticity of app demand is smaller than one. Thus apps aren't a superior good and the share of money spent on apps decreases with rising disposable income. For a scatterplot graphically showing the functional relation between GDP per capita and the conversion ratio see Figure 1 in appendix. We further

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[1]The paid version of our app has only gotten reviews from 11 countries so far.

added real GDP growth rate in percent (Column 2), the percentage of internet users by country (Columns 4 and 5) and the institutional index (Column 5).

Real GDP growth rate was statistically significant with a negative coefficient at the 10 % level in Column (3), which appears to be explainable as a result of the fact that faster growing countries are on average less wealthy (Solow 1956).

Downloads per capita weren't statistically significant in any ordinary least squares estimate. In Column (1) an increase in downloads per capita of one leads to an increase in conversion ratio of 0.20. This statistical evidence contradicts our initial assumptions about downloads per capita. It must be further noted that the number of requests per download and downloads per capita are positively correlated contrary to our assumption that more downloads means on average less usage time. On top of that, the number of free downloads per capita is highly correlated ($r = 0.7948$) with GDP per capita. This seems obvious as a higher dispersion of iOS devices leads to more downloads. Therefore downloads per capita don't seem to be a suitable proxy for the free version's expected utility. It rather appears to be another possible measure for the internal margin of technology adoption, if it was controlled by country specific popularity factors.

In Column (2) GDP per capita is statistically significant at the 1% level. For example the expected conversion rate for Switzerland with a gross domestic product per capita of 79,033$ is ceteribus paribus about 0.1618% higher than in Italy with a gross domestic product per capita of 33,315$. Given an average conversion ratio of 0.547% these differences are noticeable. [2] In all other possible specifications in columns (1-5) GDP per capita is statistically significant at least at the 5% level. This confirms the assumption in our model, that GDP per capita is the driving factor for cross-country differences in conversion ratio.

In Column (1) Requests per Downloads are statistically significant at the 10% level, while in Columns 2-5 they are statistically significant at the 5% level. In Column (2) given an increase in average usage time of 10 minutes (which is equivalent to 40 requests) increases the purchase probability by about 0.5488%. This confirms our model in equation (15) that states that the free version's individually perceived quality is the second major source for paid downloads. Neither the percentage of internet users (p-value = 0.609) nor the institutional index (p-value = 0.97) are highly insignificant. Both typically used factors to explain for differences in technology adoption don't seem to have any influence at all. In Columns (2,4 and 5) which are all identically specified expect for other country specific economic factors being added, the coefficients for GDP

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[2] See Figure (3) for a boxplot of the dependent variable conversions ratio.

per capita are almost identical. This shows that the causal influence of GDP per capita on the conversion ratio is particularly robust - even when additional country specific factors are added.

Due to the small variance of the explaining factor search rank for the keyword iOS 6, it is quite insignificant in any of the outputs in Table 1. Given a very small cross-country variance of search ranks for the main keywords it doesn't seem as if any form of cross-country differences in the app's popularity would significantly influence search ranks (see Figure (1) for a boxplot of the search rank variable). We already assumed that the second direct purchase channel was only responsible for a small fraction of total app purchases. Therefore the statistical insignificance was expectable given that we only added the explaining variable to control for the second direct purchase channel.

The value of R^2 in Columns 1-5 lies between 0.43-0.45 indicating good fit. About half of the dependent variable's observed variation is caused by the dependent variables used in our ordered least squares model.

Explanatory Variable	OLS Regression				
	(1)	(2)	(3)	(4)	(5)
Constant	0.0012578 (0.0021091)	0.0004194 (0.0021665)	0.0023959 (0.0022904)	0.0002339 (0.0021316)	0.0003295 (0032244)
GDP per capita	$5.5 \cdot 10^{-8}$** $(2.8 \cdot 10^{-8})$	$1.11 \cdot 10^{-7}$*** $(4.21 \cdot 10^{-8})$	$8.07 \cdot 10^{-8}$* $(4.73 \cdot 10^{-8})$	$1.05 \cdot 10^{-7}$** $(5.91 \cdot 10^{-8})$	$1.06 \cdot 10^{-7}$** $(5.12 \cdot 10^{-8})$
Search Rank iOS6	−0.0000044 (0.0000806)	0.0000005 (0.0000816)	−0.0000289 (0.0000771)	−0.000009 (0.000077)	−0.0000089 (0.0000779)
Requests per capita	0.0001246* (0.0000692)	0.0001372** (0.0000687)	0.0001356** (0.000062)	0.00014** (0.0000657)	0.0001405** (0.0000683)
Downloads per capita	0.2091344 (0.3837199)	0.1268445 (0.3888741)			
GDP-squared		$-6.64 \cdot 10^{-13}$* $(3.81 \cdot 10^{-13})$	$-3.57 \cdot 10^{-13}$ $(5.02 \cdot 10^{-13})$	$-5.93 \cdot 10^{-13}$ $(4.76 \cdot 10^{-13})$	$-5.98 \cdot 10^{-13}$ $(4.83 \cdot 10^{-13})$
GDP growth rate			−0.0002632* (0.0001368)		
Internet user				0.0000111 (0.0000198)	0.0000113 (0.0000221)
Institutional Index					−0,000002 (0.000053)
R-squared	0.4293	0.4491	0.4832	0.4501	0.4501
Root MSE	0.00224	0.00223	0.00216	0.0022	0.00225
Number of observations	54	54	54	54	54

Tab. 1: OLS regressions. Imputed values and robust standard errors given in parentheses. * significant at 10 percent; ** significant at 5 percent; *** significant at 1 percent.

We test for heteroskedasticity using Breusch-Pagan test (Breusch and Pagan 1979). It tests whether the estimated variances of the residuals from a regression are dependent on the values of the independent variables and thus the model is heteroskedastic. Its test statistic follows a Chi- Squared distribution with k degrees of freedom.The null hypothesis of homoscedastic standard errors can be rejected at p-levels around 0.02 - 0.04 for every column in Table 1. Due to heteroscedasticity the ordinary least squares estimator isn't the best linear unbiased estimator. Throughout this paper heteorscedasticity - robust standard errors (HCSE) were used to correct confidence intervals and significance levels for the observed strong degree of heteroscedasticity.

When using country specific variables for economic activity potential multicollinearity is always an important concern due to the traditionally high correlation between different economic indicators. Potential problems being caused by a high degree of collinearity could be that:

Small changes in the data produce wide swings in the parameter estimates. Coefficients might have very high standard errors and low significance levels even though they are jointly significant. Coefficients might have the "wrong" sign or implausible magnitude.

To avoid explaining country specific variables that would cause multicollinearity in advance we used a rule of thumb of not using variables which are very highly correlated having a correlation r > 0.95. (Farrar and Glauber (1967)). Table 3 shows the correlation matrix of all explaining variables used in our multiple linear OLS model.

Afterward we tested for multicollinaerity using variance inflation factor (VIF). This quantifies the severity of multicollinearity in an ordinary least squares regression analysis. It provides an index that measures how much the variance (the square of the estimate's standard deviation) of an estimated regression coefficient is increased because of collinearity. Our variance inflation factor amounts to value amounts to values around 1.52. Usually it's a role of thumb that if the VIF is smaller than 10 then, multicollinearity can be safely ignored.

5.2   Instrumental Variable Regression Model

We use an IV-model with GDP per capita in 2007 as the only exogenous instrumental variable and GDP per capita being the instrumented variable. Columns (1) - (3) of Table 2 report estimated parameters and their standard errors from a version using gross domestic product per capita in 2007 in US-dollars to correct for reverse causality problems. In Column (1) the only country specific factor is GDP per capita in 2012. We added the percentage of internet users (Column 2 and 3) as well as an index for institutional efficiency (Column 3).

In Column (1) GDP per capita is statistically significant at the 1% level. In Columns 2 and 3 it is statistically significant at the 5% level. In Columns 2 and 3 given an increase of the GDP per capita of 10,000$ the conversion rate increases by 0.052%. Thus the expected conversion rate for Switzerland with a gross domestic product per capita of 79,033$ is ceteribus paribus about 0.242% percent higher than in Italy with a gross domestic product per capita of 33,315$. Given an average conversion ratio of 0,547% these differences are noticeable. This confirms the assumption in our model, that GDP per capita is the driving factor for cross-country differences in conversion ratio. In all columns Requests per Downloads are statistically significant at the 10% level. In Columns 2 and 3 given an increase in average usage time of 10 minutes (which is

equivalent to 40 requests) increases the purchase probability by about 0.4556%. This confirms our model that states that the free version's individually perceived quality is the second major source for paid downloads.

Originally we wanted to use two instrumental variables gross domestic product per capita 2007 and competitors' ratings per capita to correct for the two possible mechanisms of reverse causality described in the last section. Table 3 in the appendix shows the output for the two stages least squares regression with two endogenous variables namely gross domestic capita per capita in 2012 and search rank for the keyword iOS 6. In Table 3 none of the explaining variable's coefficients are statistically significant any more.

Testing for the instrumental relevance of competitors' ratings per capita reveals that it is a very weak instrument (p = 0.217) explaining the noticeable less statistically significant values for the exogenous variables in Table 3.

Given a very small cross-country variance of search ranks for the main keywords it doesn't seem as if any form of cross-country differences in the app's popularity would significantly influence search ranks. Therefore in OLS regression the search ranks for iOS 6 isn't significant at all. Furthermore the only possible instrumental variable is very weak (p-value = 0.217) and a possibly high correlation between the two used IV-variables poses additional threats from multicollinearity. In the next section we test for endogeneity to show that we can drop the IV variable competitor's ratings per capita without bad conscience.

Explanatory Variable	IV Regression		
	(1)	(2)	(3)
Constant	0.0017151	0.0009127	0.0004373
	(0.0019543)	(0.001948)	(0.0030935)
GDP per capita	$7.33 \cdot 10^{-8}$***	$5.3 \cdot 10^{-8}$**	$5.2 \cdot 10^{-8}$**
	$(1.64 \cdot 10^{-8})$	$(2.08 \cdot 10^{-8})$	$2.17 \cdot 10^{-8}$
Request per download	0.0001173*	0.0001161*	0.0001139*
	(0.0000644)	(0.0000634)	(0.0000639)
Search Rank iOS6	-0.0000212	-0.000018	-0.0000176
	(0.0000758)	(0.0000734)	(0.0000729)
Internet user		0.0000225	0.0000208
		(0.0000142)	(0.0000161)
Institutional Index			0.0000096
			(0.0000533)
Chi-squared	35.08	47.88	51.56
R-squared	0.4177	0.4442	0.4451
Root MSE	0.00213	0.00208	0.00208
Number of observations	53	53	53

Tab. 2: IV regressions. Imputed values and robust standard errors given in parentheses: * significant at 10 percent; ** significant at 5 percent; *** significant at 1 percent.

To check for endogeneity of search rank for iOS 6 and of GDP per capita we use a Hausmann test. The test evaluates the significance of an estimator versus an alternative estimator. When using the Wu-Hausmann test statistic we compare instrumental variable (IV) estimates to ordinary least squares (OLS) estimates (Wu 1973). If the null hypothesis which says that differences in coefficients aren't systematic can be rejected it is proven that the given instrumented variable is endogenous. In our case the chi-squared distribution of the Hausmann statistic takes on a negative value.

According to Hausman and Taylor (1981) in the case of a failure of the matrix in the Wald statistic to be positive due to a finite sample problem that is not part of the model structure, forcing a solution by using a generalized inverse may be misleading. Hausmann and Taylor (1981) suggests that in this instance the apporpriate conclusion might be simply to take the result as zero and by implication not reject the null hypothesis. Even if we use a generalized

inverse the null rejection can't be rejected as the p-value of the chi-square statistics amounts to 0.6529. Thus both instrumented variables probably aren't endogenous.

Given that search rank for iOS 6 was already insignificant in the OLS regression it doesn't seem surprising that its even smaller reverse causality effect isn't significant.

Furthermore it could be assumed from the start that as the App Store and the whole app economy today constitute at most a little fraction of a country economy, possible reverse causality effects on GDP due to technological advancements are very limited in the short term. Nonetheless, long-term effects of a universal adoption of smartphones will be significant.

6   Conclusion

In the last sections we have analyzed the particular country specific factors underlying the internal technology adoption of the Apple App Store around the world. We find that mostly GDP per capita and in parts diffusion of the latest available predecessor technology were important factors determining the speed of technology adoption. GDP per capita is significant at the 5% level in nearly every specification of our multiple linear regression model, so that we are able to derive strong causality. Noticeably we couldn't find significant institutional and cultural factors causing differences in the cross-country adoption of the Apple App Store. We conclude that GDP per capita is the major force driving the intensive margin of technology adoption. This underlying mechanism makes it very difficult for developing countries to catch up technologically and leads to a "poverty trap"with poor economic performance reinforcing itself. Only a drastic mobilization of all available input goods such as it has happened in several west asian boom countries alongside with massive investitions into modern technology can - as has been historically shown - help ot significantly reduce technological gaps. Even such drastic, mostly central-planned interventions weren't able to permanently close technology gaps between the affected countries and the First World. The example of the Soviet Union shows how economic growth based on capital intensity and labour participation rate can have impressive short term benefits for the average standard of living, but in the long term might not be favorable. Given that about half of the intensive margin of technology adoption can be explained by GDP per capita and the diffusion of the latest available predecessor technology it seems obvious that implemented rightly the massive mobilization of input goods is the only way to escape the "poverty trap" and to slowly close the technology gap. As the rate of technology adoption is highly dependent on a country's wealth it takes very long for developing countries to catch up in terms of total factor productivity.

7   Appendix

Conversion	Instrumental variables (2SLS) Coefficient	Standard Error	z	P>|z|
Constant	0.0296772	0.0263396	1.13	0.260
GDP per capita	$6.29 \cdot 10^{-9}$	$5.94 \cdot 10^{-8}$	0.11	0.916
Search Rank iOS 6	-0.0012084	0.001063	-1.14	0.256
Requests per download	0.0001091	0.0002424	-0.45	0.652
Internet users in %	0.0000057	0.0000497	-0.11	0.909

Chi-squared	14.34
R-squared	.
Root MSE	0.00472
Number of observations	53

Tab. 3: IV regression with instrumented variables: SearchRankiOS6 GDPperCapita and instruments: Requests per Download Internet User Ratings per Capita In Million GDP 2007. Imputed values and robust standard errors given in parentheses: * significant at 10 percent; ** significant at 5 percent; *** significant at 1 percent.

Explanatory Variable	GDP per capita	Intstitutional index	Internet user	Search rank iOS6	Downloads per capita	Requests per download
			Correlations			
GDP per capita	1.0000					
Institutional Index	0.6765	1.0000				
Internet Users	0.7422	0.7030	1.0000			
Search Rank iOS6	-0.3838	-0.3321	-0.3323	1.0000		
Downloads per capita	0.7948	0.6981	0.6487	-0.4865	1.0000	
Requests per download	0.0672	0.1907	0.0475	-0.2994	0.1757	1.0000

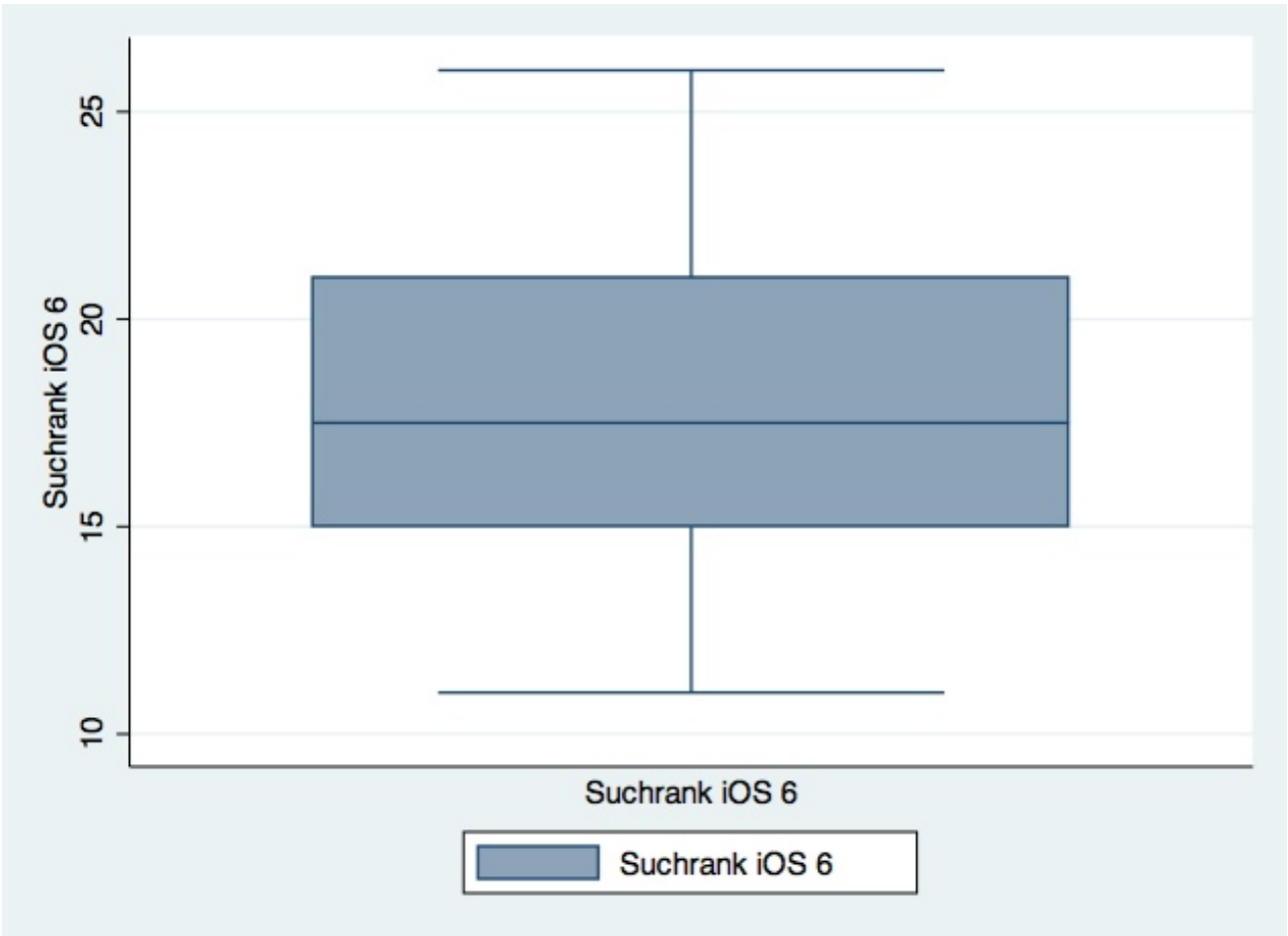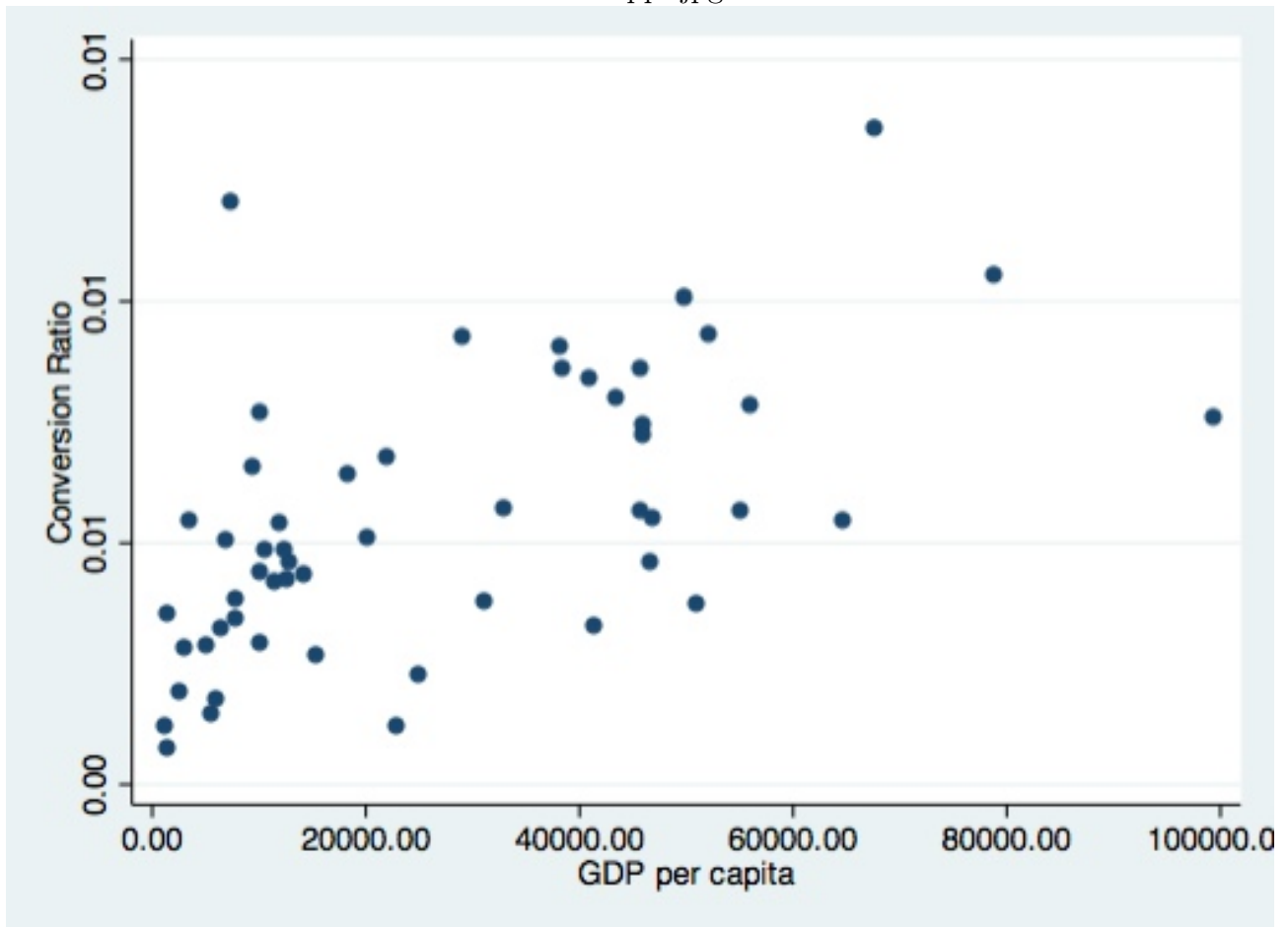Tab. 4: Correlation of all variables ever used in any regression

Fig. 1: **Search Rank for iOS 6:** This figures shows the STATA boxplot for the explaining variable search rank. Usually more than 95% of related downloads take place in app ranked in the top 5 search results for the given keyword.
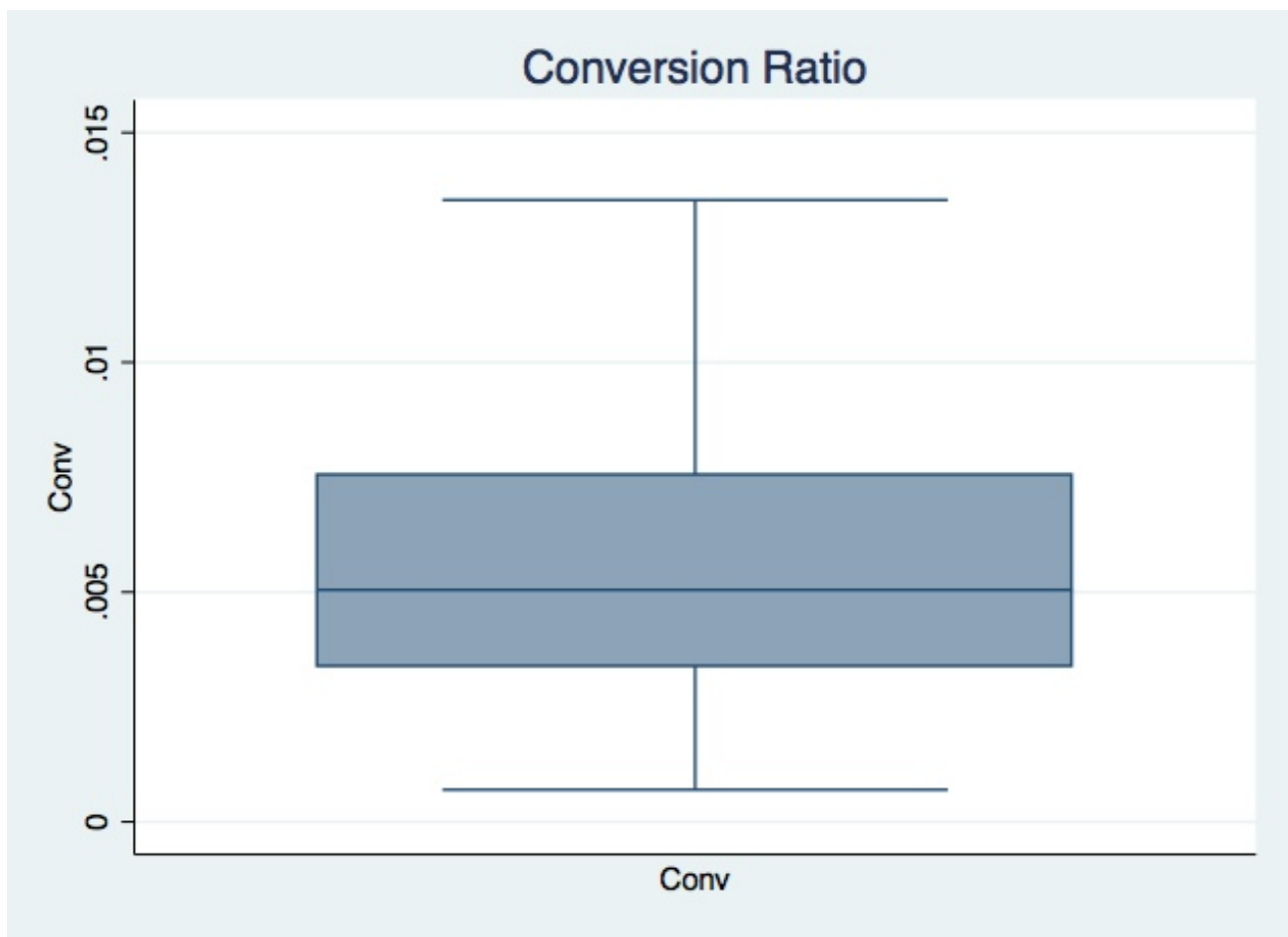
for Apps.jpg

Fig. 2: **Scatterplot: GDP per capita vs. Conversion Ratio:** In the scatterplot the nonli-
    near functional form can be clearly seen.

Fig. 3: **Conversion Rate:** This figures shows the STATA boxplot for the dependant variable conversion rate.

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