UNIVERSIDADE DE SÃO PAULO – USP
INSTITUTO DE RELAÇÕES INTERNACIONAIS – IRI

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**ICT AND AGRICULTURAL DEVELOPMENT:
THE IMPACTS OF INFORMATION AND COMMUNICATION-TECHNOLOGY ON
AGRICULTURE**

SÃO PAULO/SP

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Tese de doutorado apresentada ao Programa de Pós-Graduação em Relações Internacionais do Instituto de Relações Internacionais (IRI) da Universidade de São Paulo (USP) sob a orientação do Prof. Dr. João Paulo Cândia Veiga.

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*To Fernanda and Eva,
for simply being
(my life).*

*To Zique and Cintia,
for always putting
my education first.*

ABSTRACT

Within a context of continuous population and economic growth, the future projections for agricultural products' demand is impressive. At the same time, agriculture already exercises significant pressure on natural resources. As a consequence, the world needs to produce higher agricultural volumes while limiting agriculture's impacts on the environment. This thesis evaluates whether empirical indications exist that demonstrate how Information and Communication Technology (ICT) infrastructure development and usage could impact the sustainable development of agriculture. Drawing from the empirical literature on infrastructure's impacts on development, two statistical models are created. The first analyses impacts of Internet and mobile usage on cereal yields at a country level using Fixed Effects Panel Regression for 212 countries in five 5-year periods, from 1990 to 2014. The second uses a Propensity Score Matching Model to evaluate how the installation of 3G technology during the period between 2005 and 2009 in Brazilian municipalities located in the Amazon region affected deforestation. Based on the methodology and datasets used, results indicate that the growth of Internet users could have a positive impact on cereal productivity in a country. Results for mobile device users are inconclusive. Finally the second models indicate that municipalities in which 3G technology was installed had lower deforestation rates than similar municipalities lacking 3G technology.

RESUMO

Em um contexto de crescimento populacional e econômico, as projeções de demanda para productos agrícolas no futuro são expressivas. Ao mesmo tempo, a agricultura já exerce pressão significativa nos recursos naturais do planeta. Como consequência, é preciso obter maior oferta de produtos e, ao mesmo tempo, limitar o impacto ambiental da atividade agrícola. Essa tese avalia o papel da infraestrutura e uso de Tecnologia da Informação e Comunicação (TIC) no desenvolvimento sustentável da agricultura. Baseando-se na literatura empírica sobre impacto de infraestrutura no desenvolvimento, dois modelos estatísticos foram criados. O primeiro analisa os impactos do uso de internet e telefones celulares na produtividade de cereais utilizando uma regressão em painel de efeitos fixos para 212 países no período entre 1990 e 2014. O segundo utiliza um modelo *Propensity Score Matching* para avaliar o impacto da instalação de tecnologia 3G no desmatamento de municípios localizados na região da Amazônia Legal brasileira. De acordo com a metodologia e dados utilizados, os resultados indicam que um crescimento no uso da internet pode positivamente impactar a produtividade de cereais em um país. Para o caso do uso de telefones celulares os resultados são inconclusivos. Finalmente, de acordo com o modelo, há indicações de que municípios que receberam a tecnologia 3G no período estudado tiveram taxas de desmatamento reduzidas quando comparadas a municípios similares que não receberam a tecnologia.

ACRONYMS

3G – Third generation of wireless mobile telecommunications technology¹

ANATEL - Brazilian Agency of Telecommunications

CAR – Brazilian Rural Environmental Registry

DiD - Difference in Difference model

DV – Dependent variable

ERB – Mobile transmitter antenna (*Estação Radio Base*)

FAO - United Nations Food and Agriculture Organization

GDP – Gross domestic product

IBGE – Brazilian Institute of Geography and Statistics

ICT – Information and Communication Technology

IV – Independent variable

MDG – Millennium Development Goals

MMA – Brazilian Ministry of the Environment

OLS – Ordinary least squares model

RCT - Randomized Control Trials

UN – United Nations

US – United States of America

¹ Based on International Mobile Telecommunications-2000 (IMT-2000) specifications

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1 INTRODUCTION: AGRICULTURAL DEVELOPMENT IN THE INFORMATION AGE

1.1 CONTEXT

Two megatrends are driving substantial growth in projected demand for food: The world's population will reach 9 billion by 2050, and per capita income is rising in several regions of the world. Agriculture already exercises significant pressure on natural resources. So, how can the planet's agricultural systems produce enough calories to meet booming demand without exerting even more pressure on the planet, all while promote shared prosperity in rural areas?

Agriculture is associated with 71% of tropical deforestation (LAWSON et al 2014), occupies 40-50% of the planet's land (SMITH et al 2007) and is responsible for 1/4 of total global anthropogenic emissions of greenhouse gases (GHG) (SMITH et al 2014), yet is essential for humanity's survival. Food production accounts for 69% of the world's water withdrawal², while water stress threatens critical food production. Such challenges will only increase. The world needs to close a 70 percent "food gap" between the crop-based calories available in 2006 and expected calorie demand in 2050. It must also close an 80 percent gap for animal-based calories (RANGANATHAN et al 2016). If agricultural production continues unchanged, global consumption of natural resources will outstrip the Earth's capacity to provide those resources by 2.9 times by 2050 (WWF 2012).

Therefore, the world needs to be able to "produce more with less," producing higher agricultural supply volumes while limiting agriculture's impacts on the environment. This will be a significant challenge.

Fischer et al. (2014) estimate that in order to meet projected demand, staple crops' yields must increase by an average rate of 1.1% per year in the period (1.3% would be recommended to reduce non-predicted risks). They note, however, that staple crops' yields are currently

² Aquastat website by the UN Food and Agriculture Organization (FAO), access on January 27th 2017, available at http://www.fao.org/nr/water/aquastat/water_use/index.stm

increasing by only 1.0% per year. It is important to note that their model considers land expansion, so, such growth would be require additional agricultural area expansion. In other words, even given those rates, land resources would still face significant pressure, which in turn could create higher global deforestation rates. They conclude that the most effective way to increase yields would be to reduce the gaps between high and low productivity regions.

Given that cereals (staple crops) account for 58% of annual harvested crop area globally and directly provide around 50% of world food calories (NELSON et al. 2010), the challenge is even greater.

Such productivity-gap reductions will only be achieved with technology. It seems obvious: any agricultural scientist will enumerate countless essential techniques - such as more efficient inputs or plant varieties. That was the logic behind Norman Bourlaug's first Green Revolution. In the Sixties, the American agronomist led a movement that brought technology to the fields – such as better soil management techniques or use of better seed varieties – generating immense yield gains. Commonly defined as the “Agricultural Green Revolution,” it allowed global population growth and helped to increase prosperity at a global scale (BOURLAUG 1976).

In fact, some authors argue that such boosts in yields were critical to future economic growth in many countries. They argue, for example, that low agricultural productivity in Africa is a key explanatory factor for the region's relatively slow economic growth (DIAL et al. 2006).

However, it is possible that traditional agricultural technologies brought by the “Green Revolution” cannot carry agriculture through the second revolution. This research hypothesizes that the next green revolution in agriculture could be about information technology (TING et al 2011, BULL et al 2011, WORLD BANK 2012, BRONSON & KNEZEVIC 2016). The emergence of the “big data revolution”, the “Internet of things” and the “sharing economy” is changing life in cities, making urban societies more efficient across all aspects of daily life (RIFKIN 2010, CASTELLS 2010, RIFKIN 2014). However, this revolution has not yet reached the rural world (BRIDGES 2001).

Six billion mobile subscriptions exist worldwide. So, three-quarters of the planet's population has access to a mobile phone that may or may not be connected to the Internet. In fact, in some developing countries, more people have access to mobiles than to potable water, financial services or electricity. According to the World Bank, *"mobile communication now offers major opportunities to advance human development – from providing basic access to education or health information to making cash payments and stimulating citizen involvement in democratic processes"*. Not only that, it also concludes that mobile applications have important cascade effects that stimulate growth, entrepreneurship and productivity in the broader economy. According to its findings, a 10% expansion of cell phone usage would increase some countries' annual economic growth by 0.6 to 0.8 percentage points (WORLD BANK 2012). In fact, some studies have shown that greater access to and use of mobile ICT can have significant effects on rural income (DIXIE & JAYARAMAN 2011).

For example, precision agriculture is already implemented in specific and more capital-intensive operations, but it is not yet widespread. Some tractors already have GPS's that store the exact location of each planted seed. This information is valuable because it enables nearly fully automated harvesting machinery. Technology giants, such as Google, are investing more in agricultural intelligence (WALL STREET JOURNAL 2015). Fertilizers and other inputs could also be monitored and used more efficiently in controlled environments, applying more where it is needed and less where it is not (BONGIOVANNI & LOWENBERG-DEBOER 2004).

All of these impacts, for better or for worse, are only possible with efficient Internet and mobile phone coverage. Even simpler developments depend more and more on this variable. Communications technology brings access to information on the field, a key input for human capital and, as a consequence, potentially on the way agriculture is produced.

Therefore, ICT infrastructure in rural areas can not only connect farmers to information from intelligence clusters, extension programs and markets but it can also create a feedback loop by sending information back to markets in real time, helping them adjust faster and more accurately.

One might argue that the current lack of reliable coverage could be a significant bottleneck. In Brazil, for example, the system developed by the government for farmers to finalize their Environmental Rural Registry (CAR) – a virtual map of farm property indicating production

and protection areas – is entirely virtual and dependent on the availability of information and communication technology (TNC 2015). Therefore, the lack of cellular coverage in remote areas could already be negatively impacting this important environmental regulation.

Finally, although it lies outside the scope of this thesis, it is important to recognize that information and communication technologies' advancement will also bring challenges for rural development. One of the most significant relates to confidentiality and use of information collected from rural actors, which could impact agricultural markets' organization positively or negatively, possibly squeezing farmers' gains. For example, it has been reported that a multinational agricultural production company already possess field-by-field information, which used to be proprietary data, for roughly one-third of all United States farmland (CARBONELL 2016). While this demonstrates the power of ICT for agriculture, it also raises significant challenges over the confidentiality of information and ethical use of this technology.

1.2 RESEARCH QUESTION AND HYPOTHESIS

This research sheds light on debate about ICT and rural development. Are there empirical indications that information and communication infrastructure and utilization has a role to play in humanity's quest to sustainably feed itself in the future? Could such advances in access to information allow agricultural markets and farmers to become more efficient and mitigate food production's effects on the environment?

Drawing from the extensive literature about infrastructure's impacts on agricultural output, this research scrutinizes the afore-mentioned questions through econometric modeling techniques. Introducing new dependent and independent variables to the debate on infrastructure and agricultural development, the current thesis produced two empirical models to test the relationships between those variables.

In summary, the central research question is: does communication (Internet and mobile phones) infrastructure and utilization impact sustainable agricultural development? The specific research questions in each section are presented below.

The first model analyzed this question at a global level, using countries as the unit of analysis, cereal yields as the core dependent variable and Internet and mobile users as the core independent variable. This section explores whether the increase in mobile and Internet users in a country impacts that country's agricultural commodity production.

The second model analyzed the subnational level, using municipalities as the unit of analysis, deforestation as the dependent variable and the implementation of 3G coverage as the treatment (core independent variable). The specific research question in this case is whether the installation of 3G coverage can impact deforestation rates in a given municipality.

Based on the research questions above, some general hypotheses were formulated in order to be tested:

General hypothesis: The advance of information and communication technology infrastructure and utilization in rural areas improves sustainable agricultural development.

Specific hypothesis 1: greater ICT infrastructure utilization has a positive and significant correlation with yield increases.

Specific hypothesis 2: greater ICT infrastructure installation has a negative and significant correlation with deforestation rates.

1.3 JUSTIFICATION

The literature and empirical studies that intend to measure impacts of infrastructure on agricultural development are abundant. However, they tend to focus only on roads, electrification and irrigation as the main independent variables related to infrastructure. As described in the Literature Review, few studies have focused on ICT. Additionally, such studies tend to be based on individual interventions in specific regions or projects, therefore limiting the generalizable capacity of their conclusions.

Finally, dependent variables chosen to represent "development" in the literature tend to reflect the traditional vision of economic growth as a development indicator. Therefore,

previous studies measured, primarily, the economic impacts of infrastructure. Additionally, social indicators, such as inequality reduction, are also regular objects of study as dependent variables. Other development-related issues, such as efficient land use, have not been explored according to the author's knowledge.

Therefore, the present study is innovative – it adds new analytical variables to the debate about ICT impact on global agricultural development.

First, this study introduced ICT infrastructure and utilization (especially Internet and mobile coverage) as the core independent variables. This is a research innovation in a world currently classified as an information society – a society that is more integrated into information-based networks (RIFKIN 2010, CASTELLS 2010, RIFKIN 2014).

Secondly, this study also innovated on the choice of dependent variables. Traditionally, development studies focused on agriculture's economic growth in order to measure the impact of new infrastructure. This study instead focuses on agricultural productivity, an indicator that captures not only economic but also social and environmental development. If more food is produced in a smaller area, the pressure for additional resources is diminished. The positive economic-socio-environmental impacts of higher yields are clear. Additionally, since agriculture still creates significant tropical deforestation around the world (LAWSON et al 2014), ICT impact on deforestation rates will also be tested as a dependent variable.

1.4 METHOD: TWO EMPIRICAL MODELS

This research used two empirical models to test the hypotheses presented. As described above, the first operated at a global scale, utilizing countries as the unit of analysis, while the second sub-national model utilized municipalities/counties as the unit of analysis.

The first model was based on cross-country analysis. Data from international databanks, such as the United Nations Food and Agriculture Organization (FAO) and the World Bank, fed into a panel-data model. ICT infrastructure information was the core independent variable and agricultural yield was the core dependent variable. Obviously, other potential explanatory variables are included in the model for control. As described in the literature review, similar

cross-country models are important and allow for discussions at global level. However, they are also subject to technical criticisms such as endogeneity (especially due to simultaneity and omitted variables). Another frequent criticism is that the model does not capture regional differences within countries.

Therefore, a second complementary sub-national model was developed with municipal-level information from national datasets, such as Brazilian Agency of Telecommunications (ANATEL) and the Brazilian Institute of Geography and Statistics (IBGE). Municipalities were used as cross-sectional data, limiting the regional-scale limitations of the global model described above. Given idiosyncrasies such as a mobile phone regulation in Brazil that obliges investments in small cities regardless of their economic attractiveness (this topic will be thoroughly discussed in the chapter on the Brazilian model), the endogeneity issue is limited. Finally, a Propensity Score Matching and Difference in Difference model was used to estimate impacts. In short, this model compared the outcomes of a “treatment” to a “treated group” (municipalities where ICT infrastructure was installed) and a “control group” (municipalities where ICT infrastructure was not installed) by finding “matches” between the two groups (municipalities with the same characteristics). The model therefore incorporated a more detailed geographic approach by characterizing dependent and independent variables at the municipality level. It also introduced deforestation as the new dependent variable and 3G coverage at the municipality level as the treatment variable. It is important to highlight, however, that regional differences in ICT infrastructure exist even within municipalities – between, for example, urban and rural areas.

This study’s model selection intended to shift the logical framework from broad geographical coverage and lower data accuracy with broader generalization capacity to more concentrated geographical coverage and more accurate datasets with limited generalization capacity. The international model was based on a cross-country, fixed effects panel. It intended to set the stage for discussion since global applicability is its primary asset. However, despite the author’s best efforts, any global model that tests the impact of any variable on agricultural development can be subject to criticism for endogeneity. In other words, so many factors affect yields at a global level, and countries can be such broad units of analysis with great local-level variation, that a global model will always be imperfect. Even given the legitimate criticisms, this approach is still justified as an exploratory exercise. The conclusions need to

be interpreted with care but can still inform important policy outcomes. The sub-national model intended to address some of the aforementioned problems of endogeneity, but did not solve them all. Smaller units of analysis (such as municipalities) are, at least, helped control for other endogenous variables that could explain variations on the dependent variable.

Figure 1 summarizes the two models.

1.5 THE THESIS STRUCTURE

Chapter 2 is a literature review on infrastructure impacts on agricultural development. It presents both the rationale (theoretical and policy-oriented studies) and the research results (empirical studies). The global model developed is described in Chapter 3. It explains the model, describes the methodological choices, databases utilized and indicators chosen and constructed. Results are then presented and some initial conclusions drawn. Chapter 4 focuses on the sub-national Brazilian model, following a similar structure to the previous chapter. It does include, however, a critical discussion about local policies defining ICT investments. This description necessarily defends the methodological choices and, specifically, the value in choosing a propensity score-matching model. Finally, Chapter 5 presents the general discussions and conclusions, as well as suggestions for future research.

	Global model	Sub-national model
Statistical model	Fixed Effects panel (OLS also tested)	Propensity Score Matching, with Difference in Difference
Scope	Global	Brazilian Legal Amazon
Cross-dimensional section (unit of analysis)	Countries	Municipalities
Temporal section	Five 5-year periods from 1990 to 2014	Pre-treatment: 2004 Treatment: 2005-09 Post-treatment: 2010
Dependent variable	Crop yield	Deforestation
Independent variable (core)	Internet and mobile use	3G availability (treatment)
Independent variable (controls)	Economic Development Human Capital Inputs and Technology Agricultural Markets	Population Economic Development Micro-region Agricultural importance Agricultural expansion Size (area)

Figure 1 - Summary of the two empirical models utilized in this study

2 RATIONALE AND LITERATURE REVIEW

In order to introduce the arguments and assumptions regarding ICT's influence on agricultural activity, this chapter presents a review of the literature describing the impacts of infrastructure on development, with a special focus on agriculture and rural development.

First, the rationale behind the main hypothesis of the paper – that ICT infrastructure and utilization could create more sustainable rural development – is introduced through papers from several fields, particularly reports by international organizations intended for policy makers. This section also specifically highlights studies that have focused on negative effects of information and communication technology on development.

The second section presents an extensive review of the academic and empirical literature on infrastructure and development. It begins with broader studies that assessed infrastructure's generalized impacts on economic development issues. The review then turns to studies of non-ICT infrastructure impacts on agriculture. It closes with studies focused specifically on ICT and agriculture.

According to Ahmed & Donovan (1992), empirical studies about the effects of infrastructure development published since the 1950s can be classified into three groups: (a) systematic approach, based on primary data attempting to measure the impacts on specific locations; (b) appraisal, evaluation and assessment of infrastructure projects, such as the those by multi-lateral agencies and (c) books, articles and papers using secondary information, based on deductive logic and sometimes quoting results from studies of types (a) and (b).

It is worth highlighting that this research and the three models developed would fall under group (a) according to above classification, which justifies the more abundant literature presented under this category.

2.1 RATIONALE: THEORETICAL PERSPECTIVE ON ICT AND RURAL DEVELOPMENT

One of the main assumptions behind this research lies in the theory that the advance of ICT infrastructure and utilization could catalyze increased access to information for farmers, agricultural supply chain actors, companies, policy makers and local communities. Greater access to information would, in turn, result in a better use of economic, human and environmental assets.

Zepeda (2001), in a report to the United Nations Food and Agriculture Organization (FAO), gives an overview of current economic thinking related to investments and agricultural productivity. She points that physical capital has long been recognized as one of the most important inputs for agricultural productivity. However, she indicates that economic research has also identified human capital as a crucial part of the definition of productivity. This debate is even more relevant in the context of the current study. As ICT infrastructure can be considered physical capital, it in fact also has a significant effect on human capital. Access to communication technologies is an important source of information, integration to global networks and, therefore, improved human capital. It might be one of the few infrastructure investments with such a characteristic. Furthermore, according to the author,

“... social capital is the stock of personal relationships and knowledge of institutions that an individual or household has. This affects the individual's access to risk-minimizing inputs like credit, insurance and land title. In other words, social capital measures the ability to utilize social networks and institutions. Status, gender and group affiliations are often used as proxies for social capital in economic studies. However, education and transportation, as well as the range of social institutions available, can also influence social capital” (ZEPEDA 2001).

Therefore, given the current relatively low usage rates of mobile phones and Internet connections in rural areas, one can propose that ICT infrastructure investments could improve human capital. Human capital is an important input to agricultural production and, consequently, could be a significant variable in defining productivity and awareness about sustainability and regulatory requirements.

Additionally, according to the World Bank (2012), ITC in rural areas can both increase agricultural production efficiency and accelerate long-term agricultural development. First, it

gives farmers access to agricultural information, such as prices, disease and weather information, farming practices and market practices. It also surfaces data that creates value-chain efficiency by for example, improving logistics systems by tracing products from farm to market. The authors also argue that ICT in rural areas creates access to markets (WORLD BANK 2012). Given the preceding factors, it is possible to infer a fourth effect: improved agricultural sustainability. If farmers, value chains and markets become more efficient, it is plausible to assume that they will “do more with less”, promoting the sustainable development of agriculture in all areas while staying more informed about market sustainability requirements and environmental regulations. This chain of logic justifies the rationale that ICT could contribute to the two benefits tested by this research: increased yields and reduced deforestation.

Similarly, in an African Development Bank report, Verdier-Chouchane & Karagueuzian (2016) argue that ICT has the potential to transform agriculture across the African continent by promoting a more inclusive and sustainable model. ITC, the authors argue, would benefit smallholders, address land reform issues, provide adequate financial services, and share price and market information. It is interesting to note the authors’ argument that ICT would also serve to boost global value chains connected to the continent.

As mentioned, additional arguments exist for how expanding ICT can affect not only economic and yield growth but also a wider range of sustainability-related goals. The International Telecommunications Union (ITU) listed the contribution of ICTs towards the Millennium Development Goals (MDGs) in *Measuring the Information Society*. It states that ICT provides more accurate weather information, which in turn helps increase agricultural production, contributing to the MDG1 - Eradicate extreme poverty and hunger (ICT 2014). In a report commissioned by the Bill and Melinda Gates Foundation, Naef et al. (2014) share the areas of highest potential impact across sectors for mobile data. According to the authors, “*Mobile data offers a view of an individual’s behaviors in a low-cost, high-resolution, real-time way. This provides tremendous opportunities for creative uses in development programs.*” While analyzing different sectors for ex-post, current and future applications, they highlight agriculture yield predictions as the highest-impact potential application for ICT data in the future. Samarajiva (2012) also compiled the results of a study about the impacts of ICT on the poor, or as it is described, the bottom of the pyramid. Research conducted in south Asian

countries (Thailand, Sri Lanka, India, Pakistan and Bangladesh) on agricultural micro enterprises identified many benefits derived from mobile phones: maintaining or enhancing social/status/recognition, carrying out day-to-day work efficiently, maintaining relationship with family and friends, reducing travel costs and contacting others in an emergency.

Finally, recent literature describes the so-called “digital divide” —the idea that developing countries are lagging behind the developed world in adopting communication technologies, thereby, expanding the gap between developed and developing populations and driving an ever-increasing disadvantage for the poor in a globalized world (BRIDGES 2001, UN 2000, UNDP 2001, WORLD BANK 1999, WORLD BANK 2012). Although not focused on agriculture and rural development, such reports argue that a lack of access to information and communication technology prevents benefits from advances in efficiency, social integration and access to information from reaching “excluded”, or disconnected, populations.

This section summarized the international political debate surrounding this topic based on reports by major international organizations that compile results and theoretic argumentation by several authors. The next session focuses on relevant academic studies and papers.

2.2 LITERATURE REVIEW

A large body of theoretical and empirical literature analyzes the potential effects of infrastructure on agricultural development. The preceding section (Rationale) already introduced the debate, primarily from the international development perspective, so this section turns to a literature review of empirical studies.

2.2.1 Studies based on secondary information

The first group of studies below amount to an interesting theoretical contextualization exercise, but prove less interesting to further development of this research. This literature

does, however, help to define key assumptions behind this study. Conclusions from empirical studies based on secondary information tend to summarize common points and conclusions from the primary empirical literature, described by Ahmed & Donovan (1992) as groups B and C.

Dethier & Effenberger (2012) wrote an extensive literature review of empirical studies analyzing agricultural growth, farmer income, rural development, trade policy and food security. The authors, collectively, identified a set of critical issues for the future of agricultural development in non-traditional areas: markets and prices, agronomic research, agricultural extension, credit, rural infrastructure, connection to markets, employment and trade policy.

Cook (2013) explores the literature studying the role and relationship of infrastructure, particularly electrical infrastructure in rural areas, to economic growth and development. The author concludes that initiatives for rural electrification have influenced small agricultural business development by creating income-generating activities and improving access and affordability. A further noteworthy conclusion states that other contextual issues affected affordability of access to installed electrical infrastructure - I in this case, *“participation in community-based initiatives and the availability of localized credit facilities to help develop and finance access and use of energy”* (COOK 2013).

Llanto (2012) offers another informative overview of the results of several empirical studies evaluating infrastructure's effects on agricultural productivity for Asian countries. Each of the reviewed studies evaluated only three independent variables: roads, electricity and irrigation. Only one (FAN *et al.* 2002) evaluated the impact of a single communications infrastructure system (phones) in one single country (China).

2.2.2 Studies based on primary data analysis & evaluation of projects' results

The following group of studies is the most interesting and applicable to this study's objectives. This literature compiles research based on primary data analysis, both at generalized (Group A) and project-based (Group B) levels.

This section segregates studies according to their main dependent and independent variables. As described above, traditional empirical literature on general infrastructure and development tends to focus on logistics and energy infrastructure as independent variables and economic growth as the dependent variable. Given these studies' lower level of applicability to this study, just a few examples are given. The next section focuses on more relevant studies whose dependent variables are specifically related to traditional agricultural development variables, such as yields and agricultural market asymmetries. Nonetheless, there is a trend to analyze roads and electrification infrastructure as key independent variables. The following a group of studies utilize ICT infrastructure and utilization as the key dependent variable, but maintain traditional dependent variables for agricultural development. The final grouping refers to studies that chose new dependent variables that incorporate other aspects of sustainable development, such as deforestation.

2.2.2.1 CLUSTER A: IV - traditional infrastructure (roads & electricity) DV - general economic development indexes (GDP growth)

A study by Canning (1998) demonstrated that while transportation infrastructure increases disproportionately relative to population, it increases proportionally to GDP per capita as the country achieves "middle-income threshold" status. Additionally, the author indicates that non-transportation infrastructure increases proportionally to population and at a more rapid pace than expected relative to GDP per capita.

Cook (2013) surveys studies in this category, with a focus on electrification and rural development. The author describes studies finding that infrastructure matters for income growth in lower-income countries (ROMP & DE HAAN 2005 *apud* COOK 2013), that under-investment in electricity and telecommunications could be help explain poor economic performance in Sub-Saharan Africa (ESFAHANI AND RAMIREZ 2003 *apud* COOK) and that a lack of electricity negatively impacts poorer countries' aggregate economic productivity (ESCRIBANO et al. 2010 *apud* COOK 2013).

2.2.2.2 CLUSTER B: IV - traditional infrastructure (roads & electricity) DV – traditional agricultural development (productivity and market asymmetries)

Although the literature on infrastructure and development begins in the 50s, Antle (1983) is among the inaugural studies on the effects of infrastructure on agricultural productivity using the cross-sectional data-analysis methods. He established a Cobb-Douglas production function³ model in which productivity levels were a function a series of independent variables included is his model: land, labor, livestock, fertilizers, education, research and infrastructure. Infrastructure was the key studied variable, which he defined as “GDP of transport and communication industries per square Km of land area”. His datasets were based on 47 least developed and 19 developed countries. The study found a strong positive relationship between infrastructure and aggregate agricultural productivity. Critics observed that infrastructure variables used by Antle (1983) failed to capture information about the quality and extent of infrastructure coverage within the countries. Moreover, critics argued that using cross-sectional data limited inferences about causation or understanding of relationships involved (AHMED & DONOVAN 1992), a common criticism of any similar study.

Binswanger et al. (1987) published a comparable study, but utilized a model that incorporated much more comprehensive data. The authors compiled data for 58 countries and used both cross-country analyses and in- country time-series analyses. The model also incorporated additional explanatory and variables, such as climate and extension, and price variables to explain productivity levels. Some infrastructure variables were also more detailed. Rather than using a common aggregate for all infrastructure, which Antle (1983) attempted with GDP, the authors split infrastructure into actual physical units, such as road density and irrigation use. Again, the findings showed infrastructure having a positive effect on yields: roads alone had contributed to 7% of the yield growth in the studied period (1971-1981). However, even if the study had incorporated more explanatory variables and information

³ Such method originally was introduced by Cobb and Douglas in their 1929 paper entitled “*The Theory of Production*”. Simplisticly, it defined labour and phisical capital as as the main variables to exlain production outputs. As the literature evolved, other input variables and control have been added by different research aproaches to extplain production outputs, but the rationale behind the original proposition is still maintained for regressions evaluating casuality between inputs and production outputs.

about infrastructure quality, it shared Antle's (1983) flaw by ignoring distribution of infrastructure across a country's landscape.

Similarly, using cross-sectional data from 83 counties and 30 provinces in China, Felloni et al (2001) assessed the impact of electricity and transport infrastructure on the country's agricultural yield and production. They concluded that road density and electricity availability are significant predictors of production and productivity.

Assunção et al (2014) investigated the influence of electrification infrastructure on yield variation in Brazil. By using panel-data analysis and creating a "counter-factual" model for electrification-infrastructure expansion, the authors tried to mitigate the omitted factors and endogeneity problems associated with traditional OLS models. The study concluded a positive correlation appears between the expansion of electrification infrastructure and key cash crops' yield growth.

Another group of studies tested the impact of traditional agricultural infrastructure on agricultural market asymmetries.

Using spatially explicit data for sub-Saharan Africa, Dorosh et al. (2010) found that agricultural productivity is highly correlated with travel time from rural areas to urban markets. Using the same method, the authors found that adopting more productive technologies on the field is negatively correlated with travel time to urban centers. The study concludes that rural areas that within a 4-hour travel radius from a city (with more than 100,000 people) produce 45% of maximum potential production. On the other hand, areas that are more than 8 hours travel from a big consumption center produce only 5% of maximum potential production. The study, therefore, makes a strong argument for the positive influence of road infrastructure on agricultural productivity. Finally, when comparing East and West Sub-Saharan Africa, the authors conclude that the afore-mentioned effect is much more apparent in the East than in the West, because the West has more infrastructure and a relatively well-connected road network. These findings support the hypothesis that new infrastructure has a more significant impact in areas with less existing infrastructure. Additionally, such findings buttress main hypothesis driving this research: if roads reduce travel time, and shorter travel times improve agricultural productivity, it is logical to assume that other travel time-reducing factors would have the same impact. Internet and mobile connectivity increases communication and

reduces the need to travel, thereby reducing travel times and supporting the argument that ICT would have positive effect on yields.

2.2.2.3 CLUSTER C: IV - ICT infrastructure and utilization, DV – traditional agricultural development (yields and market asymmetries)

Some empirical studies concluded that expanding ICT access in rural areas would boost agricultural development mainly through market integration and increased efficiency. Muto & Yamano (2009) studied market participation of banana and maize farmers using panel data from 2 surveys conducted in 856 households across 94 Ugandan communities between 2003 and 2005. Mobile coverage in these communities grew from 41 to 87 in the period. Study results indicated that the number of farmers who sold bananas increased from 50 to 60% in communities more than 20 miles away from city centers. The authors did not, however, identify any influence by mobile device on maize market participation. The authors conclude that *“mobile phone coverage expansion induces market participation of farmers who are located in remote areas and produce perishable crops”*. Studies by Abraham (2007) and Jensen (2009) produced similar results. Both analyzed the effects of mobile phone use by fisherman. Mittal et al. (2010) studied the same topic, but related to farmers in India. In all cases, evidence revealed that mobiles were used for market integration, reduced information asymmetries and, therefore, contributed to productivity enhancements. Byerlee et al (2010) presented similar conclusions. Goyal (2010) analyzed the impact of an Indian program that installed Internet kiosks in rural areas to provide price information and new marketing opportunities for farmers.

Other authors have researched ICT infrastructure effects on markets. Park & Koo (2005) took an innovative approach to evaluating telecommunication infrastructure's impacts on agricultural trade patterns. Applying data from OECD countries between 1997 and 2001 to a gravitational model, they concluded that investments in telecommunication infrastructure had a greater influence on import than on exports.

2.2.2.4 CLUSTER D: IV - traditional infrastructure (roads & electricity) DV – new agricultural development variables (deforestation)

The literature on empirical cases has yielded divergent results describing infrastructure's impact on deforestation. While Pfaff (1999), Cropper et al. (1999) and Cropper et al (2001) concluded that road infrastructure increased deforestation rates in Brazil and Thailand, Assunção et al (2014) estimated that *“electrification caused a small net decrease in deforestation in Brazil”*.

2.3 CHALLENGES AND NEGATIVE EFFECTS

It is clear, however, that ICT can also create negative and unintentional effects. Discussions about data privacy and ethical use of information dominate critical literature, usually from fields such as social and data sciences. The policy oriented and empirical literature on ICT impacts on agriculture contains very limited studies analyzing such undesirable outcomes, although new studies are likely in this developing field. Although these potential negative side-effects are not among this study's primary questions, this section briefly summarizes some of those challenges.

Discussion connecting so-called big data to ethical issues is plentiful. Several authors argue for the need to consider ethical issues, privacy and how algorithm use can shape social and economic conditions in several spheres of human activity (KITCHIN 2014, BOYD & CRAWFORD 2012, CRAWFORD et al. 2014, KITCHIN 2017, SHIN & CHOI 2015). A growing body of literature discusses the same ethical challenges from an agricultural perspective. For example, Carbonell (2016) examines how a specific large multinational currently holds unique proprietary information on a field-by-field basis accounting for roughly one-third of US farmland, putting itself in a privileged position of power asymmetry over farmers. Similarly, Bronson & Knezevic (2016) recognizes that farming is being transformed by a digital revolution that is changing the power balance among different players in food and agricultural supply chains. They suggest that big data-focused academics should further explore the

theory of potential material consequences, both positive and negatives, of big data in food systems.

Such discussions are important also in the policy-making arena. Even though such debate might be further away from societies in which ICT technology is not yet truly incorporated in rural areas, as is the case of most developing countries, ethics of big data in food systems is a significant issue in more technologically advanced places, such as the United States. A report by the U.S. Congressional Research Service briefly summarizes the challenges for policy makers:

“Big data may significantly affect many aspects of the agricultural industry, although the full extent and nature of its eventual impacts remain uncertain. Many observers predict that the growth of big data will bring positive benefits through enhanced production, resource efficiency, and improved adaptation to climate change. While lauded for its potentially revolutionary applications, big data is not without issues. From a policy perspective, issues related to big data involve nearly every stage of its existence, including its collection (how it is captured), management (how it is stored and managed), and use (how it is analyzed and used). It is still unclear how big data will progress within agriculture due to technical and policy challenges, such as privacy and security, for producers and policymakers. As Congress follows the issue a number of questions may arise, including a principal one—what is the federal role?” (STUBBS 2016).

Also, as discussed above, the digital divide still inhibits ICT’s potential positive impacts on agriculture and rural development at a global scale. For example, some authors argue that, based on experience from the first Green Revolution, both modern technology and traditional techniques will always contribute to continuous improvement of agriculture at a global scale (ESTEVA 1996). Therefore, one would not only use new technology, such as ICT, and would still need to rely on traditional techniques for future agricultural development.

Building on the theoretical debate about the positive and negative impacts on ICT from an ethical point of view, there are also emerging empirical questions about unintended negative spillovers. The traditional empirical literature on infrastructure and development in rural areas is extensive and dates from the 1950s. As the previously discussed, several studies created sufficient critical mass to identify negative development outcomes of infrastructure development, such as, roads increasing deforestation and registering negative consequences on nature degradation indices (PFAFF 1999, CROPPER et al. 1999 and CROPPER et al 2001).

However, the literature studying ICT infrastructure and rural development is much newer and more limited. This does not mean, however, that one should not expect negative and unintended consequences from ICT on rural development. Among the few empirical examples, a study measured the influence of cell phone coverage on conflicts in Africa through the empowerment of collective violent action. The authors have shown that cell phone coverage significantly and substantially increases the probability of violent conflict in Africa (PIERSKALLA & HOLLENBACH, 2013). The technology, therefore, can provide capacity for groups to better coordinate, not for good as the traditional hypothesis goes, but for violence. It is plausible that, within the scope of this thesis, negative outcomes are possible. For example, due to better Internet connectivity and mobile coverage, ill-intentioned farmers could coordinate to log illegally while alerting to possible inspections by legal authorities.

Finally, an important debate about the negative effects of ICT on the environment focuses on the equipment's footprint. In other words, environmental effects across the complete life cycle mobile phones, computers, tablets, etc. A European Commission (2004) report entitled *The Future Impact of ICTs on Environmental Sustainability* analyzed the footprint of ICT equipment and made policy recommendations on how to tackle negative externalities. Such issues, while extremely important, fall outside the scope of this study, which does not intend to evaluate the impact of the ICT equipment itself, but the impact of infrastructure installation and use of the technology on agriculture and rural development.

2.4 DISCUSSION ABOUT THE LITERATURE

The literature review revealed that the rationale and assumptions underpinning this research have been shared and tested by other authors, justifying the topic, structure, and hypotheses of the present research. In fact, the main assumption justifying this hypothesis is that ICT infrastructure and utilization can catalyze the spread of accessible information. More widespread and accessible information, therefore, would positively influence many of the agricultural development variables chosen. This assumption appears constantly and remains essentially unquestioned in the literature.

However, it is noteworthy to mention that in some cases these assumptions yielded conclusions that support this study's hypothesis, while other cases yielded contradictory results, exemplifying the nature of academic inquiry. This research intends to shed light on that debate.

The literature on potential negative and unintended effects of ICT infrastructure and utilization on development has been briefly explored. Studies focus primarily on privacy and ethical information use, which is more often explored by social ethics and data sciences. Given the objectives of this research, these issues will not be addressed, but they remain a significant gap in the literature about infrastructure's impact on agriculture. Negative externalities beyond privacy and ethics, however, will be explored in this research; ICT's potential to accelerate deforestation, will be addressed by the results of this study.

Finally, this chapter re-emphasized the arguments stated in the Justification section, characterizing this research as innovative and original. To the extent of the author's knowledge, no study to date has evaluated the independent and dependent variables chosen by this research. Studying ICT infrastructure and utilization as primary independent variables affecting variables measuring the long-term sustainability of agricultural development is a contribution to the literature on infrastructure's impacts on rural development⁴.

⁴ Regarding the model presented in Chapter 3, it is important to highlight that other studies have evaluated ICT's impacts on agricultural productivity in a similar manner to what is proposed. However, the approach and scope of this research is different. This study focus on crop yields as an indication of land-use efficiency (kg per hectare). The majority of studies have chosen agricultural value added as the indicator of yield. Also, the model presented is developed at a global scale, while the majority of others focus on specific regions. Finally, specific model and methodological choices, datasets selected and assumptions made make this research unique.

3 GLOBAL MODEL: IMPACTS OF INFORMATION AND COMMUNICATION TECHNOLOGY USE ON CROP YIELDS

3.1 INTRODUCTION

This chapter intends to develop an econometrical statistical model to test the effect of ICT penetration on agricultural yields – measured as output per unit of land – and, therefore, the long-term global sustainable development of agriculture and food production.

A panel-data model was selected and built based upon its ability to capture information on ICT's impact across several countries and multiple time periods.

The panel model was developed using data from international databases, such as those hosted by the World Bank and FAO. The model is first explained, results are presented and conclusions are drawn.

3.2 METHOD

3.2.1 Scope, unit of analysis and temporal selection

The panel-data model was assembled to analyze research questions at a global scale. The unit of analysis is, therefore, countries. The chosen cross-dimensional section of this model is composed by 212 countries for which data is available. The list is available in Annex B.

With regard to temporal selection, five 5-year periods were defined: 1990-1994, 1995-1999, 2000-2004, 2005-2009 and 2010-2014. The values used for each variables are simple averages of the data available for the 5-year period in each country. This methodological choice is justified by the assumption that the majority of selected variables (such as Internet penetration) do not vary significantly from year to year. Much of the expected variation and trends can only be identified over longer periods of time. The author expected a time-lag between the cause (growth of ICT infrastructure and utilization) and the effect (yield growth).

The relationship between cause and effect would, therefore, not be captured by an annual temporal selection.

A 5-year average temporal selection is also justified by the inherent qualities of the dependent variable in question: yields. Crops productivity can vary significantly from year to year, caused primarily by natural forces such as temperature and precipitation variations as well as pests and diseases. Such volatility is excluded from the model by using a 5-year average. Moreover, it eliminates the need to include explanatory variables that would otherwise control for volatile natural factors, such as climate conditions in a specific year and/or the occurrence of agricultural pests. Finally, regarding the last period (2010-2014), there is very little data published for the year 2014 (the majority of the databases end in 2013). However, given the methodological arguments for averaging available data, values for the last 5-year period can be used with no harm.

3.2.2 Statistical model

As previously mentioned, a panel-data model was chosen to test relationships among dependent and independent variables.

First, a traditional ordinary least squares (OLS) linear regression was performed, using the “pooling” method described by Croissant & Millo (2008). Additionally, a fixed-effects model was chosen in order to control for omitted variable biases. Finally, a fixed-time effects model is also tested, controlling not only for cross-sectional fixed effects but also for time-fixed effects. Finally, a random modeling technique was also tested. Even if the testing of different modeling techniques did not solve all endogeneity-related problems, it served as a mitigation strategy, as described below.

One of the main concerns associated with an OLS model is that endogenous variables can affect both the dependent and independent variables. In other words, omitted variables could explain variations in both variables. The fixed-effects model tries to mitigate those problems. Including specific time-bound dummies to create a fixed-time effect further tackled the issue.

The use of fixed-effects models helped mitigate omitted variable bias. However, such logic only holds under the assumption that the unobserved factors potentially affecting independent and dependent variables are time-invariant. In other words, it assumes that factors that are not captured by the model and could be impacting the dependent and independent variables at the same time do not change over time. It is a risky assumption in any modeling exercise, even though it is often used in empirical studies in economics and social sciences. One might convincingly argue that unobserved factors affecting both sides of an equation, such as institutional development or cultural priorities, can change over time.

However, this assumption is deemed plausible for the current study based on the data shown in the graphs below illustrating global cereal yield variation since the beginning of the available time series (1960s). No significant or structural modifications exist in the patterns of yield growth within the period analyzed by this study. In fact, annual yield growth decreased during the study period. Therefore, it is plausible to assume that no global structural change affected yield variation over the last 20 years. It is logical to conclude that, even if omitted variables explain part of the variations in independent variables that suffered structural changes in the studied period, those omitted variables did not have major effects on the dependent variable. In other words: the time-sensitive changes in the omitted variables could affect the “right-hand side” of the model equation (independent variables) but are unlikely to have affected the “left-hand side” of the equation (dependent variable) in the same manner. It is plausible to infer that the “identifying assumption” holds in this case and that the fixed-effects model is effectively applicable in this case.

Figure 2 - Agricultural yields and Internet users

<i>period</i>	Maize	Rice	Soybeans	Wheat
1961-1989	2.4%	2.1%	1.7%	2.7%
1990-2013	1.7%	1.1%	1.1%	1.1%

Table 1 - Annual yield growth for selected crops

Additionally, independent variables were deliberately selected to also tackle omitted variable bias, serving as potential controls. First, GDP per capita indicates not only economic development but also other non-observed factors, because it can capture structural changes in a society. In order to further test and try to measure the impact of all omitted time-variant variables on the fixed-effects model, a new control variable was created: an index representing the average yield variation in a group of countries classified based on regional and income-level factors. Omitted variables that could help explain variations in the dependent variable could be captured in this newly calculated variable, reducing the impact of potential omitted-variable bias. Finally, a dummy for region and income level was also tested. More information can be found in the Data section. Obviously, even considering the

mitigation techniques and sensitivity analysis discussed here, conclusions should be understood with care.

Data availability further justified the modeling exercise's methodological choices. Data is not available for every single country across every time period, so the panel data is unbalanced. This research does not transform the unbalanced panel data into a balanced one by omitting dimensional data (countries) with missing values. This choice avoids bias against least-developed countries and smaller economies' datasets that tend to contain more missing values. Any editing would, therefore, likely exclude those countries from the sample, creating biases. Additionally, the current modeling software accepts unbalanced panels.

The statistical software "R" was used for this exercise. The package "PLM" (Linear Models for Panel Data) – developed by Croissant & Millo (2008) – was installed in order to perform the tests. Given the preceding paragraph's discussion, it is worth noting that the authors specify that tool is adequate for modeling unbalanced panels. The commands utilized are presented in Annex A. Detailed regression results are presented in Annex B.

3.3 DATA

This section describes the variables chosen for the modeling exercise, indicates their source and explains their rationale.

3.3.1 Dependent variable

3.3.1.1 *Agricultural productivity*

3.3.1.1.1 *Cereal yield (yld)*

As previously described, this study assesses the impact of ICT on agricultural development. The hypothesis is that agricultural producers can achieve better yields through greater connectivity and access to information. That hypothesis is extended to other agricultural

supply chain. For example, commodity distributors could improve efficiency and markets could become more integrated by using ICT systems.

Many previous studies measured agricultural productivity by utilizing an index based on product value per unit of land. That approach is popular because it allows different products to be combined into a single indicator. However, that index does not specifically measure the output per hectare. Similar indicators also reflect economic and market conditions, among other off-field variables, because they incorporate prices to calculate the final agricultural value.

This study focuses on sustainable agricultural development of and is based on the hypothesis that greater access to information can help producers do “more with less” in agriculture. So, the best methodological choice was to focus on the actual agricultural output per unit of area: kg per hectare.

Additionally, wheat, rice and corn provide about two-thirds of all energy in human diets (CASSMAN 1999), making cereal yield compiled by FAO and published by the World Bank the most informative dependent variable for this model. Cereal yield is a better proxy for agricultural output per unit of land, excluding any price and market-related factors. The detailed database description reads:

“Cereal yield, measured as kilograms per hectare of harvested land, includes wheat, rice, maize, barley, oats, rye, millet, sorghum, buckwheat, and mixed grains. Production data on cereals relate to crops harvested for dry grain only. Cereal crops harvested for hay or harvested green for food, feed, or silage and those used for grazing are excluded. The FAO allocates production data to the calendar year in which the bulk of the harvest took place. Most of a crop harvested near the end of a year will be used in the following year.” (WORLD BANK, database)

3.3.2 Core independent variables (analytical focus)

3.3.2.1 Information and Communication Technology

In order to evaluate the impacts of ICT on agricultural yields, the central independent variable studied was ICT utilization. As described in the literature review, many studies have discussed

and shown that the lack of information can be a bottle neck for increased agricultural productivity. This study assessed the impact of ICT-based access to such information.

Several indicators on the subject are compiled and published at national level by international organization. An indicator representing the mobile Internet coverage (by area or by population) in all studied countries would be the ideal measurement for this variable. Unfortunately, no such indicator is available.

A private company, called Open Signal, is developing a map of geographically explicit Internet usage at a global scale. Using big data techniques, they are able to monitor the quality and use of mobile Internet services. The CEO of the company was contacted and this study's goals were presented⁵. It was indicated that they would be willing to share their databases for this researcher's purposes. However, discussions and deeper investigation into the data, revealed that, while their databases are impressive in some parts of the globe (eg: the US and other major urban areas), there are not as representative at a global scale. Therefore, it promises to be a very interesting data source for more locally based studies in areas in which their coverage is significant, but it did not serve the purposes of this research.

Therefore, the best-available databases to measure ICT use at a global scale in a timeframe within the scope of this study are, indeed, those published by international organizations. Every year the ITU compiles several indicators about ICT use at a national level. Many of those statistics are published by the World Bank.

3.3.2.1.1 *Internet users (int)*

Given the explanations above, the chosen variable to measure Internet infrastructure and utilization in the global model developed for this research was the number of Internet users per 100 habitants.

This indicator is a reliable proxy indicator for digital inclusion in a country. It is based on relative terms (users per 100 habitants), rather than absolute terms (eg: number of users),

⁵ Contact with Brendan Gill, Open Signal's CEO, by email on January 2015

indicating the level of technological penetration in the country. While the indicator is not geographically explicit, it is plausible to assume that an increase in the percentage would indicate a stable or improving situation in rural areas. In other words, it is a good proxy indicator to answer both central questions this variable intends to measure: has ICT infrastructure and utilization improved or worsened? Is this variation significant or not?

3.3.2.1.2 *Subscription to mobile phone lines (mob)*

Based on the same rationale, another independent variable representing ICT infrastructure and utilization was tested: the number of mobile subscriptions by 100 habitants. Even though this study focused on more innovative and promising communications technologies based on data transfer (rather than voice), this variable was still worthwhile to test. This is especially true because mobile coverage is a pre-condition for mobile data transfer. Unfortunately, database cataloging global data transfers exists. This issue was explored in more depth in the regional model (Chapter 4).

3.3.3 Other independent variables

As presented in the literature review, many studies modeled agricultural productivity. Independent variable selection does not vary significantly between them. A tacit consensus emerged around the most important variables. This study, therefore, drew from previously selected explanatory variables for agricultural yield, which can be synthesized as: economic development, human capital, farm-level inputs, technology use and climate. Also, as previously stated, many infrastructure studies explored irrigation and roads as potentially important variables. The current study included a final explanatory variable that is uncommon in similar studies but was found to have an effect on some models: agricultural market dynamics. The rationale for each is explained below.

3.3.3.1 *Economic Development*

A country's economic development is always utilized as an independent variable in empirical, country-based modeling studies. While it is often used to quantify the effects of economic growth on the studied dependent variable, it is also a commonly utilized control for country-specific dynamics that might affect other variables. Economic development tends to be closely correlated with other country characteristics – such as institutional development – making it a valuable control variable.

3.3.3.1.1 *GDP per capita (gdp)*

GDP per capita was especially relevant to this study's objectives because it tends to incorporate other potentially uncontrolled variables, such as institutional development. It also mitigated the risks of the "identifying assumption" for fixed-effects models, described previously. GDP per capita was selected to satisfy these dual purposes.

3.3.3.1.2 *Agricultural value added per rural habitant (avr)*

In order to shift this study closer to agriculture, a new variable was added: the agricultural value added per rural habitant. The variable is a proxy measurement for the level of rural development, rather than the economy writ large, which GDP per capita captures. It was calculated by dividing the World Bank data on agricultural value added by the agricultural population.

3.3.3.2 *Human Capital*

3.3.3.2.1 *Education (edu)*

Another obvious variable in the studies about productivity is the quality of human capital. The logic is simple: the more qualified the labor force is, the better the results.

The variable, education expenditure per capita, was calculated using two indicators published by the World Bank: GDP per capita (in 2005 US dollars) and education expenditure as a percentage of GDP.

3.3.3.3 Inputs and Technology Use

Farm-level inputs and technology use are two other important factors that define agricultural productivity. The more technology used in the field, the greater the expected outcomes. Two main independent variables were chosen for that objective: the use of fertilizers and irrigation. A more detailed description of each variable follows.

Of note, however, is that those variables contain the most availability gaps (see graph below), a limitation that is especially true for the fertilizer use.

3.3.3.3.1 Irrigation (wat)

Another factor that directly affects agricultural yields is irrigation use. As demonstrated in the literature review, some studies have already measured its importance. The World Bank publishes an index estimating the percentage of agricultural land under irrigation. That database, however, is not very extensive, omitting many countries and time periods. The data would significantly and negatively impact the quality of the results of this modeling exercise. Therefore, a proxy index for irrigation was calculated. Using three different World Bank datasets with better coverage and precision (total freshwater withdraws, percentage of water withdrawn used for agriculture and total arable land), the author was able to calculate water used per hectare of agricultural land (in m³/ha). This new indicator is a meaningful proxy to measure irrigation use and test its effect on the independent variable (yield).

3.3.3.3.2 Fertilizers (fer)

The use of modern fertilizers was one of the critical technological developments behind the Green Revolution in agriculture, which boosted yield in many parts of the globe during the 1960s. It is therefore obvious that any exercise modeling agricultural yield needs to

incorporate fertilizer use. The World Bank publishes a database of fertilizer use per hectare, which was the index utilized to measure this independent variable. A brief description about the indicator reads:

“Fertilizer consumption measures the quantity of plant nutrients used per unit of arable land. Fertilizer products cover nitrogenous, potash, and phosphate fertilizers (including ground rock phosphate). Traditional nutrients--animal and plant manures--are not included. For the purpose of data dissemination, FAO has adopted the concept of a calendar year (January to December). Some countries compile fertilizer data on a calendar year basis, while others are on a split-year basis. Arable land includes land defined by the FAO as land under temporary crops (double-cropped areas are counted once), temporary meadows for mowing or for pasture, land under market or kitchen gardens, and land temporarily fallow. Land abandoned as a result of shifting cultivation is excluded.” (WORLD BANK DATABASE)

One final issue associated with this list must be highlighted. While there is no doubt that fertilizer use plays a significant role in defining yield, the database presented is the only one available. It contains significant data availability gaps. No data is provided for any year in this study's first time period (1990-94), and the database lacks information for several countries. These factors may detract from this variable's explanatory power in this modeling exercise as it reduces data coverage for both the cross-sectional and temporal section.

3.3.3.4 Agricultural Markets

3.3.3.4.1 Cereal producer price (pic)

This study innovates relative to similar previous studies by including an uncommon independent variable: agricultural markets.

This variable adds important context to an analysis of agricultural development. When producers are offered better prices for their products, their immediate economic situation tends to improve. Therefore, farmers could invest in yield-boosting technologies and techniques when agricultural prices are higher because their returns would be greater. A

positive correlation is therefore expected between agricultural prices and agricultural productivity.

The FAO Cereal Producer Price index was chosen to measure this correlation.

“The FAO Agricultural Producer Price Indices measure annual changes in the selling prices received by farmers (prices at the farm-gate or at the first point of sale). The indices are constructed using price data in Standardized Local Currency (SLC)” (FAOSTAT).

3.3.3.5 *Climate and pests*

Climate conditions are a key defining factor for agricultural yields in any given year. A dry period has a direct negative effect on land productivity, as does a pest infestation. However, as previously explained, the methodological decision to use average values for 5-year periods eliminates the need to include an explanatory variable that controls for volatile climate and pests occurrences.

3.3.3.6 *Additional controls for omitted variables*

3.3.3.6.1 *Index for yield variation according to region and Income Level (reg.inc)*

In addition to the traditional explanatory variables described above, an additional control variable for non-observed variables was created: an index for yield variation according to region and income. The index overlaid cereal yield data on World Bank classifications for income and regions then grouped countries. The yield average was calculated for each group and each time period. The index was then calculated, in which the average yield in 1990-94 was equal to 1. Finally, the index was applied to all countries in the category. More information appears in Annex B.

3.3.3.6.2 Dummy for region and income level

In addition to the index above, which described yield variation, a simple dummy for region and income level was also included following the same categories described above.

Those two strategies accomplished the same objective. Controlling for group and region anticipates the likely reality that unobserved variables had varying effects in different countries, across regions within those countries, and across different income and development levels.

Figure 3 - Number of observations per variable per period

3.4 RESULTS

Results produced by the methodology, data and models described above indicate that a growing number of Internet users would have a positive impact on a country's cereal productivity. For the case of mobile phone users, however, results are inconclusive.

3.4.1 Presentation

Table 2 summarizes the results of several regressions executed using different combinations of independent variables. The columns describe models used and the coefficient calculated for each of the two key variables being analyzed by the paper: Internet usage and mobile users. The rows describe the control variable utilized in each regression. The objective was to test, one by one, how control variables impacted the explanatory power of the two key variables under scrutiny (Internet and mobile users), both in relation to the value of the coefficient and, more importantly, the variable's statistical significance. The figure also serves to draw comparisons between Internet and mobile users. Finally, the last two columns show results from the complete model, incorporating all the variables and therefore This analysis revealed that, when the Internet usage and mobile user variables are tested alone (row a), their calculated coefficients are positive and significant, as defined by this paper's central hypothesis.

Then, both Internet usage and mobile users are included (rows b and c). In this case, the coefficient for mobile users loses its significance, while the coefficient for Internet usage remains at the highest level of confidence.

In fact, throughout these analyses, no matter which additional control variable is included, Internet usage consistently maintains a positive coefficient and statistical significance. In the great majority of cases, statistical significance appears at the 99% level, the exception being when educational expenditures - the proxy for human capital quality - and GDP per capita – the proxy for economic development and an additional control for omitted variables – are introduced. In those cases, depending on the estimation model, the significance level drops slightly. However, it is important to note that significance is maintained above the 90% threshold level.

The proxy variable for rural development (agricultural value added per hectare) did not always demonstrate statistical significance, nor did the proxy variable for market conditions (cereal price index). The variables for input use (fertilizer use and proxy for irrigation) were always significant at the 95% level, and maintained an equal or lower confidence level than the Internet users.

In addition to one-on-one verifications, two combined models that aggregated all variables were tested in each of estimation method. The results appear in rows (l) and (m) of the table. Even with simultaneous inclusion of all potential controls, the Internet usage continued to demonstrate a positive and significant coefficient. This pattern is even more apparent in the last column, in which dummy variables for region and income level were included as an additional mitigating factors to control for potential omitted-variable bias.

3.4.2 Discussion and future research

These results demonstrate that, no matter which estimation model was used – including traditional independent variables described in the literature and several strategies to mitigate potential endogeneity problems – Internet coefficients maintained statistical significance and positive values. The following hypothesis is, therefore, supported: a growing number of Internet users in a country would have a positive impact on that country's cereal crop productivity. These results also offer a compelling argument in favor of the general hypothesis for this thesis: the advance of communication infrastructure and utilization can improve agricultural development.

Those results are justified by a clear logical sequence. ICT infrastructure would share more information with farmers, help markets respond to on-the-ground conditions and increase efficiency gaps in agricultural supply chains by reducing information gaps from plantation to grocery store shelf.

In fact, based on the methods described and on carefully controlled regressions, the data indicate that a 1% increase in the number of Internet users could be associated with an

increase in cereal yield of 18-33 kg per hectare with a 95% confidence level⁶. Such numbers need to be considered with care, but the mitigation strategies adopted to account for potential omitted-variable bias support the conclusion's validity.

To describe the magnitude of this conclusion (while acknowledging the limitations of the simplified calculation described), the world harvested 816 million hectares of cereals in 2014, according to the latest FAO data available. A 25kg per hectare increase in productivity would create an additional 21.4 million tons of cereals per year. According to an FAO report (BRUINSMA 2003), average cereal consumption in developing countries is 156kg per person per year. This means that 21.4 million additional tons of cereals would feed 131 million people, roughly equivalent to the total population across the Horn of Africa (Somalia, Ethiopia, Eritrea and Djibouti) plus South Sudan.

It is also possible to infer that economic development and human capital quality are significant explanatory variables for yield levels, a conclusion supported by previous studies' findings. Inputs such as water and fertilizers also influenced yield variation significantly, again in agreement with this study's hypothesis and expectations and previous studies' results. One particularly unique and noteworthy result, however, is that Internet usage tested as well as all any other variable -- and tested better than some -- in all regressions, models and combinations of control variables utilized. Even considering potential endogeneity issues, Internet usage is proving to be as valuable measurement for yield variation as the traditional variables used in the empirical literature.

As previously discussed, the analyzed variables with the strongest results were GDP per capita and per capita education expenditure. This connection was expected. Both are useful proxy indicators for economic development, human capital quality and, in the case of GDP per capita, physical infrastructure. Nonetheless, one interesting question arises from the fact that Internet usage tested as well as education expenditure per capita. Imagine a policy drafted to direct national government funding to initiatives that increase yields. Would investing in Internet infrastructure and utilization be more or less significant, and more or less expensive,

⁶ For the random model with dummy variables for region and income, the confidence drops to 90% level. However, a Lagrange Multiplier Test - (Breusch-Pagan) for unbalanced panels test wheter random models were preferred. Results failed to reject the null hypothesis of the test. It is therefore possible to infer that a random-effects model is not the most appropriate for this case, justifying why the results are presented considering only the other regressions.

than investing in traditional education infrastructure? The variables used for the two issues in this research differ in form and unit, so it is impossible to draw any comparative conclusions from the coefficient numbers beyond the fact that they are both positive and statistically significant. Also, it is clear that expenditures on education support several other positive sustainable development goals. However, re-focusing on “expanding agricultural production in fewer hectares,” future research could try to identify whether ICT infrastructure or education infrastructure is the most cost-effective way to develop human capacity for yield growth? This research also poses questions for rural extension services, from the traditional model of agents present on-site to a new web-based system that delivers information through ICT devices.

Finally, because the coefficients for mobile phone usage have not always tested as statistically significant due to the fact that they assumed different directions (such as negative coefficients) at time, results are inconclusive. Further research and testing is needed in order to reach more robust conclusions.

3.5 CONCLUSION

The results of this study support the hypothesis that the advance of information and communications technology infrastructure and utilization in rural areas improves sustainable agricultural development by helping countries increase production while reducing land area under cultivation, thereby reducing pressure for additional land resources and promoting further food security.

Technical limitations associated the methodology, data selected, and the executed model have been discussed extensively. However, due to the mitigation techniques adopted and innovative research design, the author is confident that the stated results represent a significant contribution to the fields of infrastructure installation for agricultural and sustainable development goals.

Despite the potential benefits of ICT infrastructure, it is important to recognize that: (a) yield growth could trigger other negative collateral impacts, such as indiscriminate use of fertilizers

and other farm-level agricultural production accelerants, which could cause environmental and social problems, (b) this research does not discuss legitimate ethical challenges associated with protecting data confidentiality and avoiding greater asymmetries of market power for data owners, and (c) while food loss and waste is not within the scope of this research, addressing this critical issue would also promote food security at a global scale. Each of the three issues present promising avenues to extend the research questions posed by this study.

In an increasingly connected world, information and communication technologies are having an ever-greater impact on societies. Given the above mentioned limitations, the results of this research do not answer all relevant questions, but share new insights that may prove useful for promoting sustainable agricultural development at a global level.

		<i>Models and core independent variables tested</i>							
		OLS		FIXED EFFECTS		FIXED TIME EFFECTS		RANDOM EFFECTS	
		<i>Internet</i>	<i>Mobile</i>	<i>Internet</i>	<i>Mobile</i>	<i>Internet</i>	<i>Mobile</i>	<i>Internet</i>	<i>Mobile</i>
<i>Independent variables for control</i>	(a) No control	56.351***	22.068** *	70.564***	36.743** *	70.475***	36.633** *	55.887** *	21.820** *
	(b) Internet users (int)	N.a.	-3.396	N.a.	9.725	N.a.	9.641	N.a.	-3.662
	(c) Mobile users (mob)	62.494***	N.a.	59.937***	N.a.	59.972***	N.a.	62.539** *	N.a.
	(d) GDP per capita (gdp)	0.326**	2.952	33.561***	14.242*	33.076**	14.006	32.256**	3.018
	(f) Agricultural value added (avr)	57.891***	-3.052	67.148***	11.082	67.326***	10.801	54.759** *	-3.081
	(g) Education expenditure (edu)	14.623*	4.939.	8.194.	4.675***	15.602.	15.883** *	14.512*	4.788
	(h) Water use (wat)	71.717***	-10.331*	77.525***	-8.401	77.974***	-8.330	68.449** *	-9.392*
	(i) Fertilizer use (fer)	58.828***	-1.162	62.851***	5.836	63.350***	5.338	57.710** *	-1.377
	(j) Cereal producer price (pic)	52.943***	-8.452**	44.458***	8.021*	44.606***	8.030*	53.283** *	-8.838***
	(k) Control for yield variation at region and income level (reg.inc)	68.850***	- 17.670** *	64.838***	-3.173	64.878***	-3.162	68.915** *	- 17.847** *
	(l) ALL CONTROL VARIABLES	23.675*** <i>r-squared = 0.584</i>	1.112	28.153*** <i>r-squared = 0.541</i>	0.661	28.139* <i>r-squared = 0.563</i>	0.811	21.256** <i>r-squared = 0.563</i>	1.636
	(m) ALL CONTROL VARIABLES + DUMMY FOR REGION AND INCOME	18.745* <i>r-squared = 0.656</i>	-4.372	33.143* <i>r-squared = 0.678</i>	-6.733	33.647* <i>r-squared = 0.695</i>	-6.798	14.240. <i>r-squared = 0.563</i>	-3.020

Note a: dependent variable = cereal yield (kg/ha/yr)

Note b: Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Table 2 – Summary results of the global model: the effects of Internet and mobile phone usage on cereal productivity

4 SUB-NATIONAL MODEL: EFFECT OF 3G MOBILE NETWORK AVAILABILITY ON DEFORESTATION RATES OF BRAZILIAN MUNICIPALITIES IN THE LEGAL AMAZON

4.1 INTRODUCTION

This chapter will assess the effect of ICT infrastructure installation on rural agricultural development from a different perspective than the previous chapter. Utilizing Brazilian municipalities as the unit of analysis, this chapter models the effects of newly installed 3G mobile Internet networks on deforestation. Mobile internet network infrastructure gives farmers better access to markets and to information. Therefore, farmers and rural populations could utilize 3G network coverage to learn about better production techniques, understand market demands and regulatory requirements. That hypothesis extends to the added benefit that new 3G mobile ICT infrastructure in a municipality has a significant and negative effect on deforestation rates.

A quasi-experimental design was formulated to test the hypothesis with the econometric Propensity Scoring Model. Also, a difference-in-difference methodology was adopted to compare the outcomes in each municipality before and after the treatment. The model estimates impacts on the analyzed variable by matching similar municipalities - according to control variables - where new 3G mobile Internet infrastructure was (treatment group) or was not (control group) installed. The model then compares outcomes before and after the treatment.

In this study, the treatment variable for mobile communication infrastructure installation in municipalities is 3G technology availability. The dependent variable is total accumulated deforestation as a percentage of the municipality's area. The control variables used to match similar municipalities are: economic development, the importance of agricultural activity to the municipalities' economy, agricultural expansion (which increases the likelihood of deforestation), a proxy index for the range of mobile coverage, and the sub-national region's land area and population.

This chapter introduces the subject by describing deforestation challenges and ICT infrastructure investments, with a focus on Brazil. An explanation of methodology follows, detailing the model, data and methodological choices. Results are then presented. Finally, outcomes are discussed, conclusions are presented, and suggestions for further research are shared.

4.1.1 Agriculture and deforestation: policy and market reactions

Agricultural production can expand vertically or horizontally. That means that production can increase by improving output per hectare or by expanding the planted area. The latter can cause exert pressure to convert forested land surrounding farms to farmland and therefore trigger deforestation (LAWSON et al 2014, SMITH et al 2007). Brazil offers a quintessential example. In the early 2000s, the country experienced in the highest deforestation rates on historical record, which in many cases was caused by horizontal agricultural expansion. Nepstad et al. (2014) effectively summarize how the process evolved over time and explain how different measures by public sector, private and civil society actors attempted to curb deforestation associated with agricultural commodities.

Many of the attempts to combat deforestation were led by governmental authorities. In 2004, the government launched the Detection of Deforestation in Real Time (DETER) system and the Plan for Protection and Control of Deforestation in the Amazon (PPCDAm) linked directly to the President's office (NEPSTAD et al 2014). In 2007, the list of *Municípios Prioritários in the Amazon* (Priority Municipalities in the Amazon) was created,⁷ which coordinated environmental protection authorities' actions. This last program slowed deforestation by an estimated 35% relative to business as usual (ASSUNÇÃO & ROCHA, 2014).

⁷ Decree no. 6.321 of December 21st 2007

Figure 4 - Deforestation, area of land use categories, and production (beef and soy) trends in the Brazilian Amazon

Source: NEPSTAD et al. 2014

It is important to note, however, that despite these deforestation-control programs, some forest clearance is allowed by Brazilian legislation. According to the Forest Code⁸, 20-80% of a farmer's private land must be set-aside for conservation purposes but, subject to governmental authorization, individuals do have the right to clear native vegetation. For context, 53% of Brazil's native vegetation grows on privately owned land (SOARES-FILHO et al 2014).

Non-governmental actors also played fundamental roles in this debate. International civil society organizations launched several campaigns aiming to expose links between growing agricultural commodity markets and deforestation in the region. Two Greenpeace reports ("Eating up the Amazon"⁹ from 2006 targeting soy supply chains and "Slaughtering the Amazon"¹⁰ from 2009 targeting beef supply chains) are the most well-known examples. The campaigns motivated many public commitments by companies and banks to work toward

⁸ Law no. 12.651, of Mai 25th 2012.

⁹ Available at: <http://www.greenpeace.org/international/Global/international/planet-2/report/2006/7/eating-up-the-amazon.pdf>. Accessed January 2017.

¹⁰ Available at: <http://www.greenpeace.org/international/Global/international/planet-2/binaries/2009/7/slaughtering-the-amazon-part1.pdf>. Accessed January 2017.

eliminating deforestation from their supply chains. The Soy Moratorium – an agreement signed by the soy industry association, companies and civil society – promised to remove soy grown in deforested areas in the Amazon from mainstream agricultural markets. The Moratorium was the first voluntary zero-deforestation agreement, setting the stage for similar initiatives in other commodities, such as beef and palm (GIBBS et al 2015). Since then, several other corporate commitments emerged promising to eliminate and/or reduce deforestation from agricultural supply chains, including the UN New York Declaration on Forests¹¹, the Deforestation Resolution by the Board of Directors of Consumers Goods Forum (CGF)¹² and the Soft-Commodities Compact by the Banking Environment Initiative (BEI)¹³. Each of these initiatives and processes have, regardless of how effectively they were implemented, created market signals that dis-incentivize agricultural commodity-driven deforestation.

It is clear that these policy and market dynamics had differing levels of influence on deforestation rates in the Amazon. This research introduces a discussion about a different component of this process: the impact of access to information at the local level in rural areas, as facilitated by 3G mobile network installation, on the evolution deforestation-reduction processes. In other words, could access to information have accelerated the implementation of these market and policy mechanisms by communicating their existence and implications more easily to local actors?

4.1.2 Brazilian regulation and the country's urban-rural digital divide

The Brazilian Telecommunications Agency (ANATEL) is the country's sector regulator, responsible for auctioning new mobile phone frequencies for both voice and data transfer. Within its auctioning process, ANATEL demands compromises by the bidding companies regarding coverage for rural municipalities lacking urban areas' commercial appeal. In the last

¹¹ Available at: <http://www.un.org/climatechange/summit/wp-content/uploads/sites/2/2014/07/New-York-Declaration-on-Forest-%E2%80%93-Action-Statement-and-Action-Plan.pdf>. Accessed February 2017.

¹² Available at: <http://www.theconsumergoodsforum.com/sustainability-strategic-focus/sustainability-resolutions/deforestation-resolution>. Accessed February 2017.

¹³ Available at: <http://www.cisl.cam.ac.uk/business-action/sustainable-finance/banking-environment-initiative/pdfs/the-bei-and-cgfs-soft-commodities-compact.pdf>. Accessed February 2017.

call for bids (“*editais*”) on frequencies for 3G technology, companies were obliged to follow an investment schedule to extend 3G coverage to rural areas that would not otherwise be covered. According to ANATEL’s call for bids n.º 002/2007/SPV (“*Editais 3G*”) and n.º002/2010/PVCP/SPV (“*Editais Banda H*”) such investments need to comply with the following schedule:

Class of municipalities by population	Obligatory targets
above 100,000 people	100% by May 2013
between 30,000 and 100,000 people	70% by May 2013 100% by June 2016
below 30,000 people	20% by May 2013 75% by June 2016 100% by December 2019

Source: ANATEL 2015a

Table 3 – Obligatory targets for the installation of 3G technology according to municipality population

Subject-area experts indicated that is very plausible to assume that any investments in cities with smaller populations would not have occurred without the obligations imposed by the regulator¹⁴. Data from ANATEL shows that 78% of the investment in new ERBs between 2012 and 2015 were made in municipalities with more than 30,000 people. In fact, Rezende (2014) studied economic feasibility and return on investments earned by the four top mobile technology companies, using the call for bid no. 004/2012/PVCP/SPV as the parameter. Using two different methodologies in order to analyze the return on investment, the author concluded that *“when traditional metrics for evaluating investments were applied [discounted cash flow], nearly all these projects were unfeasible since they presented low probabilities of achieving a positive NPV (Net Present Value)”*. Following the other methodology, investments were expected to yield positive results in 80% of the cases.

Finally, the call for bids n.º 004/2012/PVCP/SPV (“*Editais Banda Larga Rural e Urbana*”) also created additional obligations to expand non-3G coverage. It focuses on coverage for rural and remote areas. The companies were again obliged to follow a pre-established schedule to

¹⁴ Interview with Newton Scartezini, an experienced telecommunication executive and former CEO of a mobile infrastructure company, conducted on April 6th, 2015 by phone.

guarantee (non-3G) voice and data coverage in non-urban areas located up to 30km from the city center of all Brazilian municipalities in accordance with the following schedule:

Obligatory targets for non-3G voice and data coverage
30% of municipalities by June 30 th 2014
60% of municipalities by December 31 st 2014
100% of municipalities by December 31 st 2015

Source: ANATEL 2015a

Table 4 - Obligatory targets for the installation of 3G technology in non-urban areas

These national-level obligations, and the assertion that investments to expand 3G technology to rural areas would not have been made without the regulatory requirement, strengthen the quality of this study's results. Investment requirements and their implications significantly limit any potential omitted-variable bias that explaining both the occurrence of the treatment (installation of 3G technology) and the variation on the dependent variable (deforestation rate) at the same time. This control will be further discussed in the Method section.

However, despite the government's best efforts and indisputable development in Brazil's large urban centers, mobile coverage is still included in the country's long list of infrastructure challenges. While some cities still suffer poor cellular signals, the situation is worse in more remote and rural areas. The government's requirements in public bids did not eliminate the challenge of reaching 100% 3G network coverage in a sparsely-populated country such as Brazil.

The expansion of mobile data networks and transmission antennas were mapped on the graph below, separating municipalities with more than 30'000 people from municipalities with less than 30,000 people. A sharp increase in the number of antennas in small municipalities appears clearly in two years: 2007 and 2010, the years of the "*editais*" that established obligatory infrastructure investments in smaller municipalities. It is worth noting that, while the number of municipalities with 3G coverage is very similar across small and large cities, the majority of municipalities in the country have less than 30'000 people. So, 3G coverage in smaller cities is much lower in relative terms. In 2014, 95% of municipalities with more than 30'000 people were covered by 3G, but coverage extended to only 62% of smaller cities. Also, as expected, the number of antennas is positively correlated with the total

population in a municipality (see graphs below). However, there is also an apparent negative correlation between the rural population percentage in a municipality and 3G coverage. In other words, municipalities with larger rural populations have less coverage.

Given the above, it appears that the digital divide in Brazil is no longer characterized by socioeconomic factors – such as wealth inequality – but by geographic isolation.

Figure 5 - Number of mobile transmission antennas according to municipalities' population (2013)

Figure 6 - Number of mobile transmission antennas vs. rural population

Figure 7 - Evolution of 3G coverage according to population size (Big=>30,000) (Small=<30,000)

Figure 8 - Total number of mobile antennas installed in Brazil according to the category of the municipalities (Big=>30,000) (Small=<30,000)

Figure 9 - Total area occupied by the municipalities

Figure 10 - Number of antennas per municipality vs total population

Source: author's calculations based on ANATEL and IBGE databases.

4.2 METHOD

One of the main challenges when evaluating the impact of an intervention (in this case, the installation of ICT infrastructure) is to successfully establish a counterfactual. In other words, what would have happened to the actors (municipalities) if they had not participated in the

treatment (received 3G infrastructure)? Without tackling that question, no plausible inferences can be made about the impact of an action on a selected outcome, because it is impossible to clarify whether such outcomes would have happened anyway, independent of the intervention.

The first, ideal option, is to randomly select study participants and randomly apply the treatment to members of the study and then calculate the impact as the difference in average outcomes between the group that received the intervention (treatment group) and the group that did not (control). This approach, defined as Randomized Control Trials (RCTs), commonly utilized in medical experiments, is increasingly being used in policy and economic evaluations (DUFLO et al 20017). However, in many cases the RCT is not a feasible option. This is especially true for academic research that evaluates an impact post-facto, after the interventions occurred, as is the case in the present study. RCTs are also not feasible for very large and costly interventions, such as infrastructure installation planned for different objectives and dependent on the government.

Assunção et al. 2014 analyzed the impact of electricity infrastructure on yields and deforestation in Brazil. The authors utilized an instrumental variable developed by Lipcomb et al. (2013) that predicted electricity availability considering minimized construction costs based exclusively on geographical characteristics. The authors intended to correct for bias caused by the endogenous placement of electricity infrastructure by isolating supply-side factors that influenced the investments. In other words, the study isolated unobserved factors that could explain both electricity infrastructure expansion (independent variable) and yield growth and increased deforestation (dependent variables studied). Lipcomb's instrument served as the counterfactual.

In this study, however, a different approach is taken given the much shorter time period and lesser time variance. While electrification investments in rural areas have occurred since the middle of the 20th century, the penetration of mobile communication technologies started only in the first decade of the 21st century. Therefore, data points on mobile communication technologies are much more tightly clustered on the time spectrum, weakening any counterfactual based on time variance.

The best approach to create a counterfactual for this study proved to be quasi-experimental design strategies. In this case, a Propensity Score Matching Model created two groups of municipalities: one that was subject to the studied “treatment” – in this case the installation of 3G network infrastructure – and a control group that was not. The model then matched each municipality in one group to another in the control group that shared the most characteristics. Several variables that could explain the studied outcome were included in this matching exercise, creating the counterfactual. Finally, the model compared the effects of the “treatment” in the matched municipalities in both groups.

The initial work on Propensity Score Matching dates from the 1980s (ROSENBAUM & RUBIN 1983, ROSENBAUM & RUBIN 1985). More recently, more sophisticated computing tools and wider availability of computing power opened method to wider audiences. The Propensity Score Matching statistical package for R software developed by Sekhon (2011) was used in this exercise.

A critical issue for model implementation was the classification of similarities. For the matching exercise to successfully mitigate potential bias, it must consider a full range of variables in which the treatment and control groups might differ. One should also choose control variables that affect the probability of participation in the treatment and the outcome (HEINRICH et al. 2010). As described in the next section, the current exercise adequately addressed these issues by clearly defining the following controls: population size, level of economic development, sub-national regions, agriculture’s importance for the municipality’s economy, agricultural expansion, an index for mobile coverage availability and the municipality’s total area.

Additionally, as discussed previously, compelling evidence suggests that 3G network infrastructure would not have been installed in more sparsely areas without Brazilian regulatory mandates, limiting the endogeneity problem in this research. It was therefore relatively easy to create groups that tackle omitted-variable and endogeneity potential bias. If specific criteria determine participation in an intervention, those criteria should be included in the controls. Legislation specifically targeted municipalities with small populations for mandatory technology installations that would otherwise not occur, so the independent variable classifying municipalities according to their population size already captured several

potential omitted variables. In other words, because the model compared municipalities that did not receive the treatment with municipalities that did because of the regulatory requirements, the quasi-experimental characteristics of the model became even more robust.

To successfully execute this comparison, it was necessary to discard some municipalities from the model: municipalities that were “treated” before the “treatment” period and municipalities in which ICT infrastructure was installed during the time period when outcomes of the treatment were evaluated. These cities were excluded from the model because one control group was needed that did not receive any treatment during the entire analyzed time period.

An additional group of municipalities were excluded from the model that were targeted by the “*Municípios Prioritário na Amazonia*” (Priority Municipalities in the Amazon), a program by the Ministry of Environment to tackle deforestation in areas with higher deforestation rates. Their exclusion helped assess ICT’s impact on deforestation by avoiding bias created by those municipalities, which tended to reduce their deforestation rates more than others. A preferable means for addressing this would introduce a dependent variable to match ‘treatment’ and ‘control’ municipalities that were part of the program. However, the number of municipalities in the program was very limited, so the matching exercise would have been compromised (many non-similar municipalities would have been matched). Additionally, the fact that those municipalities tend to have the highest deforestation rates would have biased the dataset and could have significantly altered the results. Therefore, as a conservative measure, these municipalities were excluded.

The treatment period for 3G technology installation was set to 2005-2009. The pre-treatment period was set to 2004. The post-treatment year was set to 2010.

4.3 DATA

This subchapter describes the variables chosen, the datasets used and how data was treated.

4.3.1 “Treatment” variable

4.3.1.1 *Installation of 3G infrastructure - availability of 3G coverage (tr.3g.05.09)*

Using a database from ANATEL, it was possible to identify when 3G technology became available in each Brazilian municipality. Considering that, in some cases, 3G technology could have been installed in a pre-existing frequency and that 3G technology debuted in Brazil in 2004, the model assumed that any frequency identified as 3G with an implementation date defined as prior to 2004 began operating in 2004.

4.3.2 Dependent variables:

4.3.2.1 *Deforestation $((def.10/area) - (def.04/area))$*

Official deforestation data is available from 2000 to 2015. The source is the INPE’s PRODES program. Data availability is limited to the Legal Amazon region.

Dates to test pre- and post- treatment outcomes were selected for the years before and after the treatment period. In other words, it compares the situation in 2004 to 2010 for each municipality.

Forest-loss values are given as a percentage of the municipality’s total area. In other words, total deforested area in a given year was divided by the municipality’s total area.

4.3.2.2 *Variables used to define the propensity score matching*

4.3.2.2.1 *Population (pop)*

A municipality's population correlates with its attractiveness for ICT infrastructure investment and other factors related to increased yields, such as human resources availability and other types of infrastructure, making this indicator a useful control. The data source is IBGE (2013).

4.3.2.2.2 *GDP per capita (gdp)*

GDP per capita describes the economic development level of a municipality and therefore also quantifies its potential appeal for ICT infrastructure investment separate from regulatory mandates. That makes it a useful control. GDP per capita also controls for other factors related to increased yields, such as other types of infrastructure, education and local institution development (for example, the quality and availability of environmental regulators and enforcement officials). The data source is IBGE (2013).

4.3.2.2.3 *Region (DDD)*

Region controls for the climate and soil conditions, as well as other infrastructure that could impact outcomes, such as logistics (it is assumed that municipalities in the same region would be share similar infrastructure). Regions are also likely to share drivers for deforestation.

In order to serve as a control for the treatment, and not only for the dependent variable, the ANATEL sub-division of the territory by codes for long-distances direct calls (DDD) was used, rather than geo-political definitions of subnational regions as defined by IBGE.

4.3.2.2.4 *Agriculture's importance (agi.perc)*

This variable is agricultural value added as a percentage of total value added. It controlled for agriculture's importance to the local economy. This variable serves as a control for both the

treatment and the outcome, because ag-dependent municipalities are likely to face higher pressure to clear forested land for agriculture, and are likely to lack necessary economic incentives for voluntary 3G network installation. The data source is IBGE (2012).

4.3.2.2.5 *Agricultural expansion (agg)*

This variable measured how much agriculture expanded in the period. It controlled for whether an agricultural area was new or consolidated, and whether it was growing or stable. The data source is an index measuring the variation of agricultural value added for the period 2000 to 2010 from IBGE. Values are published in current Reais (R\$). Data was deflated using the Brazilian Extended National Consumer Price Index - IPCA.

4.3.2.2.6 *Mobile coverage (ERB.dens)*

As discussed before, one of the challenges associated with tabular analysis on geographically explicit issues is potential variation within the unit of analysis. In the previous chapter, this challenge was addressed at the country level. Here, the units of analysis are geographically smaller. But non-3G mobile coverage – which allows the widespread use of 3G technology – still varies within the municipalities. Therefore, an index to serve as a proxy for varying mobile coverage within a municipality's total area was developed that measures the number of ERB (antennas transmitting mobile signals) per square kilometer. The index was calculated as the total number of antennas divided by the total area of the municipality. Data sources are ANATEL for antennas and IBGE for total area.

This index was not the ideal indicator for non-3G mobile coverage, but served as a functional proxy, controlling not only for the potential adoption of 3G technology once it is installed, but also the installation itself (a company might prefer to invest in building 3G network coverage for municipalities with larger mobile coverage).

4.3.2.2.7 Municipality area (*area*)

The total area of the municipality served as a control to make the model's final results comparable and meaningful. The dependent variable was measured in sq km per year, so including this variable was important to guarantee that the model compared the outcomes of municipalities with similar sizes.

Also, municipality area is a proxy indicator for the difficulty of consistent 3G coverage: the larger the area, the more likely it is that the area is not covered. The data source is IBGE.

4.3.2.2.8 Priority municipalities for deforestation in the Amazon (*priority.mun*)

The list of the priority municipalities for deforestation in the Amazon came from the Brazilian Ministry of Environment. This dataset was used to avoid biases by identifying municipalities to exclude because they were included in governmental programs, as described above.

4.4 RESULTS

Given the model's limitations, the outputs created by following the methods detailed and using the datasets described, there is some indication that installing 3G technology may have negatively impacted the deforestation rate. In other words, the treatment group has demonstrated lower deforestation rates than the control group for the defined period, controlling for the afore-mentioned variables.

4.4.1 Presentation

The total number of observations included in the model amounted to 510 once the dataset was balanced by excluding municipalities for which complete dataset for all variables was not available. The propensity score-matching software utilized did not accept unbalanced datasets. Also, as discussed, the municipalities included in the *Municípios Prioritários* list and

those that received the treatment during the period used to observe the outcomes (2010) were also excluded from the sample.

Based on the total number of observations (municipalities) in the final dataset, 86 received the treatment in the study period, while 424 did not. The distribution of the average deforestation rates for the sample appears on the graph below. Although there are fewer municipalities with higher deforestation rates, the treatment is well distributed in the sample. Regardless of this distribution, it is important to highlight once again that this propensity score matching exercise was carefully implemented to guarantee that only similar municipalities were compared.

Figure 11 - Distribution of annual average deforestation rates in the sample and treated municipalities

The first step of the modeling exercise implemented a probit model. The model was not created to analyze coefficients and values, but rather to calculate the predicted probabilities to inform the matching exercise. However, it was interesting to identify which variables would be expected to exert the greatest influence on the treatment, such as the size of the population and the index for the extension of mobile coverage. In both cases the coefficients were positive and statistically significant, meaning that municipalities with bigger populations

and better mobile coverage were more likely to receive the 3G technology, in line with expectations.

The matching exercise was then performed. As discussed, the matching exercise was designed to find the best possible matches between the control and treatment groups for comparing the outcomes. Different matching techniques were used to test the hypothesis under several modeling assumptions: Average Treatment Effect on the Control (ATC), Average Treatment Effect on the Treated (ATT) and Average Treatment Effect for all units (ATE). For each one of these estimands, the “ties” function was also changed: if one treated observation matched more than one control, the models either (a) randomly assigned one match¹⁵ or (b) matched all the observations and used the weighted result¹⁶ (SEKHON 2011). As a consequence, six regressions were run.

The matching model’s results of are presented in Table 5. The estimate for the dependent variable (deforestation) was always negative, independent of the estimating model. This result indicates that treatment group municipalities had lower deforestation rates than municipalities in the control group after the matching was performed, controlling for all the variables included in the model. In the majority of cases - all models but two - the p-value was within the 90% confidence level. Even though there are two cases in which the model did not deliver statistically significant results, in aggregate, results support the hypothesis.

Beyond the overall values of the models, estimates and p-values, the quality of the matching exercise must be evaluated. In other words, how well compared were the municipalities? Figure 12 - Checking the matching balance proprieties Figure 12 demonstrates the answer in visual form. The graphs plot the values for each specific match (control and treatment group), for each of the variables, for each estimand¹⁷. The treatment value is presented on the Y axis and the control value is presented on the X axis. The closer to the line the points are, the better the quality of the match. The lines in Figure 12 demonstrate a perfect match.

The matching exercise performance varied accordantly with the estimand choice. It worth noting that, as expected, the model with the best performance was the Average Treatment

¹⁵ Ties=FALSE

¹⁶ Ties=TRUE

¹⁷ Only the ties=TRUE models were presented. Justified by the fact that those were the most conservative results.

Effect on the Treated (ATT), which is the default recommendation by the R Matching package and the model which always tested significant at the 90% level. For almost all the control variables, the plotted values are very close to the line indicating the “perfect match”. In theory, the ATT estimand with ties (using the weighted average of the matches when there is more than one) would be the most appropriate model choice. The matching exercise results demonstrate that.

Figure 13 shows in more detail how well the matching exercise performed for the ATT estimand model at an aggregate level. It shows the difference in the mean value for each variable in the treatment and control groups, before and after the treatment¹⁸. For all cases except one, values significantly decreased. In other words, the control and treatment groups became much more similar. The area variable, apparently, experienced a worsening. It would not, however, impact the conclusions. As the results are showing the mean value, they would be biased by even a few extreme values in the sample. As illustrated on the graph, there is one municipality of exceptional size in the treatment group (Oriximiná, in the state of Pará, with a total area of 107'603 squared kms). As a consequence, that one point had to be matched with a municipality roughly half its size. Also, without this single municipality, the average size of the treated group would drop to 4384 squared kms, much similar to the 4813 sq km mean of the control group. Also, this municipality, in which 3G technology was installed, had an average deforestation rate among the highest in the treatment group (8.36 sq km/yr) -- much larger than the mean deforestation rate of the control group (3.16 sq km/yr). In other words, the potential bias caused by this municipality would contradict the main hypothesis of the paper. To conclude, this peculiar municipality impacted the mean values described on the graph above, but did not meaningfully affect the model's final estimation.

These results, even given the described limitations, tend to support this paper's hypothesis: the installation of 3G technology could apply negative pressure on deforestation rates as farmers, local communities, law enforcement and public institutions gain access to information on regulatory requirements and market demands related to deforestation.

¹⁸ The the non-numeric dummy variable for region (DDD) is not included as such annalysis is not applicable.

Finally, by analyzing the estimates of the most suitable and theoretically sound regression¹⁹, it was possible to estimate how much deforestation decelerated after the treatment. Forest loss was 0.84 percentage points lower in the municipalities that received the 3G technology than in similar municipalities in the control group. That means that nearly 1% of the municipality's forested area was saved due to 3G technology implementation between 2005 and 2009. Obviously, such assertions are compelling, but given the methodology's limitations, need to be interpreted with care.

¹⁹ Average Treatment Effect on the Treated (ATT), with ties=TRUE.

Estimand	Average Treatment Effect on the Control (ATC)		Average Treatment Effect on the Treated (ATT)		Average Treatment Effect for all units (ATE)	
	FALSE	TRUE	FALSE	TRUE	FALSE	TRUE
Ties	FALSE	TRUE	FALSE	TRUE	FALSE	TRUE
Estimate	-0.0038	-0.0037	-0.0093	-0.0084	-0.0046	-0.0045
p.value	0.018	0.722	0.016	0.108	0.002	0.615
Original number of observations	510	510	510	510	510	510
Original number of control obs	424	424	86	86	86	86
Matched number of observations	424	424	86	86	510	510

Note: If ties=TRUE, “if ... one treated observation matches more than one control observation, the matched dataset will include the multiple matched control observations and the matched data will be weighted to reflect the multiple matches. The sum of the weighted observations will still equal the original number of observations” (SEKHON 2011). If ties = FALSE, ties will be randomly broken

Table 5 - Summary results of the propensity score matching model

Figure 12 - Checking the matching balance proprieties

Figure 13 -. Control variables: difference in the mean value for treatment and control group, before and after matching
(Model using Estimand=ATT, ties=TRUE)

4.4.2 Discussion and future research

As a pioneering study analyzing mobile Internet infrastructure's influence on rural sustainable development, this thesis introduces some interesting initial insights to the debate.

The fact that all regressions using ICT infrastructure as the “treatment” consistently produced negative estimates for deforestation opens up a whole array of future research. Unfortunately, two out of the six regressions did not deliver statistically significant results. On the other side, the most promising and theoretically sound regression (using the ATC estimand with ties) performed very well.

The first opportunity emerging from these results is to further test the hypothesis and initial results by applying the same methodology to different periods and geographies. Obviously, the lack of deforestation data at the global level tends to be an issue. An initiative by the World Resources Institute (WRI) called Global Forest Watch (GFW)²⁰ publishes a dataset on tree cover loss for the whole world. Although the data is not officially recognized by governments, unlike the INPE dataset used in this thesis, it is a powerful and interesting information source for similar exercises in other geographies.

A second emerging issue, assuming additional research supports the findings of the models presented here, is the cost-benefit evaluation interventions. Although it difficult to assume that any decision to invest in mobile Internet infrastructure would be solely based on forest-conservation objectives, comparing the cost and impact of policy and investments directed exclusively to deforestation to on the cost and impact of policy and investments for communication infrastructure would be an interesting exercise.

Additionally, further research could emulate the exercise in the previous chapter to evaluate the impacts of 3G technology implementation on agricultural yields and other rural development indicators. In other words, perform exercises that would test different dependent variables, such as yields, rather than deforestation.

²⁰ www.globalforestwatch.org, access on February 2017.

Finally, this thesis did not test the impact of ICT on legal compliance with public policies. For example, follow-up research could evaluate whether mobile Internet coverage has affected adoption of the Brazilian Environmental Rural Registry (CAR) – a virtual map of rural properties provided by farmers to national environmental regulators. Creation and official submission of these registries requires Internet connectivity. Therefore one might argue that greater mobile Internet coverage in farming regions could improve compliance with this important environmental regulation. The Brazilian Ministry of the Environment published the complete CAR database in December 2016, enabling future studies and assessments. Intriguingly, the CAR dataset is geographically explicit, allowing the unit of analysis to be even smaller. As discussed, using municipalities as unit of analysis, the unit chosen in this chapter, is a sound strategy for mitigating potential regional differences in mobile coverage. However, municipal analysis cannot account for discrepancies at the sub-municipal level. The rural-urban digital divide might still apply within a municipality, for example, if areas close to cities tend to have better coverage than far-flung regions. In this chapter, the use of the mobile coverage index (number of antennas per sq km) as a control represented an effort to mitigate that problem. It was not, however, an ideal solution. With geographic explicit datasets, such as the CAR, the location of the antennas as provided by ANATEL and the deforestation data as published by both INPE and the World Resources Institute, a whole new avenue of geographically explicit econometric modelling opens up to facilitate ongoing evaluation of ICT's influence on rural development.

4.5 CONCLUSION

According to the model, using a quasi-experimental design, a constantly negative and mostly significant correlation between 3G network installation and deforestation rates exists. Controlling for key variables and considering the most robust model²¹, municipalities in the treatment group (3G network installed) experienced total deforestation rates that were lower than similar municipalities in the control group by 0.84 percentage points. That means that nearly 1% of the municipality's forested area was saved due to 3G technology implementation

²¹ Estimand = ATT and ties=TRUE

between 2005 and 2009. Obviously, such assertions are compelling, but given the methodology's limitations, need to be interpreted with care.

Three main characteristics should be evaluated in order to justify the quality of the model. The first is the choice of a comprehensive group of variables for matching that accounted for the most important issues affecting both the treatment and the outcome. The second is the actual result of the model, the direction and amplitude of the calculated coefficient, as well as the model's significance level. Even considering the potential limitations posed by the methodology, data availability and assumptions, the present research reached a high-quality standard. However, additional research on modeling impacts described utilizing new datasets, different variables and diverse estimation methodologies is needed to more thoroughly answer the question posed.

To conclude, the results tend to support the main hypothesis of this research: communication technology could be an important catalyst to delivering information to different agents involved in agricultural activities and therefore generate positive sustainability outcomes. Such an effect would likely be explained by the fact that – through higher connectivity – farmers, local businesses, local authorities and other stakeholders involved in agricultural activities would be more informed about the legal and market demands related to deforestation, while also creating greater public awareness and knowledge about the importance of responsible land and natural resource management.

Further research is still needed but it appears that smartphones could be an important weapon to tackle deforestation.

5 CONCLUSIONS AND FINAL REMARKS

Within the context of continuous population and economic growth, future projections for agricultural product demand are impressive. A study by the World Resources Institute indicates that the world must tackle a 70 percent “food gap” between the crop-based calories available in 2006 and expected demand in 2050 (RANGANATHAN et al 2016). That is no small task.

At the same time, agriculture already exerts significant pressure on natural resources, occupying roughly half of the planet’s land (SMITH et al 2007) and driving 71% of tropical deforestation (LAWSON et al 2014). Yet, billions of people still depend on agriculture to make a living, and every habitant of this planet depends on it to survive.

As a consequence, in order to sustainably feed its population by 2050, the world needs to be able to “produce more with less”, achieving higher agricultural supplies while limiting agriculture’s impacts on the environment. It will be a significant challenge.

Information and communication technology (ICT) infrastructure and utilization could be an important part of that answer. The emergence of the “big data revolution”, the “Internet of things” and the “sharing economy” is changing life in urban areas (RIFKIN 2010, CASTELLS 2010, RIFKIN 2014), but it has not yet reached the rural world (BRIDGES 2001).

This thesis shed light on an emerging debate on how ICT could impact rural development. It asked whether there are empirical indications that information and communication infrastructure and utilization could impact the sustainable development of agriculture. In doing so, it posed two specific enquiries.

First, it asked if are there empirical indications that an increase in mobile and Internet users could impact productivity of agricultural commodities at a country level. If more food is produced in less area, the pressure for additional land resources is diminished. Secondly, it asked if empirical evidence exists on whether the installation of 3G network coverage could impact the levels of deforestation in a given municipality.

In line with previous findings in the literature, this thesis' assumption lies in the theory that advancing ICT infrastructure and utilization could catalyze increased access to information for farmers, agricultural supply chain actors, companies, policy makers and local communities. Greater access to information would, in turn, result in better use of economic, human and environmental assets. More specifically, given the characteristics of mobile phones and Internet usage, it is plausible to infer that investments in ICT infrastructure could also improve the capacity and quality of human capital, an important input for production, as defined in the literature. Consequently, ICT infrastructure would also be a significant variable in defining productivity, awareness about sustainability and regulatory requirements. It would help farmers and other stakeholders involved in agricultural supply chains gain access to relevant information and be more integrated into markets, generating efficiency gains in supply chains and surfacing disincentives for clearing forested land due to legal and market constraints.

Therefore, the specific hypothesis could be summarized as: higher ICT infrastructure and utilization would have positive and significant correlation with yields and negative and significant correlation with deforestation rates. By drawing from the literature about impacts of infrastructure on rural development and by using econometric modelling techniques, two models were created to test the hypothesis.

The first, developed at the global level and using data from international databanks, created a cross-sectional panel data model. It evaluated the impacts of mobile and Internet users on cereal yields in 212 countries for which data was available for five 5-year periods (1990-1994, 1995-1999, 2000-2004, 2005-2009 and 2010-2014). A Fixed Effects model was preferred but other regression models were also tested. Controls for economic development, human capital, use of farm-level inputs and other technologies, agricultural markets, region and income level were used. Based on the methodology, data and models utilized, results indicate that the growth of Internet users would have a positive impact on cereal productivity in a country (in the case of mobile users, the results are inconclusive). Results indicate that a 1% increase in the number of Internet users could be associated with an increase in cereal yield of 18-33 kg per hectare with a 95% confidence level. Obviously, such numbers need to be interpreted with care and nuance, but the mitigation strategies adopted to account for potential omitted-variable bias support the validity of the conclusions. To describe the magnitude of this conclusion – while acknowledging the limitations of the simplified

calculation described (more details in Chapter 3) – the additional grain produced would feed 131 million people, roughly equivalent to the total population across the Horn of Africa (Somalia, Ethiopia, Eritrea and Djibouti) plus South Sudan.

Additionally, because Internet usage tested as well as any of the other variables, it is possible to infer that, even with potential endogeneity issues, Internet usage explains yield growth as substantially as traditional variables used in the empirical literature. A compelling question for future research arises from the fact that as Internet usage tested as well as the variable chosen for human capital (education expenditure per capita) to explain yield variation. Based on such a finding, would the traditional model of rural extension agents present on-site perform better or worse than a hypothetical new web-based system created to deliver information through ICT devices? Finally, it is important to recognize that other hypothetical challenges related to ICT's potential impact on yields that were not assessed in this research. Indiscriminate use of farm-level agricultural inputs, for example, such as agro-chemicals could cause environmental and health problems if irresponsibly used. This study also introduced, but did not evaluate deeply, a discussion on ethical challenges associated with protecting data confidentiality and avoiding greater asymmetries of market power for data owners as a result of higher ICT use.

The second model was developed at a sub-national level – the municipalities located in the Brazilian Legal Amazon region – using the implementation of 3G technology as the key explanatory variable and the rate of deforestation as the dependent variable. One of the main challenges when evaluating the impact of an intervention (in this case, the installation of ICT infrastructure) is to successfully establish a counterfactual. In other words, what would have happened to the actors (municipalities) if they had not participated in the treatment (received 3G infrastructure)? This study's strategy to establish a counterfactual relied on a quasi-experimental design. More specifically, a Propensity Score Matching Model was used. In a nutshell, this econometric method created two groups of individuals (municipalities): one that was subject to the studied "treatment" – in this case the implementation of 3G infrastructure – and a control group that was not. The model then matched each municipality in the treatment group to the municipality in the control group to which it was most similar. Several variables that could explain the outcome were accounted for in the matching exercise, creating a hypothetical counterfactual. Finally, the model compared the effects before and

after the “treatment” – which further characterized the model as Difference-in-Difference – for the matched municipalities in both groups. The variables utilized for the matching exercise were: population, GDP per capita, sub-national region, agriculture’s importance at municipal economy, agricultural expansion in the municipality, mobile coverage and the municipalities’ areas. The model results indicated that 3G technology installation had a negative and, in most cases, significant correlations with deforestation rates before and after the treatment. In other words, controlling for the afore-mentioned variables, the treatment group showed demonstrably lower deforestation rates than the control group for the defined period. By analyzing the results of the most suitable and theoretically sound regression²², it was possible to estimate how much deforestation decelerated after the treatment. Forest loss was 0.84 percentage points lower in the municipalities that received the 3G technology than in similar municipalities in the control group. That means that nearly 1% of the municipality’s forested area was saved due to 3G technology implementation between 2005 and 2009. Obviously, such assertions are potentially powerful, but given the limitations of the methodology, such values need to be interpreted with caveats and thorough explanations. The fact that some estimation methods did not yield statistically significant results also calls for caution. Still, the results tend to more strongly support, rather than refute, the hypothesis that 3G technology installation could have a negative impact on deforestation rates as farmers, local communities, law enforcement and public institutions are able to access more and better information on regulatory requirements and market demands related to deforestation.

To conclude, this thesis generated innovative and original research by introducing ICT infrastructure and utilization (especially Internet and mobile coverage) as the core independent variables. It also innovated on the choice of dependent variables. The small literature on ICT impacts on agriculture has traditionally focused on economic growth or social inequality. The present research introduced new dependent variables with a focus on the long-term sustainability of global agricultural production: (a) agricultural productivity and (b) deforestation rates. The results of the models developed tend to indicate that the infrastructure and utilization of Internet-related ICT does positively impact indicators of sustainable rural development and, therefore, positively contribute to the long-term sustainability of agricultural production. Further research is needed in order to re-test some

²² Average Treatment Effect on the Treated (ATT), with ties=TRUE.

of the assumptions and hypothesis of this thesis by: incorporating additional geographies (eg: subnational models in other countries), adopting different empirical modeling strategies, testing different ICT variables, and testing ICT's effect on different dependent variables such as, for example, compliance with regulations and access to financial services.

In an increasingly interconnected world, communication technologies are having a profound effect on all levels of our societies. These technologies may well be a critical missing piece in the urgent global mission to produce more food with fewer inputs and reverse deforestation. Smartphones, it appears, could be important assets for sustainable agricultural development at a global level.

6 REFERENCES

6.1 BIBLIOGRAPHY

ABRAHAM, R. (2007). **Mobile Phones and Economic Development: Evidence from the Fishing Industry in India**. *Information Technology and International Development*. MIT Press, Volume 4, Number 1, Fall 2007, Pp 5–17.

AHMED, R. & DONOVAN, C. (1992) **Issues of Infrastructural Development: a synthesis of the literature**. International Food Policy Research Institute. Washington DC, November 1992.

ALEKE, B.; OJIAKO, U. & Wainwright, D.W. (2011). **ICT adoption in developing countries: perspectives from small-scale agribusinesses**, *Journal of Enterprise Information Management*, Vol. 24, Iss 1, pp. 68 - 84

ALI, A; MUSHTAQ, K; ASHFAQ, M; ABEDULLAH & DAWSON, P.J. (to be published). **Macro Determinants of Total Factor Productivity Growth of Agriculture in Pakistan**. University of Agriculture Faisalabad.

ANATEL (2015a). **Resumo obrigações de atendimento com SMP**. Report available at http://www.anatel.gov.br/Portal/documentos/sala_imprensa/2-7-2012--10h39min37s-Regras_Atendimento_SMP_DISTritos_%C3%81rea%20Rural_com%204G.pdf , access on April 6th, 2015.

ANTLE, J.M. (1983). **Infrastructure and Aggregate Agricultural Productivity: International Evidence**. *Economic Development and Cultural Change*, Vol. 31, No. 3, pp. 609-619. The University of Chicago Press. Apr., 1983.

ASSUNÇÃO, J.; LIPSCOMB, M.; MOBARAK, A. & SZERMAN, D. (2014). **Electrification, Agricultural Productivity and Deforestation in Brazil**. *In mimeo*. July 2014.

ASSUNÇÃO, J. & ROCHA, R. (2014). **Getting Greener by Going Black: The Priority Municipalities in Brazil**. *Climate Policy Initiative report*. August 2014.

BINSWANGER, H.; YANG, C.; BOWERS, A. & MUNDLAK, Y. (1987). **On the determinants of cross-country aggregate agricultural supply**. *Journal of Econometrics* 36 (1): 111-113.

BONGIOVANNI, R. and LOWENBERG-DEBOER, J. (2004). **Precision Agriculture and Sustainability**. *Precision Agriculture*. August 2004, Volume 5, Issue 4, pp 359-387.

BRIDGES (2001). **Spanning The Digital Divide**. Understanding And Tackling The Issues. Washington, DC: Bridges.org. Executive summary retrieved at <http://unpan1.un.org/intradoc/groups/public/documents/apcity/unpan002531.pdf> in April 11th 2015.

BRONSON, K. & KNEZEVIC, I (2016). **Big Data in food and agriculture**. *Big Data & Society* January-June 2016: 1–5.

BRUINSMA, J. (ed). (2003). **World Agriculture : Towards 2015/2030: an FAO Perspective**. *Earthscan Publications Ltd*. London, 2003.

BORLAUG, N. (1976). **The Green Revolution: can we make it meet expectations?** *Proceedings of The American Phytopathological Society*, Vol. 3, 1976.

BULL, J.K; DAVIS, A.W., SKROCH, P.W. (2011). **How Smart-IT Systems Are Revolutionizing Agriculture**. *The Bridge*. Vol41, no3, Fall 2011. Washington DC: National Academy of Engineering, 2011.

BYERLEE, D., DE JANVRY, A. SADOULET, E. (2010). **Agriculture for development – revisited**. *Paper Presented at the Conference Agriculture for Development – Revisited. University of California at Berkeley*, October1–2 2010. *apud* DETHIER, J.J. & EFFENBERGER, A. (2012). *Agriculture and development: A brief review of the literature*. *Economic Systems*, 2012.

CANNING, D. (1998). **A database of world infrastructure stocks, 1950-1995**. World Bank, 1998.

CARBONELL, I. (2016). **The ethics of big data in big agriculture**. *Internet Policy Review*, 5(1)

CASSMAN, K.G. (1999). **Ecological Intensification of Cereal Production Systems: Yield Potential, Soil Quality, and Precision Agriculture**. *Proceedings of the National Academy of Sciences of the United States of America*, Vol. 96, No. 11 (May 25, 1999), pp. 5952-5959

- CASTELLS, M. (2010). **"The Rise of the Network Society"**. Wiley Blackwell, 2010.
- CHAPMAN, R. & SLAYMAKER, T. (2002) **ICTs and Rural Development: review of the literature, current interventions and opportunities for action**. Overseas Development Institute, Working Paper 192. London, November 2002.
- COOK (2013) **Electrification and Rural Development** in BHATTACHARYYA, S. (ed.) **Rural Electrification Through Decentralized Off-grid Systems in Developing Countries**. Green Energy and Technology. Springer-Verlag London 2013.
- CRAWFORD, K. MILTNER, K. & GRAY, M.L. (2014). **Critiquing Big Data: Politics, ethics, epistemology**. International Journal of Communication 8: 1663–1672.
- CROISSANT, Y. & MILLO, G. (2008). **Panel Data Econometrics in R: The plm Package**. Journal of Statistical Software 27(2). URL <http://www.jstatsoft.org/v27/i02/>
- CROPPER, M.; GRIFFITHS, C & JYOTSNA (2001). **Predicting spatial patterns on deforestation: the role of roads and protected areas in north Thailand**. *Land Economics*. May 2001.
- CROPPER, M.; GRIFFITHS, C. & MANI, M. (1999). **Roads, population pressures and deforestation in Thailand, 1976-1989**. *Land Economics*, 75 (1):58-73.
- DETHIER, J.J. & EFFENBERGER, A. (2012). **Agriculture and development: A brief review of the literature**. Economic Systems, 2012.
- DIAO, X., HAZELL, P. & RESNICK, D. & THURLOW, J. (2006). **The Role of Agriculture in Development: Implications for Sub-Saharan Africa**. *International Food Policy Research Institute Research Report 153*. Washington, 2006.
- DIXIE, G. & JAYARAMAN N. (2011). **Strengthening Agricultural Marketing with ICT**. in *ICT in Agriculture e-Sourcebook*. World Bank. Washington, DC. <http://www.ictinagriculture.org/ictinag/sourcebook/module-9-strengthening-agricultural-marketing>
- DOROSH, P., WANG, H., YOU, L. and SCHMIDT, E. (2010). **Crop Production and Road Connectivity in Sub-Saharan Africa A Spatial Analysis**. *World Bank Policy Research Working Paper 5385*. July 2010. Available at: <http://www->

wds.worldbank.org/servlet/WDSContentServer/WDSP/IB/2010/07/28/000158349_20100728133128/Rendered/PDF/WPS5835.pdf

DUFLO, E., GLENNESTER, R., & KREMER, M. (2007). **Using Randomization In Development Economics Research: A Toolkit**. *Centre for Economic Policy Research*. Discussion Paper No. 6059. London, January 2007. Available at: <http://economics.mit.edu/files/806>

ESTEVA, G (1996). **Hosting the otherness of the other: The case of the Green Revolution**. In: APFEL-MARGLIN F, MARGLIN SA (eds) "Decolonizing Knowledge: From Development to Dialogue". Clarendon: Oxford University Press, pp. 249–278

EUROPEAN COMMISSION (2004). **The Future Impact of ICTs on Environmental Sustainability**. European Commission Joint research center & Institute for Prospective Technological studies technical report series. Technical Report EUR 21384 EN. Brussels, 2004.

FAN, S. & CHAN-KANG, C. (2005). **Road development, economic growth and poverty reduction in China**. *International Food Policy Research Institute, Research paper 138*. Washington DC, 2005.

FAN, S.; ZHANG, L. & ZHANG, X. (2002). **Growth, inequality and poverty in rural China: the role of public investments**. *International Food Policy Research Institute Research Report 125*. IFPRI, Washington, D.C.

FELLONI, F.; WAHL, T.; WANDSCHNEIDER, P. & GILBERT, J. (2001). **Infrastructure and Agricultural production: cross-country evidence and implications for China**. *In mimeo*, 2001.

FISCHER T., BYERLEE D., EDMEADES G. (2014). **Crop yields and global food security: will yield increase continue to feed the world?** *ACIAR Monograph No. 158*. Australian Centre for International Agricultural Research. Canberra. xxii + 634 pp.

FREES, E.W. (2004) **Longitudinal and Panel Data: Analysis and Applications in the Social Sciences**. Cambridge University Press, August 2004.

FUGLIE, K.O. (2010) **Total Factor Productivity in the Global Agricultural Economy: Evidence from FAO Data**. *in The Shifting Patterns of Agricultural Production and Productivity*

Worldwide. The Midwest Agribusiness Trade Research and Information Center, Iowa State University, Ames, Iowa.

GIBBS, A.; RAUSH, L.; MUNGER, J.; SCHELLY, I.; MORTON, D.C.; NOOJIPADY, P.; SOARES-FILHO, B.; BARRETO, P.; MICOL, L.; WALKER, N.F. (2015). **Brazil's soy Moratorium**. *Science*. Vol 347. Issue 6220. January 23rd 2015.

GOYAL, A.,(2010). **Information, direct access to farmers, and rural market performance in Central India**. *World Bank Policy Research Working Paper 5315*. Washington, DC. 2010.

HEINRICH, C. MAFFIOLI, A. & VAZQUEZ, G. (2010). **A Primer for Applying Propensity-Score Matching**. *Inter-American Development Bank: Impact-Evaluation Guidelines Technical Notes*. No. IDB-TN-161. August 2010.

ITU (2014). **Measuring the Information Society Report 2014**. *International Telecommunication Union*. Geneva, 2014.

JENSEN, R. (2007). **The Digital Divide: Information (Technology), Market Performance, and Welfare in the South Indian Fisheries Sector**. *Quarterly Journal of Economics*, Vol. CXXII, Issue 3: 879-924.

KITCHIN, R. (2014). **"The Data Revolution: Big Data, Open Data, Data Infrastructures and Their Consequences"**. London: Sage. 2014.

KITCHIN, R. (2017). **"Thinking critically about and researching algorithms"**. *Information, Communication & Society*. Volume 20, 2017 - Issue 1: The Social Power of Algorithms.

LAWSON, S., BLUNDELL, A., CABARLE, B., BASIK, N., JENKINS, M., CANBY, K. (2014). **Consumer Goods and Deforestation: An Analysis of the Extent and Nature of Illegality in Forest Conversion for Agriculture and Timber Plantations**. *Forest Trends Report Series - Forest Trade and Finance*. September 2014. Available at: http://www.forest-trends.org/documents/files/doc_4719.pdf

LIPSCOMB, M., MOBARAK, A.M. and BARHAM, T. (2013). **Development effects of electrification: evidence from topographic placement of hydropower plants in Brazil**. *American Economic Journal: Applied Economics*, 5(2):200-231.

LLANTO, G.M. (2012). **The impact of infrastructure on agricultural productivity.** *Discussion paper series no. 2012-12.* Phillipine Institute of development studies.

MEBANE, W. & SEKHON, J.S. 2011. **Genetic Optimization Using Derivatives: The rgenoud package for R.** *Journal of Statistical Software*, 42(11): 1-26.

MITTAL, S., GANDHI, S., & TRIPATHI, G. (2010). **Socio-Economic Impact of Mobile Phones on Indian Agriculture.** *Indian Council For Research On International Economic Relations.* Working Paper No. 246. Feburary 2010.

MUTO, M & YAMANO (2009). **The Impact of Mobile Phone Coverage Expansion on Market Participation: Panel Data Evidence from Uganda.** *World Development* 37 (12): 1887–96.

NAEF, E., MUELBERT, P., RAZA, S., FREDERICK, R., KENDALL, J. and GUPTA, N. (2014). **Using mobile data for development.** *Gates Foundation Whitepaper.*

NELSON G.C., ROSEGRANT M.W., PALAZZO A., GRAY I., INGERSTOLL C., ROBERTSON R. (2010). **Food security, farming, and climate change to 2050: scenarios, results, policy options.** Research Monograph. International Food Policy Research Institute, Washington, DC.

NEPSTAD, D.; MCGRATH, D.; STIKLER, C.; ALENCAR, A.; AZEVEDO, A.; SWETTE, B.; BEZERRA, T.; DIGIANO, M.; SHIMADA, J.; DA MOTTA, R.S., ARMIJO, E.; CASTELLO, L.; BRANDO, P.; HANSEN, M.; MCGRATH-HORN, M.; CARVALHO, O.; HESS, L. (2014). **Slowing Amazon Deforestation Through Public Policy and Interventions in Beef and Soy Supply Chains.** *Science.* Vol 344. Issue 6188. June 6th 2014.

PARK, M.H. & KOO, W.W. (2005). **Recent Development in Infrastructure and Its Impact on Agricultural and Non-agricultural Trade.** *Paper presented at the American Agricultural Economics Association Annual Meeting.* Providence, Rhode Island, July 24-27, 2005.

PIERSKALLA, J.H. & HOLLENBACH, F.M. (2013). **Technology and Collective Action: The Effect of Cell Phone Coverage on Political Violence in Africa.** *American Political Science Review.* Volume 107, Issue 2, May 2013.

RANGANATHAN, J., VENNARD, D., WAITE, R., DUMAS, P., LIPINSKI, B., SEARCHINGER, T. & GLOBAGRI-WRR MODEL AUTHORS (2016). **Shifting Diets For A Sustainable Food Future.** WRI

Working Paper: Installment 11 of “Creating a Sustainable Food Future”. Available at [http://www.wri.org/sites/default/files/Shifting Diets for a Sustainable Food Future 0.pdf](http://www.wri.org/sites/default/files/Shifting_Diets_for_a_Sustainable_Food_Future_0.pdf)

RESTUCCIA, D., TAO YANG, D., ZHU, X. (2008). **Agriculture and Aggregate Productivity: A Quantitative Cross-Country Analysis**. *Journal of Monetary Economics*. Volume 55, Issue 2, March 2008, Pages 234–250

REZENDE, C.V. (2014). **Telefonia móvel 4G no Brasil: avaliação dos investimentos pela teoria das opções reais**. Masters thesis for the business and administration masters degree at Federal University of Uberlândia. Unberlândia, Feb. 20th 2014. Available at <http://penelope.dr.ufu.br/handle/123456789/4141>

RIFKIN, J. (2010) **“The Age Of Access”**. Putnam Publishing Group , 2010.

RIFKIN, J. (2014) **“The Zero Marginal Cost Society: The Internet of things, the collaborative commons, and the eclipse of capitalism”**. Palgrave Macmillan, 2014.

ROMP, W., DE HAAN, J. (2005). **Public capital and economic growth: A critical survey**. *European Investment Bank Papers*, 10(1), Luxemburg. *apud* WORLD BANK: **Ag and development, brief review of the literature**.

ROSENBAUM, P. & RUBIN D. (1983). **Constructing a Control Group Using Multivariate Matched Sampling Methods that Incorporate the Propensity Score**. *The American Statistician* 39:33-38.

ROSENBAUM, P. & RUBIN D. (1983). **The Central Role of the Propensity Score in Observational Studies for Causal Effects**. *Biometrika* 70(1): 41-55.

SAMARAJIVA R. (2012) **How the Poor Use ICTs: Findings From Multi-Country Studies of Teleuse at the Bottom of the Pyramid**, *paper presented at the Regional FAO Workshop on the Use of Mobile Technologies in Agriculture*. Bangkok, Thailand, April 3, 2012, [http://linneasia.net/wp-content/uploads/2012/04/Samarajiva FAO BKK.pdf](http://linneasia.net/wp-content/uploads/2012/04/Samarajiva_FAO_BKK.pdf).

SCARTEZINI, N. (2015). **Personal interview**, conducted by telephone. April 6th 2015.

SEKHON, J.S. (2011). **Multivariate and Propensity Score Matching. Software with Automated Balance Optimization: The Matching package for R.** *Journal of Statistical Software*, 42(7): 1-52.

SEKHON, J.S. (2015). **Package Matching (Version 4.9-2).** *Descriptive text on the R software package, available on:* <https://cran.r-project.org/web/packages/Matching/Matching.pdf>, retrieved on February 20th 2017.

SHIN, D. & CHOI, M.J. (2015). **Ecological views of big data: Perspectives and issues.** *Telematics and Informatics*. 32: 311–320.

SMITH, P., MARTINO, D., CAI, Z., GWARY, D., JANZEN, H., KUMAR, P., MCCARL, B., ONGLE, S., O'MARA, F., RICE, C., SCHOLLES, B., SIROTENKO, O. (2007). **Agriculture.** In: *Climate Change 2007: Mitigation. Contribution of Working Group III to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change*, Cambridge University Press. Cambridge: 2007.

SMITH P, CLARK H, DONG H, ELSIDDIG EA, HABERL H, HARPER R, HOUSE J, JAFARI M, et al. (2014). **Chapter 11 - Agriculture, forestry and other land use (AFOLU).** In: *Climate Change 2014: Mitigation of Climate Change. IPCC Working Group III Contribution to AR5*. Cambridge University Press. Cambridge: 2014.

SOARES-FILHO, B.; RAJAO, R.; MACEDO, M.; CARNEIRO, A.; COSTA, W.; COE, M.; RODRIGUES, H.; ALNECAR, A. (2014). **Cracking Brazil's Forest Code.** *Science*. Vol. 334. Issue 6182. April 25th 2014.

STUBBS, M. (2016). **Big Data in U.S. Agriculture.** U.S. Congressional Research Service report. Washington DC. January 6, 2016.

TING, K.C.; ABDELZAHER, T., ALLEYNE, A.; RODRIGUEZ, L. (2011). **Information technology and Agriculture: global challenges and opportunities.** *The Bridge*. Vol41, no3, Fall 2011. Washington DC: National Academy of Engineering, 2011.

TNC (2015). **Cadastro Ambiental Rural: nasce a identidade do imóvel rural.** Curitiba, 2015. Available at: <http://www.nature.org/media/brasil/cadastro-ambiental-rural.pdf>

TORRES-REYNA, O. (2010). **Getting Started in Fixed/Random Effects Models using R**. Power point presentation used in the Princeton Data and Statistic services. Fall 2010. Available at: <http://www.princeton.edu/~otorres/Panel101R.pdf>

UN (2000). **Report of the High-level Panel on Information and Communication Technology**. *United Nations*. New York. 17–20 April, 2000.

UNDP (2001) **Human Development Report 2001: Making Technologies Work for Human Development**. *United Nations Development Program*. Washington, D.C.

VERDIER-CHOUCHANE, A. & KARAGUEUZIAN, C. (2016). **Moving towards a green productive agriculture in Africa: The role of ICTs**. *African Development Bank: Africa Economic Brief*. Volume 7, Issue 7, 2016.

WALL STREET JOURNAL, The (2015). **Google Ventures Invests in Agricultural Technology Startup**. May, 19th 2015. Available at: <http://www.wsj.com/articles/google-ventures-invests-in-agricultural-technology-startup-1432040405>

WARD, P.; FLORAX, R. & FLORES-LAGUNES, A. (2014) **Climate change and agricultural productivity in Sub-Saharan Africa: A spatial sample selection model**. *European Review of Agricultural Economics* (2014) 41 (2): 199-226.

WORLD BANK (2001) **World Development Report 2000–2001: Attacking Poverty**. World Bank. Washington, 2001.

WORLD BANK (2007). **World Development Report 2008: Agriculture for Development**. World Bank and Oxford University Press. Washington, DC/Oxford. 2007.

WORLD BANK (2012). **Information and Communications for Development 2012: Maximizing Mobile**. Washington, DC: The World Bank.

WORLD WILDLIFE FUND (2012). **Living Planet Report 2012**. Available at: http://d2ouvy59p0dg6k.cloudfront.net/downloads/lpr_living_planet_report_2012.pdf

ZEPEDA, L. (ed) (2001). **Agricultural Investment and Productivity in Developing Countries**. *FAO Economic And Social Development Paper 148*.

ZHANG, X. & FAN, S. (2001). **How productive is infrastructure? New approach and evidence from rural India.** *Environment and Production Technology Division discussion paper no. 84.* International Food Policy Research Institute. Washington, October 2001.

6.2 DATABASES

ANATEL: <http://www.anatel.gov.br/dados/>

FAO STAT: <http://www.faostat.fao.org>

IBGE: <http://www.sidra.ibge.gov.br/>

INPE/PRODES: <http://www.dpi.inpe.br/prodesdigital/prodesmunicipal.php>

WORLD BANK: <http://data.worldbank.org/>

7 ANNEX A: COMMANDS IN “R”

PANEL DATA MODELS

```
# ATTACH THE DATABASE FROM THE FILE
attach(file.imported)

# SET DATA AS PANEL
panel.data.name<-plm.data(file.imported,index=c("cross.sectional.variable","time.variable"))

#DEFINEDEPENDENTANDINDEPENDENTVARIABLES(REGRESSORS)
Y<-cbind(dependent.variable)
X<-cbind(independent.variable1,independent.variable2,...)

#DESCRIPTIVE STATISTICS
summary(Y)
summary(X)

#POOLED OLS ESTIMATOR
pooling<-plm(Y~X,data=panel.data.name,model="pooling")
summary(pooling)

#BETWEEN ESTIMATOR
between<-plm(Y~X,data=panel.data.name,model="between")
summary(between)

#FIXEDEFFECTS(WITHIN)ESTIMATOR
fixed<-plm(Y~X,data=panel.data.name,model="within")
summary(fixed)

#FIXED TIME EFFECTS
fixed.time <- plm(Y~X+factor(time.variable), data= panel.data.name, model="within")
summary(fixed.time)

#RANDOM EFFECTSESTIMATOR
random<-plm(Y~X,data=panel.data.name,model="random")
summary(random)
```

PROPENSITY SCORE MATCHING MODELS

```
# 1st it is needed to install the packages "Macthing" and "rbounds"

# PROPENSITY SCORING MODEL (INCLUDES PROBIT MODEL AS 1st STEP)
attach(panel.data.name)
df <- data.frame(panel.data.name)
Tr <- cbind(treatment.binary.variable)
Y <- cbind(dependent.variable)
X <- cbind(independent.variable1,independent.variable2,...)
glm1 <- glm(Tr ~ X, family=binomial(link = "probit"), data= panel.data.name)
summary(glm1)
```

```
rr1 <- Match(Y = Y, Tr = Tr, X = glm1$fitted)
summary(rr1)
```

```
#CHECKING THE BALANCE PROPRIETY
```

```
MatchBalance(Tr~X, match.out=rr1,nboots=0,data= panel.data.name)
```

```
#PLOTING THE BALANCE PROPRIETY
```

```
qqplot(var1[rr1$index.control],var1[rr1$index.treated])
```

```
abline(coef=c(0,1),col=2)
```

Sources: derived from:

KATCHOVA, A. (2013). **Panel Data Models in R**. Econometrics Academy's on line lecture. Available at <https://sites.google.com/site/econometricsacademy>. Access on June6th2015.

TORRES-REYNA, O. (2010). **Getting Started in Fixed/Random Effects Models using R**. Power point presentation used in the Princeton Data and Statistic services. Fall 2010. Available at: <http://www.princeton.edu/~otorres/Panel101R.pdf>

8 ANNEX B: Supporting material for the global model

SUMMARY OF VARIABLES

simbol	Variable	Unit	Database	Comments
yld	cereal yield	Kg/ha/yr	World Bank	-
int	Internet users	per 100 people	World Bank	-
mob	Mobile subscription	per 100 people	World Bank	-
gdp	GDP per capita	In 2005 usd	World Bank	-
avr	Agricultural value added per rural habitant	In 2005 usd	World Bank	Calculated as: (Agricultural value added) / (Agricultural population)
edu	Education expenditure per capita	In 2005 usd	World Bank	Calculated as: (GDP per capita) * (Education expenditure as percentage of GDP)
wat	Water used per ha of arable land	m3/ha/yr	World Bank	The variable is calculated proxy. Three other variables were used to calculate it: (total freshwater withdraws per year) * (percentage of water withdrawn used for agriculture) / (total arable land)
fer	Fertilizers per hectare	Kg/ha	World Bank	-
pic	Producer price index for cereals	2004-06=100	World Bank	-
reg.inc	Index for yield variation according to region and income level	1990-94=1	Several	An index created by the author to control for other omitted variables. It groups countries to measure yield variation at the regional level and according to income level. It uses FAO yield data (yld) and World Bank classification for income and regions (see table below). The yield average of all upper-medium-income latin-american countries is created for each period. An index is calculated in which average yield in 1990-94 is equal to 1. Then it is applied to all countries in the category.

DESCRIPTIVE STATISTICS

yld	int	mob	gdp
Min. : 194.1	Min. : 0.0000	Min. : 0.0000	Min. : 93.39
1st Qu.: 1354.9	1st Qu.: 0.1391	1st Qu.: 0.5095	1st Qu.: 847.62
Median : 2245.6	Median : 3.5376	Median : 15.6977	Median : 2940.69
Mean : 2844.5	Mean : 16.2954	Mean : 38.9193	Mean : 10621.28
3rd Qu.: 3586.7	3rd Qu.: 23.6458	3rd Qu.: 74.6980	3rd Qu.: 12678.09
Max. : 73270.1	Max. : 95.2416	Max. : 262.8727	Max. : 140840.95
NA's : 177	NA's : 53	NA's : 44	NA's : 107
avr	edu	wat	pic
Min. : 45.38	Min. : 3.041	Min. : 0.0	Min. : 0.00
1st Qu.: 239.88	1st Qu.: 35.586	1st Qu.: 130.2	1st Qu.: 70.91
Median : 524.07	Median : 154.445	Median : 854.0	Median : 103.22
Mean : 1238.23	Mean : 539.587	Mean : 4065.5	Mean : 106.16
3rd Qu.: 1053.92	3rd Qu.: 643.660	3rd Qu.: 3530.6	3rd Qu.: 131.05
Max. : 38640.05	Max. : 4497.326	Max. : 115185.2	Max. : 431.58
NA's : 260	NA's : 356	NA's : 555	NA's : 399
reg.inc	fer		
Min. : 0.7592	Min. : 0.00		
1st Qu.: 1.0000	1st Qu.: 16.05		
Median : 1.1380	Median : 83.13		
Mean : 1.2231	Mean : 248.71		
3rd Qu.: 1.2545	3rd Qu.: 189.46		
Max. : 7.0787	Max. : 13491.64		
	NA's : 577		

NUMBER OF OBSERVATIONS PER PERIOD PER VARIABLE

period	yld	int	mob	gdp	avr	edu	wat	fer	pic	reg.inc
1990-94	175	204	203	183	141	107	52	0	123	212
1995-99	175	194	201	192	158	155	57	0	132	212
2000-04	177	203	206	195	166	157	131	158	135	212
2005-09	178	203	204	197	177	155	94	163	136	212
2010-14	178	203	202	186	158	130	171	162	135	212
Total	883	1007	1016	953	800	704	505	483	661	1060

RESULTS OF REGRESSIONS

OLS

X	Yields (yld)
Y	Internet users (int)
Model	OLS

Pooling Model

Call:
plm(formula = Y ~ X, data = modelog, model = "pooling")

Unbalanced Panel: n=212, T=2-5, N=877

Residuals :

Min.	1st Qu.	Median	3rd Qu.	Max.
-4470	-1090	-346	638	66800

Coefficients :

	Estimate	Std. Error	t-value	Pr(> t)
(Intercept)	2008.2016	123.2085	16.299	< 2.2e-16 ***
X	56.3511	4.5558	12.369	< 2.2e-16 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares: 9.511e+09
Residual Sum of Squares: 8095500000
R-Squared: 0.14883
Adj. R-Squared: 0.14785
F-statistic: 152.993 on 1 and 875 DF, p-value: < 2.22e-16

X	Yields (yld)
Y	Mobile subscription (mob)
Model	OLS

Pooling Model

Call:
plm(formula = Y ~ X, data = modelog, model = "pooling")

Unbalanced Panel: n=212, T=2-5, N=877

Residuals :

Min.	1st Qu.	Median	3rd Qu.	Max.
-4920	-1180	-406	709	68000

Coefficients :

	Estimate	Std. Error	t-value	Pr(> t)
(Intercept)	2018.4391	137.1883	14.713	< 2.2e-16 ***
X	22.0687	2.3201	9.512	< 2.2e-16 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares: 9517300000
Residual Sum of Squares: 8625400000
R-Squared: 0.093714
Adj. R-Squared: 0.092678

F-statistic: 90.4786 on 1 and 875 DF, p-value: < 2.22e-16

X	Yields (yld)
Y	Internet users (int) + Mobile subscription (mob)
Model	OLS
Pooling Model	
Call: plm(formula = Y ~ X, data = modelog, model = "pooling")	
Unbalanced Panel: n=212, T=2-5, N=875	
Residuals :	
Min.	1st Qu. Median 3rd Qu. Max.
-4650	-1100 -332 616 66700
Coefficients :	
	Estimate Std. Error t-value Pr(> t)
(Intercept)	2050.3953 133.2801 15.3841 < 2.2e-16 ***
Xint	62.4948 8.1287 7.6882 4.021e-14 ***
Xmob	-3.3969 4.0002 -0.8492 0.396

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1	
Total Sum of Squares: 9510700000	
Residual Sum of Squares: 8.076e+09	
R-Squared: 0.15085	
Adj. R-Squared: 0.14891	
F-statistic: 77.4569 on 2 and 872 DF, p-value: < 2.22e-16	

X	Yields (yld)
Y	Internet users (int) + Mobile subscription (mob) + GDP per capita (gdp)
Model	OLS
Pooling Model	
Call: plm(formula = Y ~ X, data = modelog, model = "pooling")	
Unbalanced Panel: n=212, T=1-5, N=834	
Residuals :	
Min.	1st Qu. Median 3rd Qu. Max.
-5160	-997 -314 598 67100
Coefficients :	
	Estimate Std. Error t-value Pr(> t)
(Intercept)	1.8006e+03 1.4581e+02 12.3493 < 2.2e-16 ***
Xint	3.2605e+01 1.0035e+01 3.2490 0.001205 **
Xmob	2.9523e+00 4.2166e+00 0.7002 0.484023
Xgdp	5.4099e-02 1.0482e-02 5.1612 3.072e-07 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1	
Total Sum of Squares: 9.433e+09	
Residual Sum of Squares: 7753900000	

R-Squared: 0.17801
 Adj. R-Squared: 0.17504
 F-statistic: 59.9148 on 3 and 830 DF, p-value: < 2.22e-16

X	Yields (yld)
Y	Internet users (int) + Mobile subscription (mob) + Ag value added (avr)
Model	OLS
Pooling Model	
Call: plm(formula = Y ~ X, data = modelog, model = "pooling")	
Unbalanced Panel: n=212, T=1-5, N=752	
Residuals :	
Min.	1st Qu. Median 3rd Qu. Max.
-5870	-1050 -328 487 66900
Coefficients :	
	Estimate Std. Error t-value Pr(> t)
(Intercept)	1937.430518 165.484541 11.7076 < 2.2e-16 ***
xint	57.891067 10.261752 5.6414 2.393e-08 ***
xmob	-3.052066 4.632617 -0.6588 0.51021
xavr	0.184101 0.088676 2.0761 0.03823 *

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1	
Total Sum of Squares: 9168400000	
Residual Sum of Squares: 7720800000	
R-Squared: 0.15788	
Adj. R-Squared: 0.1545	
F-statistic: 46.7456 on 3 and 748 DF, p-value: < 2.22e-16	

X	Yields (yld)
Y	Internet users (int) + Mobile subscription (mob) + Education expenditure per capita (edu)
Model	OLS
Pooling Model	
Call: plm(formula = Y ~ X, data = modelog, model = "pooling")	
Unbalanced Panel: n=209, T=1-5, N=637	
Residuals :	
Min.	1st Qu. Median 3rd Qu. Max.
-4650	-971 -210 711 20800
Coefficients :	
	Estimate Std. Error t-value Pr(> t)
(Intercept)	2023.02573 96.03485 21.0655 < 2.2e-16 ***
xint	14.62381 6.55713 2.2302 0.02608 *
xmob	4.93984 2.89361 1.7072 0.08828 .
xedu	0.97459 0.11620 8.3874 3.234e-16 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares: 2756300000
 Residual Sum of Squares: 1883600000
 R-Squared: 0.31663
 Adj. R-Squared: 0.31339
 F-statistic: 97.7625 on 3 and 633 DF, p-value: < 2.22e-16

X	Yields (yld)
Y	Internet users (int) + Mobile subscription (mob) + Water used per hectare of arable land (wat)
Model	OLS
Pooling Model	
Call: plm(formula = Y ~ X, data = modelog, model = "pooling")	
Unbalanced Panel: n=187, T=1-5, N=492	
Residuals :	
Min.	1st Qu. Median 3rd Qu. Max.
-12000	-923 -109 816 49300
Coefficients :	
	Estimate Std. Error t-value Pr(> t)
(Intercept)	1218.419713 207.729778 5.8654 8.270e-09 ***
Xint	71.717331 9.122881 7.8613 2.455e-14 ***
Xmob	-10.331530 4.696542 -2.1998 0.02829 *
Xwat	0.275793 0.018266 15.0989 < 2.2e-16 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1	
Total Sum of Squares: 7761900000	
Residual Sum of Squares: 4525200000	
R-Squared: 0.41699	
Adj. R-Squared: 0.4134	
F-statistic: 116.345 on 3 and 488 DF, p-value: < 2.22e-16	

X	Yields (yld)
Y	Internet users (int) + Mobile subscription (mob) + Fertilizer per ha (fer)
Model	OLS
Pooling Model	
Call: plm(formula = Y ~ X, data = modelog, model = "pooling")	
Unbalanced Panel: n=127, T=1-5, N=452	
Residuals :	
Min.	1st Qu. Median 3rd Qu. Max.
-7560	-1030 -204 587 66500
Coefficients :	
	Estimate Std. Error t-value Pr(> t)
(Intercept)	1681.75608 308.18584 5.4570 8.031e-08 ***

```

Xint      58.82820    10.63144    5.5334 5.352e-08 ***
Xmob      -1.16206     5.83015   -0.1993  0.84210
Xfer       0.83400     0.34549    2.4139  0.01618 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares:    7605100000
Residual Sum of Squares: 6397600000
R-Squared:      0.15877
Adj. R-Squared: 0.15314
F-statistic: 28.1851 on 3 and 448 DF, p-value: < 2.22e-16

```

X	Yields (yld)
Y	Internet users (int) + Mobile subscription (mob) + Cereals Producer price (pic)
Model	OLS
Pooling Model	
Call: plm(formula = Y ~ X, data = modelog, model = "pooling")	
Unbalanced Panel: n=210, T=1-5, N=657	
Residuals :	
Min.	1st Qu. Median 3rd Qu. Max.
-3660	-1050 -209 825 5330
Coefficients :	
	Estimate Std. Error t-value Pr(> t)
(Intercept)	2221.9352 120.8901 18.3798 < 2.2e-16 ***
Xint	52.9433 4.5480 11.6410 < 2.2e-16 ***
Xmob	-8.4523 2.6483 -3.1916 0.001483 **
xpic	1.0623 1.2263 0.8663 0.386648

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1	
Total Sum of Squares: 2075800000	
Residual Sum of Squares: 1451400000	
R-Squared: 0.30079	
Adj. R-Squared: 0.29758	
F-statistic: 93.6362 on 3 and 653 DF, p-value: < 2.22e-16	

X	Yields (yld)
Y	Internet users (int) + Mobile subscription (mob) + Control for region and yield variation (reg.inc)
Model	OLS
Pooling Model	
Call: plm(formula = Y ~ X, data = modelog, model = "pooling")	
Unbalanced Panel: n=212, T=2-5, N=875	
Residuals :	
Min.	1st Qu. Median 3rd Qu. Max.
-15800	-1040 -311 781 53600

```

Coefficients :
              Estimate Std. Error t-value Pr(>|t|)
(Intercept) -490.3882   240.1637  -2.0419  0.04146 *
Xint         68.8504    7.5234   9.1515 < 2.2e-16 ***
Xmob        -17.6705    3.8711  -4.5647  5.72e-06 ***
Xreg.inc     2430.5749  197.2913  12.3197 < 2.2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares:    9510700000
Residual Sum of Squares: 6877500000
R-Squared:              0.27686
Adj. R-Squared: 0.27437
F-statistic: 111.158 on 3 and 871 DF, p-value: < 2.22e-16

```

X	Yields (yld)
Y	Internet users (int) + Mobile subscription (mob) + GDP per capita (gdp) + Agricultural value added (avr) + Education expenditure (edu) + Water use per ha (wat) + Fertilizer per ha (fer)+ Cereals producer prices (pic) + Control for region and yield variation (reg.inc)
Model	OLS
Pooling Model	
Call: plm(formula = Y ~ X, data = modelog, model = "pooling")	
Unbalanced Panel: n=112, T=1-5, N=230	
Residuals : Min. 1st Qu. Median 3rd Qu. Max. -4040.0 -686.0 -88.3 662.0 5060.0	
Coefficients : <pre> Estimate Std. Error t-value Pr(> t) (Intercept) 1879.510136 375.378423 5.0070 1.133e-06 *** Xint 23.675606 7.362592 3.2157 0.001497 ** Xmob 1.112342 3.543164 0.3139 0.753864 Xgdp 0.019359 0.017834 1.0856 0.278863 Xavr 0.149678 0.050880 2.9418 0.003613 ** Xedu 0.184244 0.310071 0.5942 0.552989 Xwat 0.113592 0.023367 4.8612 2.219e-06 *** Xfer 0.563038 0.327151 1.7210 0.086650 . Xpic 1.768897 1.825535 0.9690 0.333622 Xreg.inc -385.802500 284.620012 -1.3555 0.176648 --- Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1 Total Sum of Squares: 808710000 Residual Sum of Squares: 336400000 R-Squared: 0.58403 Adj. R-Squared: 0.56701 F-statistic: 34.32 on 9 and 220 DF, p-value: < 2.22e-16 </pre>	

Fixed effects

X	Yields (yld)
Y	Internet users (int)
Model	Fixed effects

Oneway (individual) effect within Model

Call:
plm(formula = Y ~ X, data = modelog, model = "within")

Unbalanced Panel: n=212, T=2-5, N=877

Residuals :

Min.	1st Qu.	Median	3rd Qu.	Max.
-14600	-888	-127	766	53500

Coefficients :

	Estimate	Std. Error	t-value	Pr(> t)
X	70.5640	6.6926	10.544	< 2.2e-16 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares: 7.241e+09
Residual Sum of Squares: 6202600000
R-Squared: 0.14341
Adj. R-Squared: -0.13008
F-statistic: 111.168 on 1 and 664 DF, p-value: < 2.22e-16

X	Yields (yld)
Y	Mobile subscription (mob)
Model	Fixed effects

Oneway (individual) effect within Model

Call:
plm(formula = Y ~ X, data = modelog, model = "within")

Unbalanced Panel: n=212, T=2-5, N=877

Residuals :

Min.	1st Qu.	Median	3rd Qu.	Max.
-14700	-973	-139	744	54700

Coefficients :

	Estimate	Std. Error	t-value	Pr(> t)
X	36.7434	4.3269	8.4919	< 2.2e-16 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares: 7243600000
Residual Sum of Squares: 6.534e+09
R-Squared: 0.097964
Adj. R-Squared: -0.19004
F-statistic: 72.1123 on 1 and 664 DF, p-value: < 2.22e-16

X	Yields (yld)
Y	Internet users (int) + Mobile subscription (mob)
Model	Fixed effects
Oneway (individual) effect within Model	

```

Call:
plm(formula = Y ~ X, data = modelog, model = "within")

Unbalanced Panel: n=212, T=2-5, N=875

Residuals :
    Min. 1st Qu.  Median 3rd Qu.    Max.
-14400   -896    -127    740   53500

Coefficients :
            Estimate Std. Error t-value Pr(>|t|)
xint  59.9373      9.6091  6.2375 7.933e-10 ***
xmob   9.7257      6.0388  1.6105  0.1078
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares:    7239700000
Residual Sum of Squares: 6168900000
R-Squared:    0.1479
Adj. R-Squared: -0.12668
F-statistic: 57.3655 on 2 and 661 DF, p-value: < 2.22e-16

```

X	Yields (yld)
Y	Internet users (int) + Mobile subscription (mob) + GDP per capita (gdp)
Model	Fixed effects
Oneway (individual) effect within Model	
Call: plm(formula = Y ~ X, data = modelog, model = "within") Unbalanced Panel: n=212, T=1-5, N=834 Residuals : Min. 1st Qu. Median 3rd Qu. Max. -18000.0 -821.0 -92.3 767.0 50200.0 Coefficients : Estimate Std. Error t-value Pr(> t) xint 33.561523 11.631358 2.8854 0.0040449 ** xmob 14.242390 6.215524 2.2914 0.0222740 * xgdp 0.046352 0.012791 3.6238 0.0003141 *** --- Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1 Total Sum of Squares: 6978500000 Residual Sum of Squares: 5718600000 R-Squared: 0.18054 Adj. R-Squared: -0.10276 F-statistic: 45.4597 on 3 and 619 DF, p-value: < 2.22e-16	

X	Yields (yld)
Y	Internet users (int) + Mobile subscription (mob) + Agricultural value added (avr)
Model	Fixed effects
Oneway (individual) effect within Model	

```

Call:
plm(formula = Y ~ X, data = modelog, model = "within")

Unbalanced Panel: n=212, T=1-5, N=752

Residuals :
      Min.   1st Qu.   Median   3rd Qu.    Max.
-14200.0   -902.0    -77.8     732.0   53100.0

Coefficients :
      Estimate Std. Error t-value Pr(>|t|)
xint 67.148949  12.331553   5.4453 7.882e-08 ***
xmob 11.082658   7.316507   1.5147  0.1304
xavr -0.036662   0.106029  -0.3458  0.7297
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares:    6943300000
Residual Sum of Squares: 5854600000
R-Squared:              0.15681
Adj. R-Squared:         -0.17921
F-statistic: 33.2887 on 3 and 537 DF, p-value: < 2.22e-16

```

X	Yields (yld)
Y	Internet users (int) + Mobile subscription (mob) + Education expenditure per capita (edu)
Model	Fixed effects
Oneway (individual) effect within Model	
Call: plm(formula = Y ~ X, data = modelog, model = "within")	
Unbalanced Panel: n=209, T=1-5, N=637	
Residuals : Min. 1st Qu. Median 3rd Qu. Max. -7550.0 -769.0 -26.8 663.0 13300.0	
Coefficients : Estimate Std. Error t-value Pr(> t) xint 15.47515 8.19473 1.8884 0.0596495 . xmob 15.90008 4.67535 3.4008 0.0007353 *** xedu 0.64327 0.15004 4.2873 2.24e-05 *** ---	
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1	
Total Sum of Squares: 1778700000 Residual Sum of Squares: 1262100000 R-Squared: 0.29046 Adj. R-Squared: -0.061808 F-statistic: 57.9928 on 3 and 425 DF, p-value: < 2.22e-16	

X	Yields (yld)
Y	Internet users (int) + Mobile subscription (mob) + water used per hectare of arable land (wat)
Model	Fixed effects

Oneway (individual) effect within Model

Call:

```
plm(formula = Y ~ X, data = modelog, model = "within")
```

Unbalanced Panel: n=187, T=1-5, N=492

Residuals :

Min.	1st Qu.	Median	3rd Qu.	Max.
-10200	-790	0	760	36700

Coefficients :

	Estimate	Std. Error	t-value	Pr(> t)
xint	77.525238	11.849142	6.5427	2.583e-10 ***
xmob	-8.401487	7.732587	-1.0865	0.2781
xwat	0.319449	0.023925	13.3520	< 2.2e-16 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares: 5736900000

Residual Sum of Squares: 3075600000

R-Squared: 0.46388

Adj. R-Squared: 0.12837

F-statistic: 87.1039 on 3 and 302 DF, p-value: < 2.22e-16

X	Yields (yld)			
Y	Internet users (int) + Mobile subscription (mob) + Fertilizer per ha (fer)			
Model	Fixed effects			
Oneway (individual) effect within Model				
Call:				
plm(formula = Y ~ X, data = modelog, model = "within")				
Unbalanced Panel: n=127, T=1-5, N=452				
Residuals :				
Min.	1st Qu.	Median	3rd Qu.	Max.
-14400.0	-832.0	-64.8	729.0	53100.0
Coefficients :				
	Estimate	Std. Error	t-value	Pr(> t)
xint	62.85113	13.20218	4.7607	2.921e-06 ***
xmob	5.83600	8.52482	0.6846	0.49410
xfer	0.86068	0.41192	2.0894	0.03745 *

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1				
Total Sum of Squares: 5926800000				
Residual Sum of Squares: 4918900000				
R-Squared: 0.17005				
Adj. R-Squared: -0.16244				
F-statistic: 21.9922 on 3 and 322 DF, p-value: 5.5677e-13				

X	Yields (yld)
Y	Internet users (int) + Mobile subscription (mob) + Cereals Producer price (pic)

Model	Fixed effects				
Oneway (individual) effect within Model					
Call: plm(formula = Y ~ X, data = modelog, model = "within")					
Unbalanced Panel: n=210, T=1-5, N=657					
Residuals :					
	Min.	1st Qu.	Median	3rd Qu.	Max.
	-3140.0	-803.0	-30.2	704.0	4790.0
Coefficients :					
	Estimate	Std. Error	t-value	Pr(> t)	
xint	44.4589	5.6264	7.9018	2.188e-14	***
xmob	8.0215	3.9418	2.0350	0.042446	*
xpic	5.4347	1.7010	3.1950	0.001498	**

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1					
Total Sum of Squares: 1.397e+09					
Residual Sum of Squares: 955450000					
R-Squared: 0.31608					
Adj. R-Squared: -0.010474					
F-statistic: 68.4002 on 3 and 444 DF, p-value: < 2.22e-16					

X	Yields (yld)
Y	Internet users (int) + Mobile subscription (mob) + Control for region and yield variation (reg.inc)
Model	Fixed effects

Oneway (individual) effect within Model

Call:
plm(formula = Y ~ X, data = modelog, model = "within")

Unbalanced Panel: n=212, T=2-5, N=875

Residuals :

Min.	1st Qu.	Median	3rd Qu.	Max.
-12600.0	-929.0	-91.9	797.0	42600.0

Coefficients :

	Estimate	Std. Error	t-value	Pr(> t)	
xint	64.8388	8.8241	7.3479	5.967e-13	***
xmob	-3.1730	5.6568	-0.5609	0.575	
xreg.inc	2501.2346	223.0312	11.2147	< 2.2e-16	***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares: 7239700000
Residual Sum of Squares: 5181500000
R-Squared: 0.28429
Adj. R-Squared: 0.052223
F-statistic: 87.3859 on 3 and 660 DF, p-value: < 2.22e-16

X	Yields (yld)
---	--------------

Y	Internet users (int) + Mobile subscription (mob) + GDP per capita (gdp) + Agricultural value added (avr) + Education expenditure (edu) + water use per ha (wat) + Fertilizer use (fer) + Cereals producer prices (pic) + Control for region and yield variation (reg.inc)				
Model	Fixed effects				
Oneway (individual) effect within Model					
Call: plm(formula = Y ~ X, data = modelog, model = "within")					
Unbalanced Panel: n=112, T=1-5, N=230					
Residuals :					
	Min.	1st Qu.	Median	3rd Qu.	Max.
	-3070	-368	0	459	3070
Coefficients :					
	Estimate	Std. Error	t-value	Pr(> t)	
Xint	28.153062	10.968256	2.5668	0.011621	*
Xmob	0.661575	5.668816	0.1167	0.907309	
Xgdp	0.040043	0.025293	1.5832	0.116282	
Xavr	0.186060	0.067217	2.7680	0.006628	**
Xedu	-0.477237	0.432080	-1.1045	0.271804	
Xwat	0.086568	0.034407	2.5160	0.013326	*
Xfer	0.754503	0.455822	1.6553	0.100749	
Xpic	4.583317	2.947909	1.5548	0.122900	
Xreg.inc	82.805495	452.436634	0.1830	0.855121	

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1					
Total Sum of Squares: 391220000					
Residual Sum of Squares: 179210000					
R-Squared: 0.54191					
Adj. R-Squared: 0.037589					
F-statistic: 14.3271 on 9 and 109 DF, p-value: 4.8642e-15					

Fixed time effects

X	Yields (yld)			
Y	Internet users (int)			
Model	Fixed time effects			
Oneway (individual) effect within Model				
Call:				
plm(formula = Y ~ X + factor(t), data = modelog, model = "within")				
Unbalanced Panel: n=212, T=2-5, N=877				
Residuals :				
Min.	1st Qu.	Median	3rd Qu.	Max.
-14600	-867	-132	733	53100
Coefficients :				
	Estimate	Std. Error	t-value	Pr(> t)
X	70.4752	6.7119	10.5000	< 2e-16 ***
factor(t)2	206.5807	335.3587	0.6160	0.53811
factor(t)3	199.9243	336.2812	0.5945	0.55237
factor(t)4	564.2069	335.9413	1.6795	0.09353 .

```

factor(t)5 142.9951 336.2733 0.4252 0.67080
---
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares: 7.241e+09
Residual Sum of Squares: 6173800000
R-Squared: 0.14739
Adj. R-Squared: -0.13164
F-statistic: 22.8195 on 5 and 660 DF, p-value: < 2.22e-16

```

X	Yields (yld)
Y	Mobile subscription (mob)
Model	Fixed time effects
Oneway (individual) effect within Model	
Call: plm(formula = Y ~ X + factor(t), data = modelog, model = "within")	
Unbalanced Panel: n=212, T=2-5, N=877	
Residuals :	
Min.	1st Qu. Median 3rd Qu. Max.
-14700	-964 -140 757 54300
Coefficients :	
	Estimate Std. Error t-value Pr(> t)
X	36.6330 4.3378 8.4450 <2e-16 ***
factor(t)2	157.4859 344.3635 0.4573 0.6476
factor(t)3	105.3687 345.1938 0.3052 0.7603
factor(t)4	531.9208 346.1642 1.5366 0.1249
factor(t)5	69.8005 345.1363 0.2022 0.8398
--- Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1	
Total Sum of Squares: 7243600000	
Residual Sum of Squares: 6505200000	
R-Squared: 0.10194	
Adj. R-Squared: -0.19197	
F-statistic: 14.9838 on 5 and 660 DF, p-value: 5.9818e-14	

X	Yields (yld)
Y	Internet users (int) + Mobile subscription (mob)
Model	Fixed time effects
Oneway (individual) effect within Model	
Call: plm(formula = Y ~ X + factor(t), data = modelog, model = "within")	
Unbalanced Panel: n=212, T=2-5, N=875	
Residuals :	
Min.	1st Qu. Median 3rd Qu. Max.
-14400	-909 -129 763 53100
Coefficients :	
	Estimate Std. Error t-value Pr(> t)
xint	59.9720 9.6240 6.2315 8.256e-10 ***

```

xmob      9.6410      6.0459  1.5946   0.1113
factor(t)2 181.5549   336.0203  0.5403   0.5892
factor(t)3 185.4444   336.4957  0.5511   0.5817
factor(t)4 553.4758   337.1922  1.6414   0.1012
factor(t)5 113.1887   336.9154  0.3360   0.7370
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares:    7239700000
Residual Sum of Squares: 6140400000
R-Squared:               0.15184
Adj. R-Squared:         -0.12829
F-statistic: 19.6034 on 6 and 657 DF, p-value: < 2.22e-16

```

X	Yields (yld)
Y	Internet users (int) + Mobile subscription (mob) + GDP per capita (gdp)
Model	Fixed time effects
Oneway (individual) effect within Model	
Call: plm(formula = Y ~ X + factor(t), data = modelog, model = "within")	
Unbalanced Panel: n=212, T=1-5, N=834	
Residuals :	
Min.	1st Qu.
-18000.0	-806.0
Median	3rd Qu.
-67.6	741.0
Max.	
49800.0	
Coefficients :	
	Estimate Std. Error t-value Pr(> t)
xint	33.076719 11.655699 2.8378 0.0046922 **
xmob	14.006308 6.220215 2.2517 0.0246907 *
xgdp	0.047368 0.012826 3.6931 0.0002413 ***
factor(t)2	207.509094 344.365906 0.6026 0.5470081
factor(t)3	154.749315 345.193195 0.4483 0.6540963
factor(t)4	615.185502 345.450568 1.7808 0.0754353 .
factor(t)5	171.829184 344.843412 0.4983 0.6184636

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1	
Total Sum of Squares: 6978500000	
Residual Sum of Squares: 5686100000	
R-Squared: 0.18521	
Adj. R-Squared: -0.10362	
F-statistic: 19.9703 on 7 and 615 DF, p-value: < 2.22e-16	

X	Yields (yld)
Y	Internet users (int) + Mobile subscription (mob) + Agricultural value added (avr)
Model	Fixed time effects
Oneway (individual) effect within Model	
Call: plm(formula = Y ~ X + factor(t), data = modelog, model = "within")	

Unbalanced Panel: n=212, T=1-5, N=752

Residuals :

	Min.	1st Qu.	Median	3rd Qu.	Max.
	-14200.0	-868.0	-87.4	721.0	52800.0

Coefficients :

	Estimate	Std. Error	t-value	Pr(> t)
xint	67.326893	12.361670	5.4464	7.859e-08 ***
xmob	10.801174	7.334432	1.4727	0.1414
xavr	-0.034141	0.106294	-0.3212	0.7482
factor(t)2	256.624551	403.988278	0.6352	0.5256
factor(t)3	186.517124	404.356590	0.4613	0.6448
factor(t)4	632.574966	405.244778	1.5610	0.1191
factor(t)5	167.588409	404.793121	0.4140	0.6790

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares: 6943300000

Residual Sum of Squares: 5825100000

R-Squared: 0.16105

Adj. R-Squared: -0.18208

F-statistic: 14.6172 on 7 and 533 DF, p-value: < 2.22e-16

X	Yields (yld)
Y	Internet users (int) + Mobile subscription (mob) + Education expenditure (edu)
Model	Fixed time effects

Oneway (individual) effect within Model

Call:
plm(formula = Y ~ X + factor(t), data = modelog, model = "within")

Unbalanced Panel: n=209, T=1-5, N=637

Residuals :

Min.	1st Qu.	Median	3rd Qu.	Max.
-7480.0	-775.0	-19.8	649.0	13200.0

Coefficients :

	Estimate	Std. Error	t-value	Pr(> t)
xint	15.60247	8.25663	1.8897	0.0594861 .
xmob	15.88319	4.69738	3.3813	0.0007889 ***
xedu	0.63967	0.15087	4.2399	2.751e-05 ***
factor(t)2	40.78126	238.26807	0.1712	0.8641825
factor(t)3	95.39222	233.33401	0.4088	0.6828777
factor(t)4	162.19554	236.31461	0.6864	0.4928676
factor(t)5	167.68117	237.04191	0.7074	0.4797153

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares: 1778700000
Residual Sum of Squares: 1259800000
R-Squared: 0.29175
Adj. R-Squared: -0.069947
F-statistic: 24.7746 on 7 and 421 DF, p-value: < 2.22e-16

X	Yields (yld)
Y	Internet users (int) + Mobile subscription (mob) + Water use per ha (wat)
Model	Fixed time effects
Oneway (individual) effect within Model	
Call: plm(formula = Y ~ X + factor(t), data = modelog, model = "within")	
Unbalanced Panel: n=187, T=1-5, N=492	
Residuals :	
Min.	1st Qu. Median 3rd Qu. Max.
-10200	-779 0 721 36400
Coefficients :	
	Estimate Std. Error t-value Pr(> t)
xint	77.974847 11.926231 6.5381 2.701e-10 ***
xmob	-8.330629 7.767368 -1.0725 0.2844
xwat	0.318280 0.024062 13.2276 < 2.2e-16 ***
factor(t)2	251.010091 517.995769 0.4846 0.6283
factor(t)3	328.412818 507.304146 0.6474 0.5179
factor(t)4	590.769611 525.012042 1.1252 0.2614
factor(t)5	150.293743 509.374145 0.2951 0.7682

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1	
Total Sum of Squares: 5736900000	
Residual Sum of Squares: 3061300000	
R-Squared: 0.46638	
Adj. R-Squared: 0.12078	
F-statistic: 37.2072 on 7 and 298 DF, p-value: < 2.22e-16	

X	Yields (yld)
Y	Internet users (int) + Mobile subscription (mob) + Fertilizer per ha (fer)
Model	Fixed time effects
Oneway (individual) effect within Model	
Call: plm(formula = Y ~ X + factor(t), data = modelog, model = "within")	
Unbalanced Panel: n=127, T=1-5, N=452	
Residuals :	
Min.	1st Qu. Median 3rd Qu. Max.
-14400.0	-822.0 -73.9 788.0 52500.0
Coefficients :	
	Estimate Std. Error t-value Pr(> t)
xint	63.35044 13.24387 4.7834 2.642e-06 ***
xmob	5.33804 8.55503 0.6240 0.53310
xfer	0.84743 0.41458 2.0441 0.04177 *
factor(t)2	353.34457 609.50959 0.5797 0.56251
factor(t)3	162.75255 608.33531 0.2675 0.78923
factor(t)4	870.42357 612.19562 1.4218 0.15606
factor(t)5	131.86116 610.34855 0.2160 0.82909

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1	

Total Sum of Squares: 5926800000
 Residual Sum of Squares: 4881300000
 R-Squared: 0.1764
 Adj. R-Squared: -0.16806
 F-statistic: 9.72989 on 7 and 318 DF, p-value: 5.5069e-11

X	Yields (yld)
Y	Internet users (int) + Mobile subscription (mob) + Cereals producer prices (pic)
Model	Fixed time effects
Oneway (individual) effect within Model	
Call: plm(formula = Y ~ X + factor(t), data = modelog, model = "within")	
Unbalanced Panel: n=210, T=1-5, N=657	
Residuals :	
Min.	1st Qu. Median 3rd Qu. Max.
-3120.0	-827.0 -51.7 698.0 4810.0
Coefficients :	
	Estimate Std. Error t-value Pr(> t)
xint	44.6066 5.6467 7.8997 2.259e-14 ***
xmob	8.0302 3.9548 2.0305 0.042906 *
xpic	5.3465 1.7091 3.1283 0.001875 **
factor(t)2	27.2915 197.0330 0.1385 0.889899
factor(t)3	172.4121 196.6962 0.8765 0.381215
factor(t)4	-22.1120 195.1724 -0.1133 0.909849
factor(t)5	32.6484 197.0297 0.1657 0.868467

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1	
Total Sum of Squares: 1.397e+09	
Residual Sum of Squares: 952850000	
R-Squared: 0.31794	
Adj. R-Squared: -0.016883	
F-statistic: 29.3012 on 7 and 440 DF, p-value: < 2.22e-16	

X	Yields (yld)
Y	Internet users (int) + Mobile subscription (mob) + Control for region and yield variation (reg.inc)
Model	Fixed time effects
Oneway (individual) effect within Model	
Call: plm(formula = Y ~ X + factor(t), data = modelog, model = "within")	
Unbalanced Panel: n=212, T=2-5, N=875	
Residuals :	
Min.	1st Qu. Median 3rd Qu. Max.
-12500.0	-922.0 -89.8 791.0 42400.0
Coefficients :	

	Estimate	Std. Error	t-value	Pr(> t)	
xint	64.8781	8.8423	7.3372	6.464e-13	***
xmob	-3.1626	5.6656	-0.5582	0.5769	
xreg.inc	2490.7494	223.4654	11.1460	< 2.2e-16	***
factor(t)2	140.9399	308.3658	0.4571	0.6478	
factor(t)3	179.3791	308.7809	0.5809	0.5615	
factor(t)4	437.8662	309.5934	1.4143	0.1577	
factor(t)5	57.1541	309.2065	0.1848	0.8534	

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1					
Total Sum of Squares: 7239700000					
Residual Sum of Squares: 5162700000					
R-Squared: 0.28689					
Adj. R-Squared: 0.049914					
F-statistic: 37.7023 on 7 and 656 DF, p-value: < 2.22e-16					

X	Yields (yld)
Y	Internet users (int) + Mobile subscription (mob) + GDP per capita (gdp) + Agricultural value added (avr) + Education expenditure (edu) + Water use per ha (wat) + Fertilizer use per ha (fer) + Cereals producer prices (pic) + Control for region and yield variation (reg.inc)
Model	Fixed time effects
Oneway (individual) effect within Model	
Call: plm(formula = Y ~ X + factor(t), data = modelog, model = "within")	
Unbalanced Panel: n=112, T=1-5, N=230	
Residuals :	
Min.	1st Qu.
-2890	-381
Median	3rd Qu.
0	391
Max.	
2760	
Coefficients :	
	Estimate Std. Error t-value Pr(> t)
xint	28.139987 11.012935 2.5552 0.012046 *
xmob	0.811399 5.669968 0.1431 0.886482
xgdp	0.040292 0.025382 1.5874 0.115420
xavr	0.208034 0.068081 3.0557 0.002847 **
xedu	-0.527253 0.432491 -1.2191 0.225535
xwat	0.078885 0.034658 2.2761 0.024870 *
xfer	0.780070 0.461515 1.6902 0.093950 .
xpic	4.408976 2.968482 1.4853 0.140470
xreg.inc	51.928370 452.194417 0.1148 0.908794
factor(t)2	372.685565 340.267505 1.0953 0.275903
factor(t)3	274.867065 337.884722 0.8135 0.417776
factor(t)4	-23.680034 329.596615 -0.0718 0.942862
factor(t)5	655.643205 342.415997 1.9148 0.058245 .

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1	
Total Sum of Squares: 391220000	
Residual Sum of Squares: 170730000	
R-Squared: 0.56359	
Adj. R-Squared: 0.048206	
F-statistic: 10.4306 on 13 and 105 DF, p-value: 8.0254e-14	

Random effects

X	Yields (yld)
Y	Internet users (int)
Model	Random effects
Oneway (individual) effect Random Effect Model (Swamy-Arora's transformation)	
Call: plm(formula = Y ~ X, data = global.model, model = "random")	
Unbalanced Panel: n=212, T=2-5, N=877	
Effects:	
	var std.dev share
idiosyncratic	9341255 3056 1.019
individual	-170378 NA -0.019
theta :	
Min.	1st Qu. Median Mean 3rd Qu. Max.
-0.04897	-0.04897 -0.03860 -0.04164 -0.03860 -0.01875
Residuals :	
Min.	1st Qu. Median Mean 3rd Qu. Max.
-4530	-1110 -338 -1 661 67400
Coefficients :	
	Estimate Std. Error t-value Pr(> t)
(Intercept)	2017.6607 120.2768 16.775 < 2.2e-16 ***
X	55.8877 4.5024 12.413 < 2.2e-16 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1	
Total Sum of Squares: 9731300000	
Residual Sum of Squares: 8264100000	
R-Squared: 0.15077	
Adj. R-Squared: 0.1498	
F-statistic: 155.341 on 1 and 875 DF, p-value: < 2.22e-16	

X	Yields (yld)
Y	Mobile subscription (mob)
Model	Random effects
Oneway (individual) effect Random Effect Model (Swamy-Arora's transformation)	
Call: plm(formula = Y ~ X, data = global.model, model = "random")	
Unbalanced Panel: n=212, T=2-5, N=877	
Effects:	
	var std.dev share
idiosyncratic	9840412 3137 1.016
individual	-154110 NA -0.016
theta :	
Min.	1st Qu. Median Mean 3rd Qu. Max.
-0.04161	-0.04161 -0.03287 -0.03541 -0.03287 -0.01604

```

Residuals :
    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
 -4960   -1190    -413     -1    697   68600

Coefficients :
              Estimate Std. Error t-value Pr(>|t|)
(Intercept) 2030.6411   134.2605  15.1246 < 2.2e-16 ***
X             21.8203     2.2835   9.5557 < 2.2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares:    9704100000
Residual Sum of Squares: 8778100000
R-Squared:                0.095421
Adj. R-Squared: 0.094387
F-statistic: 92.2988 on 1 and 875 DF, p-value: < 2.22e-16

```

X	Yields (yld)
Y	Internet users (int) + Mobile subscription (mob)
Model	Random effects
Oneway (individual) effect Random Effect Model (Swamy-Arora's transformation)	
call: plm(formula = Y ~ X, data = global.model, model = "random")	
Unbalanced Panel: n=212, T=2-5, N=875	
Effects:	
	var std.dev share
idiosyncratic	9332726 3055 1.019
individual	-174202 NA -0.019
theta :	
	Min. 1st Qu. Median Mean 3rd Qu. Max.
	-0.05021 -0.05021 -0.03956 -0.04262 -0.03956 -0.01921
Residuals :	
	Min. 1st Qu. Median Mean 3rd Qu. Max.
	-4720 -1110 -343 -1 622 67400
Coefficients :	
	Estimate Std. Error t-value Pr(> t)
(Intercept)	2062.2908 129.8662 15.8801 < 2.2e-16 ***
Xint	62.5397 8.1210 7.7009 3.662e-14 ***
Xmob	-3.6624 3.9684 -0.9229 0.3563

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1	
Total Sum of Squares: 9736600000	
Residual Sum of Squares: 8247300000	
R-Squared: 0.15297	
Adj. R-Squared: 0.15103	
F-statistic: 78.7381 on 2 and 872 DF, p-value: < 2.22e-16	

X	Yields (yld)
Y	Internet users (int) + Mobile subscription (mob) + GDP per capita (gdp)
Model	Random effects
Oneway (individual) effect Random Effect Model (Swamy-Arora's transformation)	
Call: plm(formula = Y ~ X, data = global.model, model = "random")	
Unbalanced Panel: n=212, T=1-5, N=834	
Effects:	
	var std.dev share
idiosyncratic	9238461.6 3039.5 0.994
individual	51692.4 227.4 0.006
theta :	
Min.	1st Qu. Median Mean 3rd Qu. Max.
0.002786	0.011010 0.011010 0.011380 0.013700 0.013700
Residuals :	
Min.	1st Qu. Median Mean 3rd Qu. Max.
-5170	-990 -311 0 587 66900
Coefficients :	
	Estimate Std. Error t-value Pr(> t)
(Intercept)	1.7982e+03 1.4664e+02 12.2629 < 2.2e-16 ***
Xint	3.2569e+01 1.0035e+01 3.2456 0.001219 **
Xmob	3.0183e+00 4.2228e+00 0.7147 0.474966
Xgdp	5.4125e-02 1.0483e-02 5.1629 3.045e-07 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1	
Total Sum of Squares: 9375700000	
Residual Sum of Squares: 7709600000	
R-Squared: 0.1777	
Adj. R-Squared: 0.17473	
F-statistic: 59.7889 on 3 and 830 DF, p-value: < 2.22e-16	

X	Yields (yld)
Y	Internet users (int) + Mobile subscription (mob) + Agricultural value added (avr)
Model	Random effects
Oneway (individual) effect Random Effect Model (Swamy-Arora's transformation)	
Call: plm(formula = Y ~ X, data = global.model, model = "random")	
Unbalanced Panel: n=212, T=1-5, N=752	
Effects:	
	var std.dev share
idiosyncratic	10902368 3302 1.082
individual	-830432 NA -0.082
theta :	
Min.	1st Qu. Median Mean 3rd Qu. Max.
-0.27090	-0.27090 -0.19920 -0.19270 -0.13850 -0.04041

```

Residuals :
    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
 -6530   -1120    -398     -9     537   70600

Coefficients :
              Estimate Std. Error t-value Pr(>|t|)
(Intercept) 1951.274586   153.882972  12.6803 < 2.2e-16 ***
Xint         54.759319    10.332642   5.2996 1.528e-07 ***
Xmob        -3.081537     4.541182  -0.6786 0.497617
Xavr         0.232232     0.089608   2.5916 0.009739 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares:    1.0436e+10
Residual Sum of Squares: 8641100000
R-Squared:                0.17204
Adj. R-Squared: 0.16871
F-statistic: 51.7948 on 3 and 748 DF, p-value: < 2.22e-16

```

X	Yields (yld)
Y	Internet users (int) + Mobile subscription (mob) + Education expenditure (edu)
Model	Random effects
Oneway (individual) effect Random Effect Model (Swamy-Arora's transformation)	
Call: plm(formula = Y ~ X, data = global.model, model = "random")	
Unbalanced Panel: n=209, T=1-5, N=637	
Effects:	
	var std.dev share
idiosyncratic	2969579 1723 1.018
individual	-53678 NA -0.018
theta :	
	Min. 1st Qu. Median Mean 3rd Qu. Max.
	-0.048500 -0.038240 -0.038240 -0.033180 -0.028270 -0.009162
Residuals :	
	Min. 1st Qu. Median Mean 3rd Qu. Max.
	-4690.0 -975.0 -212.0 0.8 702.0 21000.0
Coefficients :	
	Estimate Std. Error t-value Pr(> t)
(Intercept)	2024.97737 94.59438 21.4070 < 2e-16 ***
Xint	14.51209 6.55041 2.2154 0.02708 *
Xmob	4.78892 2.87905 1.6634 0.09673 .
xedu	0.98342 0.11608 8.4721 < 2e-16 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1	
Total Sum of Squares: 2816300000	
Residual Sum of Squares: 1920300000	
R-Squared: 0.31816	
Adj. R-Squared: 0.31493	
F-statistic: 98.4578 on 3 and 633 DF, p-value: < 2.22e-16	

X	Yields (yld)
Y	Internet users (int) + Mobile subscription (mob) + water use per ha (wat)
Model	Random effects
Oneway (individual) effect Random Effect Model (Swamy-Arora's transformation)	
Call: plm(formula = Y ~ X, data = global.model, model = "random")	
Unbalanced Panel: n=187, T=1-5, N=492	
Effects:	
	var std.dev share
idiosyncratic	10184154 3191 1.125
individual	-1128686 NA -0.125
theta :	
Min.	1st Qu. Median Mean 3rd Qu. Max.
-0.49760	-0.34030 -0.22400 -0.27100 -0.13350 -0.06049
Residuals :	
Min.	1st Qu. Median Mean 3rd Qu. Max.
-13100	-1040 -154 13 972 54500
Coefficients :	
	Estimate Std. Error t-value Pr(> t)
(Intercept)	1212.659815 197.851926 6.1291 1.824e-09 ***
Xint	68.449089 9.099232 7.5225 2.604e-13 ***
Xmob	-9.392599 4.539866 -2.0689 0.03908 *
Xwat	0.276203 0.018482 14.9443 < 2.2e-16 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1	
Total Sum of Squares: 9806200000	
Residual Sum of Squares: 5579300000	
R-Squared: 0.43106	
Adj. R-Squared: 0.42757	
F-statistic: 123.235 on 3 and 488 DF, p-value: < 2.22e-16	

X	Yields (yld)
Y	Internet users (int) + Mobile subscription (mob) + Fertilizer use per ha (fer)
Model	Random effects
Oneway (individual) effect Random Effect Model (Swamy-Arora's transformation)	
Call: plm(formula = Y ~ X, data = global.model, model = "random")	
Unbalanced Panel: n=127, T=1-5, N=452	
Effects:	
	var std.dev share
idiosyncratic	15276108 3908 1.075
individual	-1064318 NA -0.075
theta :	
Min.	1st Qu. Median Mean 3rd Qu. Max.

```

-0.23880 -0.23880 -0.17740 -0.17480 -0.12440 -0.03677

Residuals :
  Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
-7780  -1100   -242     -8    623   69700

Coefficients :
              Estimate Std. Error t-value Pr(>|t|)
(Intercept) 1742.52374   288.63006   6.0372 3.293e-09 ***
Xint         57.71077    10.65318   5.4172 9.899e-08 ***
Xmob        -1.37773     5.71521  -0.2411  0.8096
Xfer         0.81223     0.34704   2.3405  0.0197 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares:    8.442e+09
Residual Sum of Squares: 7072100000
R-Squared:              0.1623
Adj. R-Squared: 0.15669
F-statistic: 28.9277 on 3 and 448 DF, p-value: < 2.22e-16

```

X	Yields (yld)
Y	Internet users (int) + Mobile subscription (mob) + Cereals producer prices (pic)
Model	Random effects
Oneway (individual) effect Random Effect Model (Swamy-Arora's transformation)	
Call: plm(formula = Y ~ X, data = global.model, model = "random")	
Unbalanced Panel: n=210, T=1-5, N=657	
Effects:	
	var std.dev share
idiosyncratic	2151911 1467 1.023
individual	-49270 NA -0.023
theta :	
	Min. 1st Qu. Median Mean 3rd Qu. Max.
	-0.06268 -0.04920 -0.04920 -0.04324 -0.03622 -0.01165
Residuals :	
	Min. 1st Qu. Median Mean 3rd Qu. Max.
	-3690.0 -1080.0 -198.0 0.1 857.0 5370.0
Coefficients :	
	Estimate Std. Error t-value Pr(> t)
(Intercept)	2235.2334 118.9773 18.7871 < 2.2e-16 ***
Xint	53.2833 4.5373 11.7435 < 2.2e-16 ***
Xmob	-8.8384 2.6335 -3.3562 0.000836 ***
Xpic	1.0286 1.2232 0.8410 0.400675

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1	
Total Sum of Squares: 2134300000	
Residual Sum of Squares: 1487500000	
R-Squared: 0.30305	
Adj. R-Squared: 0.29985	
F-statistic: 94.6469 on 3 and 653 DF, p-value: < 2.22e-16	

X	Yields (yld)
Y	Internet users (int) + Mobile subscription (mob) + Control for region and yield variation (reg.inc)
Model	Random effects
Oneway (individual) effect Random Effect Model (Swamy-Arora's transformation)	
Call: plm(formula = Y ~ X, data = global.model, model = "random")	
Unbalanced Panel: n=212, T=2-5, N=875	
Effects:	
	var std.dev share
idiosyncratic	7850810 2802 1.01
individual	-75776 NA -0.01
theta :	
Min.	1st Qu. Median Mean 3rd Qu. Max.
-0.025040	-0.025040 -0.019880 -0.021350 -0.019880 -0.009794
Residuals :	
Min.	1st Qu. Median Mean 3rd Qu. Max.
-15900	-1050 -305 -1 778 53900
Coefficients :	
	Estimate Std. Error t-value Pr(> t)
(Intercept)	-484.6645 239.3815 -2.0247 0.04321 *
Xint	68.9159 7.5201 9.1643 < 2.2e-16 ***
Xmob	-17.8476 3.8578 -4.6263 4.287e-06 ***
Xreg.inc	2431.4604 197.3811 12.3186 < 2.2e-16 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1	
Total Sum of Squares: 9622100000	
Residual Sum of Squares: 6949800000	
R-Squared: 0.27772	
Adj. R-Squared: 0.27523	
F-statistic: 111.634 on 3 and 871 DF, p-value: < 2.22e-16	

X	Yields (yld)
Y	Internet users (int) + Mobile subscription (mob) + GDP per capita (gdp) + Agricultural value added (avr) + Education expenditure (edu) + Water use per ha (wat) + Fertilizer use per ha (fer) + Cereals producer prices (pic) + Control for region and yield variation (reg.inc)
Model	Random effects
Oneway (individual) effect Random Effect Model (Swamy-Arora's transformation)	
Call: plm(formula = Y ~ X, data = global.model, model = "random")	
Unbalanced Panel: n=112, T=1-5, N=230	
Effects:	

```

              var std.dev share
idiosyncratic 1644160    1282  1.12
individual    -176152     NA -0.12
theta :
  Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
-0.4676 -0.2139 -0.1281 -0.1814 -0.1281 -0.0583

Residuals :
  Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
-4150.0 -695.0  -103.0    20.3   757.0   5310.0

Coefficients :
              Estimate Std. Error t-value Pr(>|t|)
(Intercept) 1882.791570  369.538585  5.0950 7.497e-07 ***
Xint         21.256586   7.396721  2.8738 0.004453 **
Xmob         1.636973   3.586481  0.4564 0.648532
Xgdp         0.014335   0.017855  0.8029 0.422925
Xavr         0.140680   0.051648  2.7238 0.006972 **
Xedu         0.349058   0.309211  1.1289 0.260183
Xwat         0.122113   0.023481  5.2004 4.541e-07 ***
Xfer         0.536053   0.326248  1.6431 0.101794
Xpic         1.202748   1.830856  0.6569 0.511911
Xreg.inc     -364.939607 288.511252 -1.2649 0.207243
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares:    968680000
Residual Sum of Squares: 393110000
R-Squared:                0.59486
Adj. R-Squared: 0.57828
F-statistic: 35.7896 on 9 and 220 DF, p-value: < 2.22e-16

```

Testing different models with dummies for region and income level

(as an additional mean to control for additional non-observed variables)

X	Yields (yld)
Y	Internet users (int) + Mobile subscription (mob) + GDP per capita (gdp) + Agricultural value added (avr) + Education expenditure (edu) + Water use per ha (wat) + Fertilizer use per ha (fer) + Cereals producer prices (pic) + Control for region and yield variation (reg.inc)
Dummies	Region and income categories (D.hi.eap,D.hi.eca,D.hi.lac,D.hi.mea,D.hi.nao,D.hi.sms,D.hi.weu,D.lm.eap,D.lm.eca,D.lm.lac,D.lm.mea,D.lm.sas,D.lm.ssa,D.lo.eap,D.lo.eca,D.lo.lac,D.lo.sas,D.lo.ssa,D.ot.sms,D.ot.ssa,D.um.eap,D.um.eca,D.um.lac,D.um.mea,D.um.sas,D.um.ssa,D.um.weu)
Model	OLS
Pooling Model	
Call: plm(formula = Y ~ X, data = global.model, model = "pooling")	
Unbalanced Panel: n=112, T=1-5, N=230	
Residuals :	
Min.	1st Qu.
Median	3rd Qu.
Max.	
-3280.00	-520.00
3.88	516.00
	4020.00

Coefficients :

	Estimate	Std. Error	t-value	Pr(> t)	
(Intercept)	1.5083e+03	8.6064e+02	1.7526	0.0812263	.
xint	1.8745e+01	8.5003e+00	2.2052	0.0285890	*
xmob	-4.3724e+00	3.8966e+00	-1.1221	0.2631821	
xgdp	2.1912e-02	2.1173e-02	1.0349	0.3019739	
xavr	1.2990e-01	5.4646e-02	2.3771	0.0184023	*
xedu	2.2516e-02	3.3993e-01	0.0662	0.9472565	
xwat	1.2194e-01	3.3045e-02	3.6903	0.0002895	***
xfer	8.8372e-01	3.8143e-01	2.3169	0.0215322	*
xpic	1.8164e+00	1.8746e+00	0.9690	0.3337415	
xreg.inc	6.9960e+02	5.1288e+02	1.3641	0.1740970	
XD.hi.eap	7.0405e+01	1.0343e+03	0.0681	0.9457999	
XD.hi.eca	-8.7639e+02	1.3768e+03	-0.6365	0.5251720	
XD.hi.lac	-5.6950e+02	9.9510e+02	-0.5723	0.5677645	
XD.hi.mea	-3.4107e+03	1.6001e+03	-2.1315	0.0342819	*
XD.hi.nao	-5.3702e+02	9.0591e+02	-0.5928	0.5539906	
XD.hi.sms	-1.5842e+03	9.1766e+02	-1.7263	0.0858470	.
XD.hi.weu	3.6548e+02	7.4012e+02	0.4938	0.6219900	
XD.lm.eap	-2.6455e+02	8.4775e+02	-0.3121	0.7553244	
XD.lm.eca	-6.6757e+02	7.7461e+02	-0.8618	0.3898293	
XD.lm.lac	-4.9769e+02	8.1418e+02	-0.6113	0.5417156	
XD.lm.mea	-1.1076e+03	8.9211e+02	-1.2416	0.2158681	
XD.lm.sas	-8.3222e+02	8.6817e+02	-0.9586	0.3389322	
XD.lm.ssa	-1.3214e+03	8.3109e+02	-1.5899	0.1134438	
XD.lo.eap	4.5627e+02	1.0970e+03	0.4159	0.6779240	
XD.lo.eca	-2.8405e+03	1.2916e+03	-2.1992	0.0290243	*
XD.lo.sas	-8.3370e+02	9.9907e+02	-0.8345	0.4050178	
XD.lo.ssa	-1.2710e+03	7.3792e+02	-1.7225	0.0865481	.
XD.um.eap	-8.8025e+02	8.6264e+02	-1.0204	0.3087792	
XD.um.eca	-5.6589e+01	7.3536e+02	-0.0770	0.9387377	
XD.um.lac	-5.6986e+02	7.9665e+02	-0.7153	0.4752507	
XD.um.mea	-1.4576e+03	8.4390e+02	-1.7272	0.0856924	.
XD.um.ssa	-5.1662e+01	8.6329e+02	-0.0598	0.9523411	

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares: 808710000

Residual Sum of Squares: 277810000

R-Squared: 0.65648

Adj. R-Squared: 0.6027

F-statistic: 12.2062 on 31 and 198 DF, p-value: < 2.22e-16

X	Yields (yld)
Y	Internet users (int) + Mobile subscription (mob) + GDP per capita (gdp) + Agricultural value added (avr) + Education expenditure (edu) + Water use per ha (wat) + Fertilizer use per ha (fer) + Cereals producer prices (pic) + Control for region and yield variation (reg.inc)
Dummies	Region and income categories (D.hi.eap,D.hi.eca,D.hi.lac,D.hi.mea,D.hi.nao,D.hi.sms,D.hi.weu,D.lm.eap,D.lm.eca,D.lm.lac,D.lm.mea,D.lm.sas,D.lm.ssa,D.lo.eap,D.lo.eca,D.lo.lac,D.lo.sas,D.lo.ssa,D.ot.sms,D.ot.ssa,D.um.eap,D.um.eca,D.um.lac,D.um.mea,D.um.sas,D.um.ssa,D.um.weu)
Model	Fixed effects
Oneway (individual) effect within Model	
call:	

```
plm(formula = Y ~ X, data = global.model, model = "within")
```

Unbalanced Panel: n=112, T=1-5, N=230

Residuals :

Min.	1st Qu.	Median	3rd Qu.	Max.
-2760	-320	0	318	2160

Coefficients :

	Estimate	Std. Error	t-value	Pr(> t)	
xint	3.3143e+01	1.4132e+01	2.3452	0.021292	*
xmob	-6.7337e+00	7.0069e+00	-0.9610	0.339213	
xgdp	4.1321e-02	2.9339e-02	1.4084	0.162586	
xavr	2.5790e-01	7.5914e-02	3.3972	0.001028	**
xedu	-8.9254e-01	4.6236e-01	-1.9304	0.056814	.
xwat	2.1308e-01	5.1597e-02	4.1296	8.316e-05	***
xfer	1.2578e+00	5.5573e-01	2.2633	0.026103	*
xpic	6.6680e+00	3.0982e+00	2.1522	0.034149	*
xreg.inc	2.3409e+03	8.4412e+02	2.7732	0.006790	**
XD.hi.eap	-1.2759e+03	1.7422e+03	-0.7323	0.465936	
XD.hi.eca	-7.5963e+02	1.6237e+03	-0.4678	0.641075	
XD.hi.lac	-4.6765e+03	1.8595e+03	-2.5149	0.013743	*
XD.hi.mea	-5.9470e+03	2.0442e+03	-2.9093	0.004598	**
XD.hi.nao	-2.1355e+03	1.5912e+03	-1.3421	0.183055	
XD.hi.sms	-1.4960e+03	1.6056e+03	-0.9317	0.354052	
XD.hi.weu	7.5977e+02	1.3666e+03	0.5559	0.579680	
XD.lm.eap	-1.4752e+03	1.5040e+03	-0.9808	0.329401	
XD.lm.eca	-8.5172e+02	1.3817e+03	-0.6164	0.539234	
XD.lm.lac	-3.1432e+02	1.2973e+03	-0.2423	0.809125	
XD.lm.mea	-1.3529e+03	1.5742e+03	-0.8595	0.392451	
XD.lm.sas	-1.2777e+03	1.5817e+03	-0.8078	0.421405	
XD.lm.ssa	-8.1082e+02	1.5721e+03	-0.5158	0.607337	
XD.lo.eap	2.1087e+03	1.9930e+03	1.0580	0.292969	
XD.lo.eca	-6.2833e+03	2.2921e+03	-2.7413	0.007427	**
XD.lo.sas	-9.4683e+02	1.6326e+03	-0.5800	0.563436	
XD.lo.ssa	-3.4212e+02	1.3349e+03	-0.2563	0.798332	
XD.um.eap	-7.6090e+02	1.4617e+03	-0.5206	0.603993	
XD.um.eca	-9.5231e+02	1.3283e+03	-0.7169	0.475341	
XD.um.lac	-1.5942e+03	1.4690e+03	-1.0852	0.280846	
XD.um.mea	-2.4183e+03	1.6527e+03	-1.4632	0.147010	
XD.um.ssa	2.0796e+02	1.5942e+03	0.1304	0.896513	

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares: 391220000

Residual Sum of Squares: 125800000

R-Squared: 0.67843

Adj. R-Squared: 0.15358

F-statistic: 5.92096 on 31 and 87 DF, p-value: 2.751e-11

X	Yields (yld)
Y	Internet users (int) + Mobile subscription (mob) + GDP per capita (gdp) + Agricultural value added (avr) + Education expenditure (edu) + Water use per ha (wat) + Fertilizer use per ha (fer) + Cereals producer prices (pic) + Control for region and yield variation (reg.inc)
Dummies	Region and income categories (D.hi.eap,D.hi.eca,D.hi.lac,D.hi.mea,D.hi.nao,D.hi.sms,D.hi.weu,D.lm.eap,D.lm.eca,D.lm.la

	c,D.lm.mea,D.lm.sas,D.lm.ssa,D.lo.eap,D.lo.eca,D.lo.lac,D.lo.sas,D.lo.ssa,D.ot.sms,D.ot.ssa,D.um.eap,D.um.eca,D.um.lac,D.um.mea,D.um.sas,D.um.ssa,D.um.weu)				
Model	Fixed time effects				
Oneway (individual) effect within Model					
Call: plm(formula = Y ~ X + factor(t), data = global.model, model = "within")					
Unbalanced Panel: n=112, T=1-5, N=230					
Residuals :					
	Min.	1st Qu.	Median	3rd Qu.	Max.
	-2620	-393	0	353	2320
Coefficients :					
	Estimate	Std. Error	t-value	Pr(> t)	
xint	3.3647e+01	1.4139e+01	2.3797	0.0196204	*
xmob	-6.7987e+00	7.1723e+00	-0.9479	0.3459263	
xgdp	3.9073e-02	2.9456e-02	1.3265	0.1883169	
xavr	2.8110e-01	7.7895e-02	3.6087	0.0005248	***
xedu	-9.2491e-01	4.6347e-01	-1.9956	0.0492536	*
xwat	2.0169e-01	5.2828e-02	3.8178	0.0002586	***
xfer	1.2850e+00	5.6094e-01	2.2908	0.0245099	*
xpic	6.6351e+00	3.1295e+00	2.1202	0.0369775	*
xreg.inc	2.2878e+03	8.5376e+02	2.6797	0.0088855	**
XD.hi.eap	-1.6842e+03	1.7746e+03	-0.9491	0.3453372	
XD.hi.eca	-1.4935e+03	1.6547e+03	-0.9026	0.3693340	
XD.hi.lac	-5.0690e+03	1.9582e+03	-2.5885	0.0113777	*
XD.hi.mea	-5.7821e+03	2.0450e+03	-2.8275	0.0058787	**
XD.hi.nao	-2.5663e+03	1.6309e+03	-1.5735	0.1194060	
XD.hi.sms	-2.0846e+03	1.6480e+03	-1.2649	0.2094466	
XD.hi.weu	3.7404e+02	1.4055e+03	0.2661	0.7907992	
XD.lm.eap	-1.7554e+03	1.5590e+03	-1.1260	0.2634143	
XD.lm.eca	-1.2184e+03	1.4216e+03	-0.8571	0.3938748	
XD.lm.lac	-6.1390e+02	1.3214e+03	-0.4646	0.6434386	
XD.lm.mea	-1.7510e+03	1.6315e+03	-1.0732	0.2862880	
XD.lm.sas	-1.9563e+03	1.6705e+03	-1.1711	0.2449110	
XD.lm.ssa	-1.2297e+03	1.5902e+03	-0.7733	0.4415436	
XD.lo.eap	1.8164e+03	2.0060e+03	0.9054	0.3678492	
XD.lo.eca	-6.5477e+03	2.3811e+03	-2.7498	0.0073172	**
XD.lo.sas	-1.5719e+03	1.6773e+03	-0.9372	0.3513785	
XD.lo.ssa	-5.9390e+02	1.3666e+03	-0.4346	0.6650038	
XD.um.eap	-1.1624e+03	1.5156e+03	-0.7670	0.4452618	
XD.um.eca	-1.3376e+03	1.3756e+03	-0.9724	0.3336846	
XD.um.lac	-1.8907e+03	1.5012e+03	-1.2595	0.2113877	
XD.um.mea	-2.9370e+03	1.7027e+03	-1.7249	0.0882592	.
XD.um.ssa	-2.3825e+02	1.6470e+03	-0.1447	0.8853345	
factor(t)2	1.5910e+02	3.4545e+02	0.4606	0.6463111	
factor(t)3	3.2562e+01	3.5223e+02	0.0924	0.9265680	
factor(t)4	-1.2563e+02	3.3859e+02	-0.3710	0.7115613	
factor(t)5	5.7250e+02	3.5055e+02	1.6331	0.1062290	

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1					
Total Sum of Squares: 391220000					
Residual Sum of Squares: 119170000					
R-Squared: 0.6954					
Adj. R-Squared: 0.15959					
F-statistic: 5.41388 on 35 and 83 DF, p-value: 1.4292e-10					

X	Yields (yld)
Y	Internet users (int) + Mobile subscription (mob) + GDP per capita (gdp) + Agricultural value added (avr) + Education expenditure (edu) + Water use per ha (wat) + Fertilizer use per ha (fer) + Cereals producer prices (pic) + Control for region and yield variation (reg.inc)
Dummies	Region and income categories (D.hi.eap,D.hi.eca,D.hi.lac,D.hi.mea,D.hi.nao,D.hi.sms,D.hi.weu,D.lm.eap,D.lm.eca,D.lm.lac,D.lm.mea,D.lm.sas,D.lm.ssa,D.lo.eap,D.lo.eca,D.lo.lac,D.lo.sas,D.lo.ssa,D.ot.sms,D.ot.ssa,D.um.eap,D.um.eca,D.um.lac,D.um.mea,D.um.sas,D.um.ssa,D.um.weu)
Model	Random effects
Oneway (individual) effect Random Effect Model (Swamy-Arora's transformation)	
call: plm(formula = Y ~ X, data = global.model, model = "random")	
Unbalanced Panel: n=112, T=1-5, N=230	
Effects:	
	var std.dev share
idiosyncratic	1534183 1239 1.151
individual	-200907 NA -0.151
theta :	
Min.	1st Qu. Median Mean 3rd Qu. Max.
-0.7019	-0.2834 -0.1640 -0.2439 -0.1640 -0.0727
Residuals :	
Min.	1st Qu. Median Mean 3rd Qu. Max.
-3660.0	-546.0 68.5 22.7 562.0 4380.0
Coefficients :	
	Estimate Std. Error t-value Pr(> t)
(Intercept)	1.7946e+03 8.4924e+02 2.1132 0.0358331 *
Xint	1.4240e+01 8.4608e+00 1.6831 0.0939381 .
Xmob	-3.0202e+00 3.9387e+00 -0.7668 0.4441218
Xgdp	1.6908e-02 2.1730e-02 0.7781 0.4374446
Xavr	1.1204e-01 5.4896e-02 2.0410 0.0425771 *
Xedu	2.5571e-01 3.4596e-01 0.7391 0.4607065
Xwat	1.1622e-01 3.3271e-02 3.4930 0.0005891 ***
Xfer	9.2643e-01 3.7762e-01 2.4533 0.0150185 *
Xpic	9.9651e-01 1.8713e+00 0.5325 0.5949596
Xreg.inc	7.1204e+02 5.1885e+02 1.3723 0.1715074
XD.hi.eap	7.9616e+01 1.0623e+03 0.0749 0.9403317
XD.hi.eca	-1.1211e+03 1.4393e+03 -0.7790 0.4369371
XD.hi.lac	-4.5137e+02 1.0134e+03 -0.4454 0.6565141
XD.hi.mea	-3.6225e+03 1.6803e+03 -2.1558 0.0323050 *
XD.hi.nao	-8.0852e+02 9.3031e+02 -0.8691 0.3858509
XD.hi.sms	-1.7815e+03 9.3595e+02 -1.9034 0.0584430 .
XD.hi.weu	5.8323e+00 7.5203e+02 0.0078 0.9938199
XD.lm.eap	-3.0125e+02 8.6272e+02 -0.3492 0.7273253
XD.lm.eca	-8.9548e+02 7.8762e+02 -1.1369 0.2569343
XD.lm.lac	-7.2613e+02 8.3723e+02 -0.8673 0.3868275
XD.lm.mea	-1.1377e+03 9.1086e+02 -1.2490 0.2131420
XD.lm.sas	-1.0813e+03 8.8793e+02 -1.2178 0.2247666
XD.lm.ssa	-1.5891e+03 8.3279e+02 -1.9082 0.0578100 .
XD.lo.eap	2.2449e+02 1.1112e+03 0.2020 0.8401024
XD.lo.eca	-2.8786e+03 1.3287e+03 -2.1665 0.0314645 *


```

XD.lo.sas -1.2721e+03 1.0128e+03 -1.2560 0.2106061
XD.lo.ssa -1.6453e+03 7.4957e+02 -2.1950 0.0293291 *
XD.um.eap -1.2696e+03 8.7382e+02 -1.4529 0.1478231
XD.um.eca -1.0439e+02 7.4844e+02 -0.1395 0.8892182
XD.um.lac -6.8249e+02 8.1939e+02 -0.8329 0.4058900
XD.um.mea -1.5976e+03 8.6301e+02 -1.8511 0.0656383 .
XD.um.ssa -4.1721e+02 8.6971e+02 -0.4797 0.6319590
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares:    1042500000
Residual Sum of Squares: 335980000
R-Squared:              0.67845
Adj. R-Squared: 0.62811
F-statistic: 13.4319 on 31 and 198 DF, p-value: < 2.22e-16

```

Lagrange multiplier test

```

Lagrange Multiplier Test - (Breusch-Pagan) for unbalanced panels

data: Y ~ X
chisq = 0.15834, df = 1, p-value = 0.6907
alternative hypothesis: significant effects

```

DESCRIPTION OF THE INDEX FOR YIELD VARIATION ACCORDING TO REGION AND INCOME LEVEL

An index created by the author to control for other omitted variables. It groups countries to measure yield variation at the regional level and according to income level.

It uses FAO yield data (yld) and World Bank classification for income and regions (see table below). The yield average of all upper-medium-income latin-american countries is created for each period. An index is calculated in which average yield in 1990-94 is equal to 1. Then it is applied to all countries in the category. Below the region-income classification and the final index values.

Country categories

Created by the author, based on World Bank classification

Country	Code	Income category	Regional category	Combined category
Aruba	ABW	High income	Small states	hi-sms
Andorra	AND	Upper middle income	Small states	ot-sms
Afghanistan	AFG	Low income	South Asia	lo-sas
Angola	AGO	Upper middle income	Sub-Saharan Africa	um-ssa
Albania	ALB	Upper middle income	Europe & Central Asia	um-eca
United Arab Emirates	ARE	High income	Middle East & North Africa	hi-mea
Argentina	ARG	Upper middle income	Latin America & Caribbean	um-lac
Armenia	ARM	Lower middle income	Europe & Central Asia	lm-eca

American Samoa	ASM	Upper middle income	East Asia & Pacific	um-eap
Antigua and Barbuda	ATG	High income	Small states	hi-sms
Australia	AUS	High income	North America and Oceania	hi-nao
Austria	AUT	High income	Western Europe	hi-weu
Azerbaijan	AZE	Upper middle income	Europe & Central Asia	um-eca
Burundi	BDI	Low income	Sub-Saharan Africa	lo-ssa
Belgium	BEL	High income	Western Europe	hi-weu
Benin	BEN	Low income	Sub-Saharan Africa	lo-ssa
Burkina Faso	BFA	Low income	Sub-Saharan Africa	lo-ssa
Bangladesh	BGD	Low income	South Asia	lo-sas
Bulgaria	BGR	Upper middle income	Europe & Central Asia	um-eca
Bahrain	BHR	High income	Middle East & North Africa	hi-mea
Bahamas, The	BHS	High income	Small states	hi-sms
Bosnia and Herzegovina	BIH	Upper middle income	Europe & Central Asia	um-eca
Belarus	BLR	Upper middle income	Europe & Central Asia	um-eca
Belize	BLZ	Upper middle income	Latin America & Caribbean	um-lac
Bermuda	BMU	High income	Small states	hi-sms
Bolivia	BOL	Lower middle income	Latin America & Caribbean	lm-lac
Brazil	BRA	Upper middle income	Latin America & Caribbean	um-lac
Barbados	BRB	High income	Small states	hi-sms
Brunei Darussalam	BRN	High income	Small states	hi-sms
Bhutan	BTN	Lower middle income	South Asia	lm-sas
Botswana	BWA	Upper middle income	Sub-Saharan Africa	um-ssa
Central African Republic	CAF	Low income	Sub-Saharan Africa	lo-ssa
Canada	CAN	High income	North America and Oceania	hi-nao
Switzerland	CHE	High income	Western Europe	hi-weu
Chile	CHL	High income	Latin America & Caribbean	hi-lac
China	CHN	Upper middle income	East Asia & Pacific	um-eap
Cote d'Ivoire	CIV	Lower middle income	Sub-Saharan Africa	lm-ssa
Cameroon	CMR	Lower middle income	Sub-Saharan Africa	lm-ssa
Congo, Rep.	COG	Lower middle income	Sub-Saharan Africa	lm-ssa
Colombia	COL	Upper middle income	Latin America & Caribbean	um-lac
Comoros	COM	Low income	Sub-Saharan Africa	lo-ssa
Cabo Verde	CPV	Lower middle income	Sub-Saharan Africa	lm-ssa
Costa Rica	CRI	Upper middle income	Latin America & Caribbean	um-lac
Cuba	CUB	Upper middle income	Latin America & Caribbean	um-lac
Curacao	CUW	High income	Small states	hi-sms
Cayman Islands	CYM	High income	Small states	hi-sms
Cyprus	CYP	High income	Western Europe	hi-weu
Czech Republic	CZE	High income	Western Europe	hi-weu
Germany	DEU	High income	Western Europe	hi-weu
Djibouti	DJI	Lower middle income	Middle East & North Africa	lm-mea

Dominica	DMA	Upper middle income	Latin America & Caribbean	um-lac
Denmark	DNK	High income	Western Europe	hi-weu
Dominican Republic	DOM	Upper middle income	Latin America & Caribbean	um-lac
Algeria	DZA	Upper middle income	Middle East & North Africa	um-mea
Ecuador	ECU	Upper middle income	Latin America & Caribbean	um-lac
Egypt, Arab Rep.	EGY	Lower middle income	Middle East & North Africa	lm-mea
Eritrea	ERI	Low income	Sub-Saharan Africa	lo-ssa
Spain	ESP	High income	Western Europe	hi-weu
Estonia	EST	High income	Western Europe	hi-weu
Ethiopia	ETH	Low income	Sub-Saharan Africa	lo-ssa
Finland	FIN	High income	Western Europe	hi-weu
Fiji	FJI	Upper middle income	East Asia & Pacific	um-eap
France	FRA	High income	Western Europe	hi-weu
Faeroe Islands	FRO	High income	Small states	hi-sms
Micronesia, Fed. Sts.	FSM	Lower middle income	East Asia & Pacific	lm-eap
Gabon	GAB	Upper middle income	Sub-Saharan Africa	um-ssa
United Kingdom	GBR	High income	Western Europe	hi-weu
Georgia	GEO	Lower middle income	Europe & Central Asia	lm-eca
Ghana	GHA	Lower middle income	Sub-Saharan Africa	lm-ssa
Guinea	GIN	Low income	Sub-Saharan Africa	lo-ssa
Gambia, The	GMB	Low income	Sub-Saharan Africa	lo-ssa
Guinea-Bissau	GNB	Low income	Sub-Saharan Africa	lo-ssa
Equatorial Guinea	GNQ	High income	Sub-Saharan Africa	hi-sms
Greece	GRC	High income	Western Europe	hi-weu
Grenada	GRD	Upper middle income	Latin America & Caribbean	um-lac
Greenland	GRL	High income	Small states	hi-sms
Guatemala	GTM	Lower middle income	Latin America & Caribbean	lm-lac
Guam	GUM	High income	Small states	hi-sms
Guyana	GUY	Lower middle income	Latin America & Caribbean	lm-lac
Hong Kong SAR, China	HKG	High income	Small states	hi-sms
Honduras	HND	Lower middle income	Latin America & Caribbean	lm-lac
Croatia	HRV	High income	Western Europe	hi-weu
Haiti	HTI	Low income	Latin America & Caribbean	lo-lac
Hungary	HUN	Upper middle income	Europe & Central Asia	um-eca
Indonesia	IDN	Lower middle income	East Asia & Pacific	lm-eap
Isle of Man	IMN	Low income	Small states	ot-sms
India	IND	Lower middle income	South Asia	lm-sas
Ireland	IRL	High income	Western Europe	hi-weu
Iran, Islamic Rep.	IRN	Upper middle income	Middle East & North Africa	um-mea
Iraq	IRQ	Upper middle income	Middle East & North Africa	um-mea
Iceland	ISL	High income	Western Europe	hi-weu
Israel	ISR	High income	Middle East & North Africa	hi-mea
Italy	ITA	High income	Western Europe	hi-weu

Jamaica	JAM	Upper middle income	Latin America & Caribbean	um-lac
Jordan	JOR	Upper middle income	Middle East & North Africa	um-mea
Japan	JPN	High income	East Asia & Pacific	hi-eap
Kazakhstan	KAZ	Upper middle income	Europe & Central Asia	um-eca
Kenya	KEN	Low income	Sub-Saharan Africa	lo-ssa
Kyrgyz Republic	KGZ	Lower middle income	Europe & Central Asia	lm-eca
Cambodia	KHM	Low income	East Asia & Pacific	lo-eap
Kiribati	KIR	Lower middle income	East Asia & Pacific	lm-eap
St. Kitts and Nevis	KNA	High income	Small states	hi-sms
Korea, Rep.	KOR	High income	East Asia & Pacific	hi-eap
Kuwait	KWT	High income	Small states	hi-sms
Lao PDR	LAO	Lower middle income	East Asia & Pacific	lm-eap
Lebanon	LBN	Upper middle income	Middle East & North Africa	um-mea
Liberia	LBR	Low income	Sub-Saharan Africa	lo-ssa
Libya	LBY	Upper middle income	Middle East & North Africa	um-mea
St. Lucia	LCA	Upper middle income	Latin America & Caribbean	um-lac
Liechtenstein	LIE	High income	Small states	hi-sms
Sri Lanka	LKA	Lower middle income	South Asia	lm-sas
Lesotho	LSO	Lower middle income	Sub-Saharan Africa	lm-ssa
Lithuania	LTU	High income	Western Europe	hi-weu
Luxembourg	LUX	High income	Western Europe	hi-weu
Latvia	LVA	High income	Small states	hi-sms
Macao SAR, China	MAC	High income	Small states	hi-sms
St. Martin (French part)	MAF	High income	Small states	hi-sms
Morocco	MAR	Lower middle income	Middle East & North Africa	lm-mea
Monaco	MCO	High income	Small states	hi-sms
Moldova	MDA	Lower middle income	Europe & Central Asia	lm-eca
Madagascar	MDG	Low income	Sub-Saharan Africa	lo-ssa
Maldives	MDV	Upper middle income	South Asia	um-sas
Mexico	MEX	Upper middle income	Latin America & Caribbean	um-lac
Marshall Islands	MHL	Upper middle income	East Asia & Pacific	um-eap
Macedonia, FYR	MKD	Upper middle income	Europe & Central Asia	um-eca
Mali	MLI	Low income	Sub-Saharan Africa	lo-ssa
Malta	MLT	High income	Western Europe	hi-weu
Myanmar	MMR	Low income	East Asia & Pacific	lo-eap
Montenegro	MNE	Upper middle income	Europe & Central Asia	um-eca
Mongolia	MNG	Lower middle income	East Asia & Pacific	lm-eap
Northern Mariana Islands	MNP	High income	Small states	hi-sms
Mozambique	MOZ	Low income	Sub-Saharan Africa	lo-ssa
Mauritania	MRT	Lower middle income	Sub-Saharan Africa	lm-ssa
Mauritius	MUS	Upper middle income	Sub-Saharan Africa	um-ssa
Malawi	MWI	Low income	Sub-Saharan Africa	lo-ssa
Malaysia	MYS	Upper middle income	East Asia & Pacific	um-eap

Namibia	NAM	Upper middle income	Sub-Saharan Africa	um-ssa
New Caledonia	NCL	High income	Small states	hi-sms
Niger	NER	Low income	Sub-Saharan Africa	lo-ssa
Nigeria	NGA	Lower middle income	Sub-Saharan Africa	lm-ssa
Nicaragua	NIC	Lower middle income	Latin America & Caribbean	lm-lac
Netherlands	NLD	High income	Western Europe	hi-weu
Norway	NOR	High income	Western Europe	hi-weu
Nepal	NPL	Low income	South Asia	lo-sas
New Zealand	NZL	High income	North America and Oceania	hi-nao
Oman	OMN	High income	Middle East & North Africa	hi-mea
Pakistan	PAK	Lower middle income	South Asia	lm-sas
Panama	PAN	Upper middle income	Latin America & Caribbean	um-lac
Peru	PER	Upper middle income	Latin America & Caribbean	um-lac
Philippines	PHL	Lower middle income	East Asia & Pacific	lm-eap
Palau	PLW	Upper middle income	East Asia & Pacific	um-eap
Papua New Guinea	PNG	Lower middle income	East Asia & Pacific	lm-eap
Poland	POL	High income	Western Europe	hi-weu
Puerto Rico	PRI	High income	Latin America & Caribbean	hi-lac
Korea, Dem. Rep.	PRK	Low income	East Asia & Pacific	lo-eap
Portugal	PRT	High income	Western Europe	hi-weu
Paraguay	PRY	Lower middle income	Latin America & Caribbean	lm-lac
French Polynesia	PYF	High income	Small states	hi-sms
Qatar	QAT	High income	Middle East & North Africa	hi-mea
Romania	ROU	Upper middle income	Western Europe	um-weu
Russian Federation	RUS	High income	Europe & Central Asia	hi-eca
Rwanda	RWA	Low income	Sub-Saharan Africa	lo-ssa
Saudi Arabia	SAU	High income	Middle East & North Africa	hi-mea
Sudan	SDN	Lower middle income	Sub-Saharan Africa	lm-ssa
Senegal	SEN	Lower middle income	Sub-Saharan Africa	lm-ssa
Singapore	SGP	High income	Small states	hi-sms
Solomon Islands	SLB	Lower middle income	East Asia & Pacific	lm-eap
Sierra Leone	SLE	Low income	Sub-Saharan Africa	lo-ssa
El Salvador	SLV	Lower middle income	Latin America & Caribbean	lm-lac
San Marino	SMR	High income	Small states	hi-sms
Somalia	SOM	Low income	Sub-Saharan Africa	lo-ssa
Serbia	SRB	Upper middle income	Europe & Central Asia	um-eca
South Sudan	SSD	Lower middle income	Sub-Saharan Africa	lm-ssa
Sao Tome and Principe	STP	Lower middle income	Sub-Saharan Africa	lm-ssa
Suriname	SUR	Upper middle income	Latin America & Caribbean	um-lac
Slovak Republic	SVK	High income	Western Europe	hi-weu
Slovenia	SVN	High income	Western Europe	hi-weu
Sweden	SWE	High income	Western Europe	hi-weu
Swaziland	SWZ	Lower middle income	Sub-Saharan Africa	lm-ssa

Sint Maarten (Dutch part)	SXM	High income	Small states	hi-sms
Seychelles	SYC	Upper middle income	Sub-Saharan Africa	um-ssa
Syrian Arab Republic	SYR	Lower middle income	Middle East & North Africa	lm-mea
Turks and Caicos Islands	TCA	High income	Small states	hi-sms
Chad	TCD	Low income	Sub-Saharan Africa	lo-ssa
Togo	TGO	Low income	Sub-Saharan Africa	lo-ssa
Thailand	THA	Upper middle income	East Asia & Pacific	um-eap
Tajikistan	TJK	Low income	Europe & Central Asia	lo-eca
Turkmenistan	TKM	Upper middle income	Europe & Central Asia	um-eca
Timor-Leste	TLS	Low income	South Asia	lo-sas
Tonga	TON	Upper middle income	East Asia & Pacific	um-eap
Trinidad and Tobago	TTO	High income	Small states	hi-sms
Tunisia	TUN	Upper middle income	Middle East & North Africa	um-mea
Turkey	TUR	Upper middle income	Europe & Central Asia	um-eca
Tuvalu	TUV	Upper middle income	East Asia & Pacific	um-eap
Tanzania	TZA	Low income	Sub-Saharan Africa	lo-ssa
Uganda	UGA	Low income	Sub-Saharan Africa	lo-ssa
Ukraine	UKR	Lower middle income	Europe & Central Asia	lm-eca
Uruguay	URY	High income	Latin America & Caribbean	hi-lac
United States	USA	High income	North America and Oceania	hi-nao
Uzbekistan	UZB	Lower middle income	Europe & Central Asia	lm-eca
St. Vincent and the Grenadines	VCT	Upper middle income	Latin America & Caribbean	um-lac
Venezuela, RB	VEN	Upper middle income	Latin America & Caribbean	um-lac
Virgin Islands (U.S.)	VIR	High income	Small states	hi-sms
Vietnam	VNM	Lower middle income	East Asia & Pacific	lm-eap
Vanuatu	VUT	Lower middle income	East Asia & Pacific	lm-eap
West Bank and Gaza	PSE	Low income	Small states	ot-sms
Samoa	WSM	Lower middle income	East Asia & Pacific	lm-eap
Yemen, Rep.	YEM	Lower middle income	Middle East & North Africa	lm-mea
South Africa	ZAF	Upper middle income	Sub-Saharan Africa	um-ssa
Congo, Dem. Rep.	COD	Low income	Sub-Saharan Africa	ot-ssa
Zambia	ZMB	Lower middle income	Sub-Saharan Africa	lm-ssa
Zimbabwe	ZWE	Low income	Sub-Saharan Africa	lo-ssa

Index values:

Combined category	1990-1994	1995-1999	2000-2004	2005-2009	2010-2014
hi-eap	1	1.075458	1.069806	1.110455	1.106546
hi-eca	1	0.887796	1.133654	1.290734	1.271604
hi-lac	1	1.19746	1.350885	1.47489	1.581664
hi-mea	1	1.168721	1.287858	3.882933	7.078665
hi-nao	1	1.097547	1.18396	1.289619	1.37939
hi-sms	1	1.073879	0.947475	1.113952	1.51913
hi-weu	1	1.075408	1.155342	1.20196	1.240499
lm-eap	1	1.039641	1.150499	1.221258	1.361211
lm-eca	1	0.977505	1.069233	1.191523	1.31289
lm-lac	1	1.077969	1.134086	1.25786	1.375398
lm-mea	1	1.113917	1.207471	1.182717	1.216909
lm-sas	1	1.109894	1.220322	1.370624	1.495025
lm-ssa	1	1.143978	1.150982	1.170869	1.254513
lo-eap	1	0.759183	0.889816	1.036025	1.109764
lo-eca	1	1.211419	1.867667	2.537717	2.988045
lo-lac	1	0.989572	0.93867	1.001147	1.006887
lo-sas	1	1.077866	1.146654	1.306185	1.501434
lo-ssa	1	1.038041	1.038184	1.146756	1.30366
ot-sms	1	1.23042	1.7533	1.496547	1.402287
ot-ssa	1	0.994514	0.979852	0.972223	0.961482
um-eap	1	1.059509	1.137957	1.22352	1.284252
um-eca	1	0.98298	1.074499	1.236319	1.25852
um-lac	1	1.08253	1.471766	1.50091	1.824252
um-mea	1	1.070522	1.198425	1.26632	1.514888
um-sas	1	1.396807	1.93519	1.919287	2.504734
um-ssa	1	1.121115	1.516298	1.705479	1.318708
um-weu	1	1.095075	1.028291	1.046217	1.252033

COMPLETE DATASET

id	t	id.sub	yld	int	mob	gdp	edu	wat	fer	pic	avr	reg.inc
ABW	1	hi-sms	NA	0.0000	0.0098	23086.9380	NA	NA	NA	NA	NA	1.0000
AND	1	ot-sms	NA	0.0000	0.7672	23342.5497	NA	NA	NA	NA	NA	1.0000
AFG	1	lo-sas	1146.8894	0.0000	0.0000	NA	NA	NA	NA	31.7175	NA	1.0000
AGO	1	um-ssa	340.3448	0.0000	0.0050	1263.3299	NA	NA	NA	NA	139.6534	1.0000
ALB	1	um-eca	2456.2986	0.0000	0.0000	1331.7543	43.5108	1730.6334	NA	68.0550	564.5443	1.0000
ARE	1	hi-mea	1767.9746	0.0000	2.7939	45947.5624	NA	NA	NA	NA	NA	1.0000
ARG	1	um-lac	2723.6582	0.0191	0.2564	4732.9879	50.6147	NA	NA	36.3650	2690.5108	1.0000
ARM	1	lm-eca	1657.2013	0.0046	0.0000	789.7092	NA	NA	NA	NA	489.8910	1.0000
ASM	1	um-eap	NA	0.0000	1.1004	NA	NA	NA	NA	NA	NA	1.0000
ATG	1	hi-sms	1844.5542	0.0000	0.0000	9916.3318	NA	250.0000	NA	NA	374.1893	1.0000
AUS	1	hi-nao	1692.4420	1.5316	3.2601	25021.0836	1245.3140	NA	NA	84.4050	5250.9541	1.0000
AUT	1	hi-weu	5339.7546	0.6382	2.1952	29871.3595	1555.3426	69.9468	NA	228.5300	1338.0772	1.0000
AZE	1	um-eca	1788.1360	0.0007	0.0013	1246.5907	75.0603	NA	NA	4.7950	240.1928	1.0000
BDI	1	lo-ssa	1356.9816	0.0000	0.0024	211.3498	8.0322	NA	NA	14.5725	107.9781	1.0000
BEL	1	hi-weu	NA	0.2033	0.6982	29053.5650	1585.8691	NA	NA	NA	NA	1.0000
BEN	1	lo-ssa	903.1710	0.0000	0.0000	460.0041	NA	NA	NA	NA	226.6604	1.0000
BFA	1	lo-ssa	814.4644	0.0000	0.0000	280.5820	9.6850	87.9283	NA	64.4650	140.9798	1.0000
BGD	1	lo-sas	2565.1236	0.0000	0.0003	279.7701	4.4647	NA	NA	77.7325	88.0646	1.0000
BGR	1	um-eca	3241.7206	0.0073	0.0177	2590.9746	125.8196	560.9825	NA	1.1275	1000.0658	1.0000
BHR	1	hi-mea	NA	0.0000	1.9323	16508.5590	NA	67505.5500	NA	NA	NA	1.0000
BHS	1	hi-sms	1645.2874	0.0000	0.8465	20545.1609	NA	NA	NA	NA	2987.8789	1.0000
BIH	1	um-eca	3558.0900	0.0000	0.0000	570.5338	NA	NA	NA	NA	NA	1.0000
BLR	1	um-eca	2602.8100	0.0002	0.0040	2061.3655	NA	154.4362	NA	0.1000	743.4459	1.0000
BLZ	1	um-lac	2054.6046	0.0000	0.1226	2962.3422	NA	NA	NA	72.0875	573.9102	1.0000
BMU	1	hi-sms	NA	0.0000	4.2873	54329.8510	1768.1208	NA	NA	NA	NA	1.0000

BOL	1	lm-lac	1416.4406	0.0000	0.0234	859.0378	41.1239	NA	NA	58.5850	251.8970	1.0000
BRA	1	um-lac	2077.4184	0.0159	0.1003	4023.3702	NA	NA	NA	7.0250	692.2883	1.0000
BRB	1	hi-sms	2627.5030	0.0000	0.4437	11642.5781	768.5774	NA	NA	NA	392.0193	1.0000
BRN	1	hi-sms	1662.1378	0.0000	2.3498	26931.7143	1055.0438	NA	NA	102.6975	484.4117	1.0000
BTN	1	lm-sas	1304.7842	0.0000	0.0000	684.0128	NA	NA	NA	24.1825	313.4549	1.0000
BWA	1	um-ssa	317.1852	0.0000	0.0000	3858.4025	242.8080	157.4423	NA	25.8300	233.4930	1.0000
CAF	1	lo-ssa	906.2958	0.0000	0.0000	348.5440	7.8653	NA	NA	NA	240.7004	1.0000
CAN	1	hi-nao	2583.9496	1.0821	3.9172	27396.6609	1871.2064	NA	NA	73.1750	NA	1.0000
CHE	1	hi-weu	6137.3696	1.6829	3.2265	48654.5743	2488.7193	NA	NA	188.7950	2064.7566	1.0000
CHL	1	hi-lac	4116.6484	0.0624	0.4538	4724.7733	117.1432	NA	NA	66.8375	1410.3869	1.0000
CHN	1	um-eap	4395.4358	0.0004	0.0402	573.0999	10.2450	3381.8197	NA	37.0450	200.2061	1.0000
CIV	1	lm-ssa	1116.4996	0.0000	0.0000	1052.4676	63.2710	NA	NA	51.6800	NA	1.0000
CMR	1	lm-ssa	1087.9420	0.0000	0.0024	875.8069	26.9241	23.5136	NA	46.1875	236.4646	1.0000
COG	1	lm-ssa	636.1794	0.0000	0.0000	1759.0109	111.9406	NA	NA	46.9675	182.7913	1.0000
COL	1	um-lac	2497.5392	0.0536	0.0483	2920.3162	NA	NA	NA	25.5225	1134.9591	1.0000
COM	1	lo-ssa	1291.1624	0.0000	0.0000	646.5175	NA	NA	NA	NA	325.0769	1.0000
CPV	1	lm-ssa	299.8060	0.0000	0.0000	783.4703	NA	NA	NA	73.4875	181.8226	1.0000
CRI	1	um-lac	3359.9080	0.0906	0.0871	3396.5319	NA	NA	NA	26.9875	693.7921	1.0000
CUB	1	um-lac	1879.0106	0.0000	0.0035	2895.5481	191.1992	NA	NA	NA	866.4842	1.0000
CUW	1	hi-sms	NA	NA	NA	NA	NA	NA	NA	NA	NA	1.0000
CYM	1	hi-sms	NA	0.0000	3.2336	NA	NA	NA	NA	NA	NA	1.0000
CYP	1	hi-weu	2305.9322	0.0544	1.3781	17030.0671	492.0228	1573.4313	NA	125.2950	1567.5693	1.0000
CZE	1	hi-weu	4055.8570	0.6135	0.0974	9407.0359	409.9469	NA	NA	85.8500	1050.7033	1.0000
DEU	1	hi-weu	5654.1938	0.4395	1.4708	29913.8988	1346.3249	NA	NA	133.8050	1246.5561	1.0000
DJI	1	lm-mea	1633.3334	0.0000	0.0000	1103.3773	NA	NA	NA	NA	135.0138	1.0000
DMA	1	um-lac	1340.5806	0.0000	0.0000	4090.3227	NA	NA	NA	NA	2003.9012	1.0000
DNK	1	hi-weu	5510.3846	0.5202	5.3858	37965.0000	2684.5557	185.3282	NA	141.2075	2877.6414	1.0000
DOM	1	um-lac	3921.2362	0.0000	0.1235	2327.7303	19.6165	NA	NA	43.0225	505.1445	1.0000
DZA	1	um-mea	847.3810	0.0002	0.0117	2407.3564	NA	365.7248	NA	42.5975	340.2044	1.0000
ECU	1	um-lac	1839.1748	0.0141	0.0342	2693.1339	NA	NA	NA	6.1650	517.1694	1.0000

EGY	1	lm-mea	5814.1210	0.0025	0.0094	896.6040	38.5067	NA	NA	46.0025	249.2570	1.0000
ERI	1	lo-ssa	410.6205	0.0000	0.0000	205.6296	NA	NA	NA	17.9850	65.9130	1.0000
ESP	1	hi-weu	2400.4354	0.1046	0.5169	19552.3234	803.9545	1567.8912	NA	111.4800	NA	1.0000
EST	1	hi-weu	1687.2850	0.3815	0.3257	NA	NA	NA	NA	55.5100	NA	1.0000
ETH	1	lo-ssa	1197.6994	0.0000	0.0000	127.1128	3.0410	NA	NA	85.8100	73.6338	1.0000
FIN	1	hi-weu	3386.0532	2.2338	8.4310	26743.8348	1777.8351	8.7507	NA	280.9825	4675.0629	1.0000
FJI	1	um-eap	2245.6226	0.0049	0.0287	2929.7092	NA	NA	NA	NA	821.2581	1.0000
FRA	1	hi-weu	6432.8592	0.3925	0.8876	28605.5834	1467.1538	272.6008	NA	141.4525	2076.3255	1.0000
FRO	1	hi-sms	NA	0.0000	2.9234	NA	NA	NA	NA	NA	NA	1.0000
FSM	1	lm-eap	NA	0.0000	0.0000	2095.1283	NA	NA	NA	NA	NA	1.0000
GAB	1	um-ssa	1614.4126	0.0000	0.0780	7111.6247	199.4627	NA	NA	NA	1229.4092	1.0000
GBR	1	hi-weu	6388.6204	0.4157	3.5017	28946.4059	1346.4519	105.2282	NA	NA	1050.3094	1.0000
GEO	1	lm-eca	1927.0887	0.0000	0.0000	1391.6878	95.9138	NA	NA	51.6800	839.4277	1.0000
GHA	1	lm-ssa	1183.9756	0.0000	0.0068	389.6171	NA	NA	NA	3.8475	NA	1.0000
GIN	1	lo-ssa	1419.4162	0.0001	0.0023	273.6174	5.5622	NA	NA	27.1200	79.8222	1.0000
GMB	1	lo-ssa	1135.9630	0.0000	0.0289	421.5837	10.9244	NA	NA	23.5775	182.6791	1.0000
GNB	1	lo-ssa	1482.6448	0.0000	0.0000	505.0454	NA	23.0740	NA	NA	NA	1.0000
GNQ	1	hi-sms	NA	0.0000	0.0000	478.0070	NA	NA	NA	NA	NA	1.0000
GRC	1	hi-weu	3633.5538	0.1333	0.3812	15916.7585	332.1876	1990.3181	NA	103.8175	NA	1.0000
GRD	1	um-lac	1021.5802	0.0000	0.2267	4246.5586	NA	NA	NA	NA	549.2642	1.0000
GRL	1	hi-sms	NA	0.0324	0.5635	23650.2616	NA	NA	NA	NA	NA	1.0000
GTM	1	lm-lac	1870.8454	0.0000	0.0357	1823.0021	28.3319	NA	NA	NA	429.8022	1.0000
GUM	1	hi-sms	2213.3334	0.1742	1.1669	NA	NA	NA	NA	NA	NA	1.0000
GUY	1	lm-lac	3341.3072	0.0000	0.0862	788.7342	29.3778	2995.7375	NA	NA	363.1953	1.0000
HKG	1	hi-sms	2000.0000	1.0178	4.4781	19325.1767	512.1987	NA	NA	NA	NA	1.0000
HND	1	lm-lac	1350.6294	0.0000	0.0000	1167.1272	39.6877	NA	NA	26.5450	290.0157	1.0000
HRV	1	hi-weu	4124.3500	0.1218	0.1752	NA	NA	NA	NA	70.9433	NA	1.0000
HTI	1	lo-lac	965.9258	0.0000	0.0000	NA	NA	1179.3796	NA	NA	NA	1.0000
HUN	1	um-eca	4142.1440	0.1457	0.4306	7384.5014	440.1582	NA	NA	34.4075	NA	1.0000
IDN	1	lm-eap	3852.2308	0.0005	0.0224	949.1234	9.4955	3775.8224	NA	17.9225	221.8669	1.0000

IMN	1	ot-sms	NA	NA	NA	17742.2747	NA	NA	NA	NA	NA	1.0000
IND	1	lm-sas	2008.5526	0.0003	0.0000	416.9180	NA	2823.9639	NA	44.4125	151.0400	1.0000
IRL	1	hi-weu	6368.0632	0.2132	1.4038	24904.6517	1252.8138	NA	NA	120.9200	NA	1.0000
IRN	1	um-mea	1604.8368	0.0002	0.0031	1956.3048	81.3043	NA	NA	10.0725	487.5894	1.0000
IRQ	1	um-mea	822.8292	0.0000	0.0000	1147.4926	NA	7472.5389	NA	3.2575	347.2633	1.0000
ISL	1	hi-weu	NA	2.3014	5.9371	40172.3961	1923.5962	NA	NA	NA	NA	1.0000
ISR	1	hi-mea	2860.1686	0.3224	1.0925	14095.3655	932.6225	3508.5874	NA	108.7700	NA	1.0000
ITA	1	hi-weu	4509.0894	0.0875	1.7792	26925.8873	1280.9572	NA	NA	127.8350	1799.5511	1.0000
JAM	1	um-lac	1374.5866	0.0184	0.4240	NA	NA	NA	NA	9.8825	640.9149	1.0000
JOR	1	um-mea	1319.1744	0.0000	0.0390	1766.5225	NA	3583.6624	NA	73.8675	342.6440	1.0000
JPN	1	hi-eap	5603.3428	0.2717	1.6875	32056.7195	1145.5736	12431.9048	NA	150.8175	2327.5399	1.0000
KAZ	1	um-eca	1055.5307	0.0003	0.0005	2561.9753	NA	NA	NA	16.4500	684.4200	1.0000
KEN	1	lo-ssa	1662.9948	0.0000	0.0033	527.8170	32.4081	302.4315	NA	35.2975	152.1382	1.0000
KGZ	1	lm-eca	2349.1617	0.0000	0.0000	538.1131	30.0087	NA	NA	NA	176.8529	1.0000
KHM	1	lo-eap	1370.1952	0.0000	0.0292	248.3205	NA	NA	NA	41.7625	149.7476	1.0000
KIR	1	lm-eap	NA	0.0000	0.0000	928.8105	NA	NA	NA	NA	563.9342	1.0000
KNA	1	hi-sms	NA	0.0000	0.0000	7817.5141	224.7455	NA	NA	NA	237.2707	1.0000
KOR	1	hi-eap	5829.0838	0.1458	0.8854	10081.0726	339.5777	NA	NA	48.3550	2035.1969	1.0000
KWT	1	hi-sms	4181.1368	0.0794	2.9367	NA	2876.2623	NA	NA	NA	NA	1.0000
LAO	1	lm-eap	2372.7088	0.0000	0.0054	274.5433	6.4201	NA	NA	9.4500	144.7836	1.0000
LBN	1	um-mea	2045.1344	0.0000	0.0000	4512.3381	83.5255	NA	NA	52.3050	1323.3213	1.0000
LBR	1	lo-ssa	1009.7546	0.0000	0.0000	111.3947	NA	NA	NA	NA	NA	1.0000
LBY	1	um-mea	700.4064	0.0000	0.0000	NA	NA	2359.5325	NA	NA	NA	1.0000
LCA	1	um-lac	NA	0.0000	0.1804	4667.9979	420.7348	NA	NA	NA	831.5857	1.0000
LIE	1	hi-sms	NA	0.0000	0.0000	72568.7365	NA	NA	NA	NA	NA	1.0000
LKA	1	lm-sas	2954.9422	0.0014	0.0549	766.2309	21.5654	10488.9476	NA	51.2300	168.8181	1.0000
LSO	1	lm-ssa	782.1064	0.0000	0.0000	541.4774	48.8628	NA	NA	NA	81.5592	1.0000
LTU	1	hi-weu	1933.8183	0.0000	0.0329	5214.8575	253.4414	NA	NA	47.2867	NA	1.0000
LUX	1	hi-weu	NA	0.2380	1.0563	54916.5514	NA	NA	NA	NA	NA	1.0000
LVA	1	hi-sms	1755.8060	0.0000	0.1037	3975.1303	165.0119	NA	NA	95.8200	727.3349	1.0000

MAC	1	hi-sms	NA	0.0185	2.8239	15847.2320	NA	NA	NA	NA	NA	1.0000
MAF	1	hi-sms	NA	NA	NA	NA	NA	NA	NA	NA	NA	1.0000
MAR	1	lm-mea	1085.7642	0.0000	0.0201	1450.9128	77.9150	1144.3070	NA	105.2675	517.0185	1.0000
MCO	1	hi-sms	NA	0.0000	2.4454	109872.2531	1003.7819	NA	NA	NA	NA	1.0000
MDA	1	lm-eca	2980.7227	0.0004	0.0000	1104.8869	NA	443.8562	NA	43.5200	351.0404	1.0000
MDG	1	lo-ssa	1931.1044	0.0000	0.0005	298.3682	6.3724	NA	NA	23.3200	109.5049	1.0000
MDV	1	um-sas	1000.0000	0.0000	0.0000	NA	NA	NA	NA	NA	NA	1.0000
MEX	1	um-lac	2543.4458	0.0190	0.3271	6780.4946	195.1179	NA	NA	38.9350	937.5451	1.0000
MHL	1	um-eap	NA	0.0000	0.1107	2482.9557	NA	NA	NA	NA	NA	1.0000
MKD	1	um-eca	2452.9163	0.0000	0.0000	2695.6440	131.3625	NA	NA	55.4433	753.4112	1.0000
MLI	1	lo-ssa	820.0478	0.0000	0.0000	332.4549	NA	NA	NA	51.9950	188.1931	1.0000
MLT	1	hi-weu	3046.6766	0.0000	0.9582	10508.3137	422.9643	NA	NA	70.5375	3166.2230	1.0000
MMR	1	lo-eap	2816.6768	0.0000	0.0012	NA	NA	NA	NA	5.4250	NA	1.0000
MNE	1	um-eca	NA	NA	NA	NA	NA	NA	NA	NA	NA	1.0000
MNG	1	lm-eap	901.0776	0.0000	0.0000	721.6623	NA	NA	NA	13.3200	561.1257	1.0000
MNP	1	hi-sms	NA	0.0000	0.9333	NA	NA	NA	NA	NA	NA	1.0000
MOZ	1	lo-ssa	415.9910	0.0000	0.0000	185.5675	NA	153.7651	NA	10.7575	75.3245	1.0000
MRT	1	lm-ssa	784.4374	0.0000	0.0000	560.5066	NA	NA	NA	NA	386.1074	1.0000
MUS	1	um-ssa	4064.1994	0.0000	0.3182	3283.5418	109.5600	NA	NA	91.3050	534.4083	1.0000
MWI	1	lo-ssa	999.8526	0.0000	0.0000	191.2190	6.2532	NA	NA	NA	49.1776	1.0000
MYS	1	um-eap	2903.1502	0.0315	1.3540	3587.1443	173.6076	8228.8332	NA	65.3125	1041.5263	1.0000
NAM	1	um-ssa	370.7366	0.0000	0.0000	2918.8276	NA	248.1639	NA	28.7125	430.4564	1.0000
NCL	1	hi-sms	2532.8244	0.0000	0.0000	NA	NA	NA	NA	NA	NA	1.0000
NER	1	lo-ssa	322.4214	0.0000	0.0000	282.1620	8.4905	33.0187	NA	38.6125	NA	1.0000
NGA	1	lm-ssa	1138.2724	0.0000	0.0042	565.4977	NA	NA	NA	12.0250	200.3145	1.0000
NIC	1	lm-lac	1628.4042	0.0066	0.0110	898.7391	26.8036	NA	NA	28.5625	308.1522	1.0000
NLD	1	hi-weu	7335.1030	1.4821	1.1825	31799.3326	1700.4789	208.2272	NA	134.6375	2289.6660	1.0000
NOR	1	hi-weu	3781.5368	2.2535	7.7876	47270.7761	3358.5810	NA	NA	136.3950	2717.5003	1.0000
NPL	1	lo-sas	1825.2336	0.0000	0.0000	246.4842	NA	NA	NA	50.9425	106.2187	1.0000
NZL	1	hi-nao	5395.2912	1.0215	3.4372	20337.5040	1219.5818	NA	NA	94.4800	7043.3965	1.0000

OMN	1	hi-mea	2003.3516	0.0000	0.2361	10985.8736	350.0079	35215.6472	NA	NA	NA	1.0000
PAK	1	lm-sas	1850.0640	0.0000	0.0108	549.2187	13.9060	7282.3701	NA	37.6675	173.3639	1.0000
PAN	1	um-lac	1890.7570	0.0038	0.0000	3419.7048	143.9648	NA	NA	100.8100	524.1316	1.0000
PER	1	um-lac	2598.1180	0.0043	0.1015	1942.4056	NA	NA	NA	42.0875	NA	1.0000
PHL	1	lm-eap	2137.0478	0.0029	0.1095	969.9234	NA	NA	NA	51.9750	274.6957	1.0000
PLW	1	um-eap	NA	0.0000	NA	9224.9928	NA	NA	NA	NA	NA	1.0000
PNG	1	lm-eap	2646.5984	0.0000	0.0000	850.2977	NA	NA	NA	NA	NA	1.0000
POL	1	hi-weu	2838.5280	0.1153	0.0296	4649.5845	194.2609	118.1038	NA	40.3000	NA	1.0000
PRI	1	hi-lac	1288.4484	0.0136	2.1199	15395.9259	NA	4351.9241	NA	NA	2518.2257	1.0000
PRK	1	lo-eap	5220.0970	0.0000	0.0000	NA	NA	NA	NA	NA	NA	1.0000
PRT	1	hi-weu	2049.8612	0.3039	0.6613	14764.8602	643.1867	NA	NA	130.8250	NA	1.0000
PRY	1	lm-lac	1894.4806	0.0000	0.0542	1499.7532	15.9379	NA	NA	32.4375	461.4089	1.0000
PYF	1	hi-sms	NA	0.0000	0.0000	NA	NA	NA	NA	NA	NA	1.0000
QAT	1	hi-mea	3008.3996	0.0000	1.1404	34901.0065	NA	NA	NA	126.9500	2404.2823	1.0000
ROU	1	um-weu	2705.2370	0.0100	0.0031	3334.0999	NA	970.0297	NA	2.1425	829.6283	1.0000
RUS	1	hi-eca	1612.2157	0.0170	0.0059	4712.5698	NA	NA	NA	1.9133	904.0267	1.0000
RWA	1	lo-ssa	1153.5996	0.0000	0.0000	234.3597	NA	NA	NA	18.7375	86.8399	1.0000
SAU	1	hi-mea	4329.1964	0.0000	0.0904	12677.4848	742.3589	4262.5821	NA	96.2250	2230.7065	1.0000
SDN	1	lm-ssa	561.4354	0.0000	0.0000	464.7319	NA	NA	NA	3.3100	317.2835	1.0000
SEN	1	lm-ssa	799.0814	0.0000	0.0002	662.4295	NA	NA	NA	70.9200	196.6432	1.0000
SGP	1	hi-sms	NA	0.5163	4.1012	18361.4909	NA	NA	NA	NA	NA	1.0000
SLB	1	lm-eap	3484.6160	0.0000	0.0082	1088.0516	30.0449	NA	NA	NA	313.9765	1.0000
SLE	1	lo-ssa	1203.6442	0.0000	0.0000	332.8133	NA	NA	NA	NA	247.9149	1.0000
SLV	1	lm-lac	1841.7376	0.0000	0.0230	1973.7753	NA	584.7478	NA	82.4875	529.3421	1.0000
SMR	1	hi-sms	NA	0.0000	4.0736	30068.1236	1086.9811	NA	NA	NA	NA	1.0000
SOM	1	lo-ssa	547.2026	0.0000	0.0000	NA	NA	NA	NA	NA	NA	1.0000
SRB	1	um-eca	3098.9393	NA	NA	NA	NA	NA	NA	2.1600	NA	1.0000
SSD	1	lm-ssa	NA	NA	NA	NA	NA	NA	NA	NA	NA	1.0000
STP	1	lm-ssa	2099.8268	0.0000	0.0000	NA	NA	NA	NA	NA	NA	1.0000
SUR	1	um-lac	3805.2844	0.0000	0.1151	3027.1232	NA	NA	NA	3.9000	639.3346	1.0000

SVK	1	hi-weu	4038.9815	0.1488	0.0402	6982.6790	330.4057	NA	NA	86.0550	NA	1.0000
SVN	1	hi-weu	4020.8993	0.4938	0.2689	NA	NA	NA	NA	71.4433	NA	1.0000
SWE	1	hi-weu	4293.2114	1.6744	8.8239	31402.0668	1772.3335	57.3566	NA	119.9325	2513.5498	1.0000
SWZ	1	lm-ssa	1312.0378	0.0000	0.0000	2020.9560	107.3828	NA	NA	NA	215.9596	1.0000
SXM	1	hi-sms	NA	NA	NA	NA	NA	NA	NA	NA	NA	1.0000
SYC	1	um-ssa	NA	0.0000	0.0000	9325.7401	848.5417	899.9970	NA	NA	734.4741	1.0000
SYR	1	lm-mea	1174.5466	0.0000	0.0000	1248.0044	NA	NA	NA	77.2150	NA	1.0000
TCA	1	hi-sms	NA	NA	NA	NA	NA	NA	NA	NA	NA	1.0000
TCO	1	lo-ssa	631.0358	0.0000	0.0000	409.9627	NA	NA	NA	NA	NA	1.0000
TGO	1	lo-ssa	794.4340	0.0000	0.0000	380.3068	21.5199	NA	NA	51.9550	192.3644	1.0000
THA	1	um-eap	2238.4568	0.0105	0.5470	1823.7513	58.4002	NA	NA	55.2075	350.8118	1.0000
TJK	1	lo-eca	947.5887	0.0000	0.0000	497.8254	40.4077	NA	NA	NA	116.1458	1.0000
TKM	1	um-eca	2384.6260	0.0000	0.0000	1780.0652	NA	NA	NA	NA	432.8009	1.0000
TLS	1	lo-sas	1827.5922	0.0000	0.0000	NA	NA	NA	NA	NA	NA	1.0000
TON	1	um-eap	NA	0.0000	0.0000	1994.7755	NA	NA	NA	NA	544.6665	1.0000
TTO	1	hi-sms	3402.9586	0.0000	0.0961	6567.9751	232.6916	NA	NA	73.3500	90.0307	1.0000
TUN	1	um-mea	1260.6058	0.0037	0.0213	2147.8275	127.8384	938.0209	NA	84.9425	633.8367	1.0000
TUR	1	um-eca	2148.7184	0.0194	0.1416	5128.7798	174.2008	930.8171	NA	0.5625	1662.1058	1.0000
TUV	1	um-eap	NA	0.0000	0.0000	1914.9685	144.7215	NA	NA	NA	823.9293	1.0000
TZA	1	lo-ssa	1241.4360	0.0000	0.0003	289.6809	6.0130	NA	NA	35.3200	113.9341	1.0000
UGA	1	lo-ssa	1499.5612	0.0000	0.0000	205.7054	NA	NA	NA	NA	86.6559	1.0000
UKR	1	lm-eca	2951.5913	0.0048	0.0020	2106.6909	NA	NA	NA	7.4700	529.3738	1.0000
URY	1	hi-lac	2556.6140	0.0312	0.0848	4314.4693	103.0721	NA	NA	13.6425	3377.4437	1.0000
USA	1	hi-nao	4898.0830	2.1613	4.8946	33386.7957	1624.2305	1058.0832	NA	93.6700	NA	1.0000
UZB	1	lm-eca	1677.6380	0.0000	0.0013	478.8510	NA	NA	NA	NA	180.7291	1.0000
VCT	1	um-lac	3212.1846	0.0000	0.0701	3231.3556	188.8774	NA	NA	NA	571.2663	1.0000
VEN	1	um-lac	2711.5972	0.0273	0.5675	5612.5335	226.0221	NA	NA	3.0850	1332.4404	1.0000
VIR	1	hi-sms	NA	0.4703	0.0000	NA	NA	NA	NA	NA	NA	1.0000
VNM	1	lm-eap	3222.4336	0.0000	0.0047	336.9966	NA	NA	NA	39.9025	120.9360	1.0000
VUT	1	lm-eap	532.8650	0.0000	0.0078	1849.8206	81.1941	NA	NA	NA	497.4431	1.0000

PSE	1	ot-sms	1111.2880	0.0000	0.0000	879.6077	NA	NA	NA	NA	383.8465	1.0000
WSM	1	lm-eap	NA	0.0000	0.0000	1713.7275	NA	NA	NA	NA	505.1022	1.0000
YEM	1	lm-mea	983.7282	0.0000	0.0213	683.0939	NA	1758.3217	NA	13.2475	NA	1.0000
ZAF	1	um-ssa	1910.8744	0.0826	0.2012	4815.2086	279.7262	728.6799	NA	50.5650	295.1163	1.0000
COD	1	ot-ssa	793.6792	0.0000	0.0000	390.0141	NA	NA	NA	NA	101.4718	1.0000
ZMB	1	lm-ssa	1494.9690	0.0034	0.0000	635.4177	13.8567	476.3698	NA	NA	196.0920	1.0000
ZWE	1	lo-ssa	1265.2490	0.0009	0.0000	653.9962	172.3115	NA	NA	0.0000	144.7671	1.0000
ABW	2	hi-sms	NA	3.6373	5.8746	23613.7080	1082.5518	NA	NA	NA	NA	1.0739
AND	2	ot-sms	NA	4.7747	16.1364	25103.7374	932.1570	NA	NA	NA	NA	1.2304
AFG	2	lo-sas	1297.3552	NA	0.0000	NA	NA	NA	NA	87.1540	NA	1.0779
AGO	2	um-ssa	588.9966	0.0242	0.0701	1167.1661	30.3163	NA	NA	NA	112.2753	1.1211
ALB	2	um-eca	2759.1632	0.0477	0.1336	1692.2884	58.0986	NA	NA	112.4840	784.1072	0.9830
ARE	2	hi-mea	3886.3120	5.1250	14.3752	45008.2558	498.7393	33050.0751	NA	NA	NA	1.1687
ARG	2	um-lac	3181.2004	0.9248	5.3243	5504.3345	186.3201	787.7630	NA	45.5020	3327.6165	1.0825
ARM	2	lm-eca	1734.5682	0.2717	0.1368	755.8797	15.4152	4320.4009	NA	102.8633	526.2976	0.9775
ASM	2	um-eap	NA	NA	2.6354	NA	NA	NA	NA	NA	NA	1.0595
ATG	2	hi-sms	1971.2052	3.5824	4.2471	10204.1910	330.6963	NA	NA	NA	317.9803	1.0739
AUS	2	hi-nao	2010.2324	18.8003	23.6289	28174.9169	1458.6739	376.5046	NA	108.2460	5969.5401	1.0975
AUT	2	hi-weu	5786.0374	11.3598	21.6911	32970.4114	1920.6735	71.0570	NA	121.2260	1408.0943	1.0754
AZE	2	um-eca	1688.0196	0.0341	1.2420	705.1157	25.4841	5678.2919	NA	75.1820	177.3224	0.9830
BDI	2	lo-ssa	1350.9970	0.0128	0.0099	159.4835	6.6496	NA	NA	30.6880	88.6222	1.0380
BEL	2	hi-weu	NA	6.1114	12.9698	31772.0646	971.1601	NA	NA	NA	9242.6440	1.0754
BEN	2	lo-ssa	1086.2970	0.0573	0.0665	486.1417	13.5935	NA	NA	NA	258.1821	1.0380
BFA	2	lo-ssa	854.8028	0.0317	0.0177	320.2805	4.6248	NA	NA	89.1260	169.6515	1.0380
BGD	2	lo-sas	2790.3056	0.0135	0.0399	317.1392	7.3783	NA	NA	79.1520	91.0472	1.0779
BGR	2	um-eca	2724.1158	1.3636	1.4653	2649.5490	85.5216	NA	NA	57.4600	857.1960	0.9830
BHR	2	hi-mea	NA	2.1549	11.4685	18130.5392	NA	NA	NA	NA	NA	1.1687
BHS	2	hi-sms	1895.2262	2.0340	2.7152	21545.7004	NA	NA	NA	NA	2910.8681	1.0739
BIH	2	um-eca	3576.8738	0.1031	0.4783	1618.2011	NA	NA	NA	75.6200	NA	0.9830
BLR	2	um-eca	2012.2404	0.1300	0.1115	1746.6736	95.8178	NA	NA	4.1880	626.0895	0.9830

BLZ	2	um-lac	2388.6918	1.6770	1.4707	3128.3961	170.4512	NA	NA	80.2540	646.8544	1.0825
BMU	2	hi-sms	NA	23.8562	16.0913	60264.8589	1297.5689	NA	NA	NA	NA	1.0739
BOL	2	lm-lac	1484.7660	0.4638	1.9987	944.4553	50.6785	NA	NA	81.5620	283.1601	1.0780
BRA	2	um-lac	2582.1154	0.9717	3.6254	4330.9808	192.3058	578.0753	NA	47.3880	906.5769	1.0825
BRB	2	hi-sms	2643.3334	1.1054	3.8626	12678.0931	539.5125	NA	NA	NA	392.1012	1.0739
BRN	2	hi-sms	1429.0566	4.6215	15.3795	26474.4481	1347.1719	2650.0600	NA	106.8460	553.4282	1.0739
BTN	2	lm-sas	1525.2300	0.1376	0.0000	879.0051	NA	NA	NA	35.6480	356.3910	1.1099
BWA	2	um-ssa	316.0018	0.4509	1.2462	4371.9097	NA	218.4886	NA	32.1440	248.5715	1.1211
CAF	2	lo-ssa	925.0134	0.0222	0.0473	345.1707	5.8351	NA	NA	NA	259.0863	1.0380
CAN	2	hi-nao	2799.7228	17.4160	15.0335	30033.5654	1745.7504	NA	NA	114.5420	NA	1.0975
CHE	2	hi-weu	6460.2610	16.4003	19.4419	49296.7630	2596.8405	NA	NA	146.9680	1931.7782	1.0754
CHL	2	hi-lac	4471.4722	1.5707	5.5014	6191.1264	196.8300	NA	NA	85.5920	1594.7790	1.1975
CHN	2	um-eap	4854.9800	0.1854	1.4365	911.9883	17.1168	3411.4086	NA	89.2460	250.2758	1.0595
CIV	2	lm-ssa	1391.6314	0.0414	0.5100	1094.0047	44.1656	273.9934	NA	81.5940	NA	1.1440
CMR	2	lm-ssa	1449.9562	0.0497	0.0290	824.6123	NA	NA	NA	72.2380	278.0581	1.1440
COG	2	lm-ssa	796.7926	0.0068	0.0786	1600.4144	71.7834	NA	NA	70.9240	164.5121	1.1440
COL	2	um-lac	2888.3384	0.7785	3.0344	3142.8823	131.4400	NA	NA	51.1200	943.3741	1.0825
COM	2	lo-ssa	1195.3826	0.0620	0.0000	603.1744	22.8060	NA	NA	NA	324.0551	1.0380
CPV	2	lm-ssa	406.0946	0.6246	0.4205	1249.8421	82.7520	NA	NA	98.2120	305.2555	1.1440
CRI	2	um-lac	3699.4914	1.8938	2.0201	3840.1533	154.0700	NA	NA	46.9780	834.3744	1.0825
CUB	2	um-lac	2159.7440	0.1283	0.0300	2655.8164	172.1888	741.3235	NA	29.9600	718.3260	1.0825
CUW	2	hi-sms	NA	NA	NA	NA	NA	NA	NA	NA	NA	1.0739
CYM	2	hi-sms	NA	3.9490	13.5920	NA	NA	NA	NA	NA	NA	1.0739
CYP	2	hi-weu	1832.3768	5.1389	10.5670	19031.3464	654.5562	1568.0770	NA	134.1740	1590.9459	1.0754
CZE	2	hi-weu	4163.8572	3.4077	7.1666	10281.6157	429.2531	6.1252	NA	98.4540	927.4184	1.0754
DEU	2	hi-weu	6380.2686	8.4655	13.1493	31743.9318	1453.2486	135.1350	NA	109.2180	957.7926	1.0754
DJI	2	lm-mea	1833.3334	0.0661	0.0233	881.4080	67.1914	NA	NA	NA	112.5589	1.1139
DMA	2	um-lac	1581.2390	1.8929	0.7006	4551.7036	276.4789	NA	NA	NA	1886.9045	1.0825
DNK	2	hi-weu	6102.6302	14.8367	30.7994	42769.2558	3421.5481	NA	NA	113.1540	3675.9714	1.0754
DOM	2	um-lac	3873.4372	0.3147	2.1811	2864.2224	32.7555	8429.4344	NA	36.2580	546.7065	1.0825

DZA	2	um-mea	972.7230	0.0467	0.0802	2381.2783	NA	NA	NA	90.8300	420.9336	1.0705
ECU	2	um-lac	1949.1956	0.2378	1.4410	2745.2941	52.5205	NA	NA	23.5140	593.6661	1.0825
EGY	2	lm-mea	6594.4358	0.1243	0.2016	1025.0662	47.5906	17732.2253	NA	59.7180	265.8873	1.1139
ERI	2	lo-ssa	530.5462	0.0087	0.0000	263.5523	10.1306	NA	NA	32.5640	71.4408	1.0380
ESP	2	hi-weu	2783.0870	3.1926	14.9401	21698.7004	975.3080	1673.9142	NA	106.3900	3241.3621	1.0754
EST	2	hi-weu	1748.8132	7.4615	12.6648	5904.8044	374.0991	9.1069	NA	70.2800	876.6527	1.0754
ETH	2	lo-ssa	1155.3786	0.0058	0.0021	133.9047	3.7738	NA	NA	76.4460	74.3077	1.0380
FIN	2	hi-weu	3040.2236	21.5773	42.0637	30119.7410	2022.5462	23.2785	NA	123.2640	4814.3788	1.0754
FJI	2	um-eap	2090.8610	0.3745	1.0616	3177.2344	169.4875	NA	NA	65.0400	847.2307	1.0595
FRA	2	hi-weu	7017.3360	4.7844	14.3890	30705.0344	1797.3827	183.3969	NA	114.2940	2369.4791	1.0754
FRO	2	hi-sms	NA	8.1111	12.3523	NA	NA	NA	NA	NA	NA	1.0739
FSM	2	lm-eap	1032.7450	1.3763	0.0000	2152.8805	137.9824	NA	NA	NA	672.8190	1.0396
GAB	2	um-ssa	1573.2824	0.1168	0.6786	7313.2647	237.5990	NA	NA	NA	1468.7645	1.1211
GBR	2	hi-weu	6918.6558	9.6736	21.8410	32471.6430	1567.2090	281.8697	NA	NA	993.9588	1.0754
GEO	2	lm-eca	2110.0562	0.1264	0.9333	880.5834	18.7265	NA	NA	109.5540	415.9561	0.9775
GHA	2	lm-ssa	1339.1750	0.0341	0.1698	422.5029	17.3830	NA	NA	17.4460	NA	1.1440
GIN	2	lo-ssa	1463.7624	0.0147	0.1212	275.4901	6.5111	NA	NA	49.3960	82.6155	1.0380
GMB	2	lo-ssa	1075.5994	0.2036	0.3436	411.9957	9.1876	NA	NA	33.3200	184.2429	1.0380
GNB	2	lo-ssa	1206.3686	0.0527	0.0000	499.8933	26.1386	529.4393	NA	159.3100	NA	1.0380
GNQ	2	hi-sms	NA	0.0778	0.0515	2290.6362	51.3003	NA	NA	NA	NA	1.0739
GRC	2	hi-weu	3699.3580	2.8187	14.1209	17064.1051	540.1584	NA	NA	117.2220	3494.2578	1.0754
GRD	2	um-lac	1101.2644	1.0494	1.0610	4719.3918	NA	NA	NA	NA	498.2053	1.0825
GRL	2	hi-sms	NA	9.2124	12.5376	25476.0037	NA	NA	NA	NA	NA	1.0739
GTM	2	lm-lac	1720.4548	0.2355	1.0939	1994.4725	31.6234	NA	NA	NA	456.8869	1.0780
GUM	2	hi-sms	2154.7620	3.4717	6.5052	NA	NA	NA	NA	NA	NA	1.0739
GUY	2	lm-lac	3917.1416	1.1070	0.2205	1044.6344	63.5840	NA	NA	NA	478.3185	1.0780
HKG	2	hi-sms	NA	10.8526	36.2050	21038.8674	573.9419	NA	NA	NA	NA	1.0739
HND	2	lm-lac	1390.1158	0.2253	0.4314	1211.0670	43.3496	NA	NA	63.5360	306.0824	1.0780
HRV	2	hi-weu	4635.4354	2.1562	3.0555	7415.2303	NA	NA	NA	95.2020	841.5991	1.0754
HTI	2	lo-lac	955.8532	0.0340	0.0834	499.6939	NA	NA	NA	NA	NA	0.9896

HUN	2	um-eca	4422.2234	2.6683	8.0538	7975.5991	368.1318	NA	NA	71.1840	878.2359	0.9830
IDN	2	lm-eap	3902.3276	0.1955	0.4911	1133.5913	11.9123	NA	NA	39.4060	250.6699	1.0396
IMN	2	ot-sms	NA	NA	NA	22787.1936	NA	NA	NA	NA	NA	1.2304
IND	2	lm-sas	2216.6776	0.1111	0.0866	513.5320	18.3068	NA	NA	58.3320	164.2711	1.1099
IRL	2	hi-weu	6800.3698	5.2852	19.4780	34465.2050	1589.9769	NA	NA	104.3480	1629.5977	1.0754
IRN	2	um-mea	1960.6622	0.1090	0.3748	2097.4101	88.5466	4515.3396	NA	29.1860	590.8887	1.0705
IRQ	2	um-mea	791.1254	NA	0.0000	1519.1668	NA	9847.1034	NA	69.7320	381.0501	1.0705
ISL	2	hi-weu	NA	26.2120	30.5376	43612.5245	2586.6686	NA	NA	NA	38107.0823	1.0754
ISR	2	hi-mea	2407.4274	6.2483	28.6577	18511.4689	1279.8087	NA	NA	159.5960	NA	1.1687
ITA	2	hi-weu	4898.1970	4.5523	25.6219	29049.6038	1334.9798	NA	NA	122.2400	1989.8161	1.0754
JAM	2	um-lac	1253.3496	1.1666	3.0815	NA	NA	4633.8216	NA	41.8360	649.6445	1.0825
JOR	2	um-mea	1492.8708	0.9001	1.2210	1878.1932	117.6333	NA	NA	78.6680	283.0257	1.0705
JPN	2	hi-eap	6005.5590	9.9872	28.9256	33499.4612	1169.0481	12891.1461	NA	125.6820	2403.4246	1.0755
KAZ	2	um-eca	807.9658	0.1406	0.1410	2035.5018	82.5111	1027.6898	NA	47.7320	416.0100	0.9830
KEN	2	lo-ssa	1514.0520	0.0417	0.0312	513.5343	27.3329	NA	NA	73.7520	148.1439	1.0380
KGZ	2	lm-eca	2227.5916	0.1388	0.0161	376.5814	18.9117	7085.2850	NA	54.6900	171.5389	0.9775
KHM	2	lo-eap	1810.3594	0.0180	0.3807	280.1473	3.1259	NA	NA	88.9420	151.3661	0.7592
KIR	2	lm-eap	NA	0.9141	0.0547	1030.8695	109.7345	NA	NA	NA	466.5950	1.0396
KNA	2	hi-sms	NA	2.9871	0.9269	9327.9351	413.6344	NA	NA	NA	243.7749	1.0739
KOR	2	hi-eap	6289.5324	7.2757	21.6065	13155.2632	432.1050	NA	NA	88.8580	2428.4960	1.0755
KWT	2	hi-sms	4122.0518	2.2083	12.1589	30649.6158	1750.4869	53997.2667	NA	NA	NA	1.0739
LAO	2	lm-eap	2664.4918	0.0237	0.1112	333.5649	6.1752	NA	NA	32.7040	167.1021	1.0396
LBN	2	um-mea	2067.8534	1.9104	11.7164	5445.2057	114.2167	5063.5017	NA	98.6220	1522.4646	1.0705
LBR	2	lo-ssa	1237.8910	0.0066	0.0000	93.3853	NA	NA	NA	NA	NA	1.0380
LBY	2	um-mea	709.9578	0.1336	0.2383	6802.9882	188.0802	2093.0096	NA	NA	NA	1.0705
LCA	2	um-lac	NA	1.0411	1.0808	5170.7476	378.5265	NA	NA	NA	657.0615	1.0825
LIE	2	hi-sms	NA	NA	25.4078	91253.3379	NA	NA	NA	NA	NA	1.0739
LKA	2	lm-sas	3159.2794	0.1734	0.7201	930.5609	29.0363	NA	NA	67.5700	173.2844	1.1099
LSO	2	lm-ssa	1053.6220	0.0183	0.2914	603.4735	75.2441	NA	NA	NA	83.6910	1.1440
LTU	2	hi-weu	2258.3800	1.5377	4.6716	4523.6371	238.6246	2.7675	NA	144.0500	891.7025	1.0754

LUX	2	hi-weu	NA	8.6838	22.5198	61589.0967	2226.1833	NA	NA	NA	3526.9398	1.0754
LVA	2	hi-sms	2024.8260	2.6422	4.6643	3763.4194	220.9023	34.6978	NA	100.6820	558.9736	1.0739
MAC	2	hi-sms	NA	3.9173	16.0497	16404.2933	604.0481	NA	NA	NA	NA	1.0739
MAF	2	hi-sms	NA	NA	NA	NA	NA	NA	NA	NA	NA	1.0739
MAR	2	lm-mea	966.6820	0.0698	0.4509	1542.6496	84.8698	1101.9475	NA	105.6800	490.0249	1.1139
MCO	2	hi-sms	NA	NA	25.5628	114245.2238	1317.2608	NA	NA	NA	NA	1.0739
MDA	2	lm-eca	2780.6590	0.1795	0.1342	611.4695	44.5173	NA	NA	36.4660	172.1683	0.9775
MDG	2	lo-ssa	1962.3280	0.0623	0.0751	277.3882	6.0005	NA	NA	46.3880	104.7091	1.0380
MDV	2	um-sas	1396.8070	0.4452	0.4437	NA	NA	NA	NA	NA	NA	1.3968
MEX	2	um-lac	2619.7250	0.8107	2.8831	7040.1154	259.8221	NA	NA	77.0300	978.5941	1.0825
MHL	2	um-eap	NA	0.3344	0.7288	2477.1085	359.9082	NA	NA	NA	NA	1.0595
MKD	2	um-eca	2845.9444	0.6242	0.9128	2494.7688	112.5345	1782.5293	NA	105.5440	757.4492	0.9830
MLI	2	lo-ssa	1070.7040	0.0232	0.0306	354.6343	10.5959	NA	NA	99.0080	198.4869	1.0380
MLT	2	hi-weu	3516.1000	3.8915	5.0210	13017.4833	573.7836	777.7778	NA	86.7040	3886.6619	1.0754
MMR	2	lo-eap	2865.5664	0.0002	0.0164	NA	NA	NA	NA	16.7220	NA	0.7592
MNE	2	um-eca	NA	NA	NA	3275.9644	NA	NA	NA	NA	NA	0.9830
MNG	2	lm-eap	679.7540	0.1588	0.3925	732.3645	35.6256	177.2141	NA	60.1060	562.8184	1.0396
MNP	2	hi-sms	NA	NA	3.2023	NA	NA	NA	NA	NA	NA	1.0739
MOZ	2	lo-ssa	824.3296	0.0228	0.0245	212.3499	6.3625	NA	NA	43.6060	91.8938	1.0380
MRT	2	lm-ssa	832.3896	0.0544	0.0000	568.0554	13.5593	NA	NA	NA	392.6564	1.1440
MUS	2	um-ssa	4769.1834	1.9692	4.0825	3957.8521	156.0676	5077.4834	NA	92.4600	508.6022	1.1211
MWI	2	lo-ssa	1364.3420	0.0367	0.0820	219.1157	10.5154	324.8935	NA	24.2100	74.0693	1.0380
MYS	2	um-eap	3019.1884	4.4725	8.8145	4573.1984	223.7152	2564.9848	NA	85.5740	1052.9763	1.0595
NAM	2	um-ssa	299.4332	0.1394	0.8010	2933.2246	211.7800	234.6930	NA	44.1540	468.2412	1.1211
NCL	2	hi-sms	3579.4508	1.7743	4.5886	NA	NA	NA	NA	NA	NA	1.0739
NER	2	lo-ssa	328.2210	0.0085	0.0070	268.3723	7.7652	NA	NA	54.1180	NA	1.0380
NGA	2	lm-ssa	1210.9454	0.0231	0.0151	542.7276	NA	NA	NA	36.9940	216.4714	1.1440
NIC	2	lm-lac	1679.5080	0.2244	0.3219	968.4166	24.9621	NA	NA	63.6480	333.5448	1.0780
NLD	2	hi-weu	7603.0018	18.3215	17.0350	35809.4704	1757.2644	NA	NA	106.3540	2793.0110	1.0754
NOR	2	hi-weu	3858.6462	21.5303	39.1151	56332.0784	4193.6075	NA	NA	112.5700	3303.0431	1.0754

STP	2	lm-ssa	2163.1716	0.3295	0.0000	NA	NA	NA	NA	NA	NA	1.1440
SUR	2	um-lac	3836.6268	0.9812	1.3129	2953.8639	NA	NA	NA	26.2780	524.0101	1.0825
SVK	2	hi-weu	4087.6490	2.1215	5.0913	8503.3949	361.8518	43.2523	NA	94.3080	660.6483	1.0754
SVN	2	hi-weu	5296.0594	7.6557	9.6033	13520.2905	676.2527	NA	NA	91.2320	841.6190	1.0754
SWE	2	hi-weu	4525.3256	22.5540	38.1766	34269.5017	2437.9540	53.9800	NA	110.1080	2406.9159	1.0754
SWZ	2	lm-ssa	1871.2958	0.1414	0.3585	2145.6681	112.2057	NA	NA	NA	200.9894	1.1440
SXM	2	hi-sms	NA	NA	NA	NA	NA	NA	NA	NA	NA	1.0739
SYC	2	um-ssa	NA	2.6724	6.3466	10521.9820	705.9966	NA	NA	NA	672.6962	1.1211
SYR	2	lm-mea	1488.9540	0.0441	0.0050	1422.7241	52.6213	2706.6516	NA	89.1700	NA	1.1139
TCA	2	hi-sms	NA	NA	NA	NA	NA	NA	NA	NA	NA	1.0739
TCD	2	lo-ssa	625.1874	0.0057	0.0000	387.6418	9.2425	NA	NA	NA	NA	1.0380
TGO	2	lo-ssa	907.6192	0.2236	0.1175	415.4596	17.4501	NA	NA	94.8760	223.0154	1.0380
THA	2	um-eap	2518.8070	0.8137	3.2000	2239.5017	93.7198	NA	NA	78.4340	354.5339	1.0595
TJK	2	lo-eca	1147.9268	0.0328	0.0049	219.3046	4.7748	13583.9998	NA	NA	63.1326	1.2114
TKM	2	um-eca	1626.1204	0.0450	0.0432	1221.6269	NA	13248.0842	NA	37.0367	251.2301	0.9830
TLS	2	lo-sas	1898.8304	NA	NA	434.7538	NA	NA	NA	NA	NA	1.0779
TON	2	um-eap	NA	0.5162	0.2057	2237.6301	123.6613	NA	NA	NA	568.3972	1.0595
TTO	2	hi-sms	3245.9298	2.0527	1.5527	7444.9613	228.2644	459.4670	NA	78.2460	103.3310	1.0739
TUN	2	um-mea	1211.6884	0.3586	0.2383	2453.1343	157.5928	854.0076	NA	93.8340	679.6106	1.0705
TUR	2	um-eca	2141.9494	0.7478	4.7073	5827.4795	101.2404	NA	NA	9.9380	1754.7321	0.9830
TUV	2	um-eap	NA	NA	0.0000	2141.8968	NA	NA	NA	NA	875.4417	1.0595
TZA	2	lo-ssa	1471.2474	0.0235	0.0751	287.9866	6.6913	NA	NA	64.8980	118.4151	1.0380
UGA	2	lo-ssa	1430.8932	0.0377	0.0842	252.0378	NA	NA	NA	NA	89.0366	1.0380
UKR	2	lm-eca	2224.1092	0.2094	0.1737	1165.3120	52.5547	NA	NA	34.0940	395.4474	0.9775
URY	2	hi-lac	3377.4168	4.4961	4.1869	5091.7473	129.6442	NA	NA	41.0820	4867.2200	1.1975
USA	2	hi-nao	5301.7914	22.6430	20.8904	37301.7454	1817.1614	1098.0241	NA	106.0680	1690.5420	1.0975
UZB	2	lm-eca	2161.7620	0.0136	0.0810	413.4679	NA	12149.6380	NA	NA	158.9692	0.9775
VCT	2	um-lac	3347.3034	1.2349	0.5579	3694.6566	212.6825	NA	NA	NA	541.7191	1.0825
VEN	2	um-lac	3098.7820	0.9971	6.6855	5505.9099	NA	NA	NA	21.2040	1422.3828	1.0825
VIR	2	hi-sms	NA	6.9435	21.8574	NA	NA	NA	NA	NA	NA	1.0739

VNM	2	lm-eap	3760.9078	0.0365	0.2035	462.8435	NA	NA	NA	64.2920	140.5859	1.0396
VUT	2	lm-eap	550.7104	0.2522	0.1138	1936.9881	133.7551	NA	NA	66.6700	520.0785	1.0396
PSE	2	ot-sms	1367.3506	NA	NA	1162.6094	NA	NA	NA	NA	446.1456	1.2304
WSM	2	lm-eap	NA	0.2301	0.5400	1889.3700	85.1831	NA	NA	NA	524.9897	1.0396
YEM	2	lm-mea	1026.0290	0.0239	0.0895	728.7873	NA	NA	NA	35.0560	NA	1.1139
ZAF	2	um-ssa	2114.5946	2.0346	5.4456	4806.2826	282.6833	637.3518	NA	72.2620	282.8834	1.1211
COD	2	ot-ssa	789.3252	0.0004	0.0211	260.7115	NA	NA	NA	NA	102.5710	0.9945
ZMB	2	lm-ssa	1438.2550	0.0409	0.0938	599.0041	12.4964	473.3715	NA	NA	210.0074	1.1440
ZWE	2	lo-ssa	1100.5084	0.0602	0.3216	696.0889	NA	NA	NA	0.0120	168.1126	1.0380
ABW	3	hi-sms	NA	19.0286	62.0733	23284.5049	1093.6282	NA	NA	NA	NA	0.9475
AND	3	ot-sms	NA	15.5459	53.4951	29219.5714	574.8685	NA	NA	NA	NA	1.7533
AFG	3	lo-sas	1255.1360	0.0507	0.6952	236.1968	NA	2588.5452	3.7380	109.3040	111.3955	1.1467
AGO	3	um-ssa	582.8564	0.2694	1.7097	1350.5416	35.3345	66.8853	2.6498	NA	164.1265	1.5163
ALB	3	um-eca	3229.9498	0.8445	22.4094	2350.5154	74.3456	1833.8661	98.9054	104.9900	919.6571	1.0745
ARE	3	hi-mea	3589.0196	27.5646	74.4699	45913.9285	NA	34220.1081	702.3991	NA	4331.0940	1.2879
ARG	3	um-lac	3448.4750	11.1304	21.8093	5096.6548	174.9077	NA	39.1299	77.3240	3690.1755	1.4718
ARM	3	lm-eca	1890.8838	2.8732	2.8461	1141.7505	27.3962	2510.9414	29.7238	96.3860	655.7637	1.0692
ASM	3	um-eap	NA	NA	3.5970	NA	NA	NA	NA	NA	NA	1.1380
ATG	3	hi-sms	1598.0590	13.8753	46.1580	10869.6442	372.8001	325.0000	15.9167	NA	275.6543	0.9475
AUS	3	hi-nao	1812.7768	49.7227	63.8522	31902.8584	1561.3474	347.5180	48.2397	115.3480	7448.1764	1.1840
AUT	3	hi-weu	5975.2138	41.2911	85.5310	36786.9448	2070.9166	71.9919	220.1256	108.9500	1417.7174	1.1553
AZE	3	um-eca	2550.1784	1.8177	10.7028	1058.0224	36.5454	4137.5896	10.0169	81.9300	255.3901	1.0745
BDI	3	lo-ssa	1281.4208	0.1704	0.7384	148.9527	4.5781	226.7059	0.9198	64.0760	76.7795	1.0382
BEL	3	hi-weu	8491.1892	42.1760	75.6463	35301.8660	2122.3603	45.0837	327.1950	100.2660	11142.9783	1.1553
BEN	3	lo-ssa	1082.3724	0.6851	2.8739	528.9810	18.1707	23.0806	5.7406	NA	288.3862	1.0382
BFA	3	lo-ssa	941.3024	0.2419	1.3353	366.4933	NA	93.0727	7.7866	94.2040	108.3935	1.0382
BGD	3	lo-sas	3401.8276	0.1407	0.8663	373.9341	8.8278	NA	173.1925	83.6100	104.6886	1.1467
BGR	3	um-eca	2992.8346	10.4466	33.5352	3144.1840	105.3926	218.7688	113.9825	108.4040	940.8688	1.0745
BHR	3	hi-mea	NA	16.4513	52.6693	18226.6229	NA	NA	3022.6765	NA	NA	1.2879
BHS	3	hi-sms	3095.2380	15.9600	33.2783	23724.7338	675.9049	NA	NA	NA	3021.5981	0.9475

BIH	3	um-eca	3307.0496	4.8732	19.3821	2427.0397	NA	NA	36.2658	99.0820	NA	1.0745
BLR	3	um-eca	2371.3212	5.0373	8.2098	2407.2206	143.1906	146.6861	139.5100	70.6260	751.1378	1.0745
BLZ	3	um-lac	2704.2674	5.8139	19.0480	3834.9757	206.4910	1008.8083	276.2524	89.6760	838.6538	1.4718
BMU	3	hi-sms	NA	52.0008	45.7278	72738.9876	1252.2145	NA	NA	NA	NA	0.9475
BOL	3	lm-lac	1744.1904	2.9258	12.2419	972.5551	58.3269	NA	4.2609	95.2460	307.3297	1.1341
BRA	3	um-lac	3034.7464	9.7660	22.0285	4473.2024	175.4648	NA	141.3640	86.0440	1215.6225	1.4718
BRB	3	hi-sms	2625.7886	26.6472	38.3452	13597.0127	771.3878	3859.0014	113.2674	NA	354.3772	0.9475
BRN	3	hi-sms	744.0710	17.3109	44.2844	26303.6346	975.0120	NA	196.5000	107.1280	771.4226	0.9475
BTN	3	lm-sas	1842.9910	1.7071	0.6770	1106.2720	65.2753	NA	9.0158	65.8440	397.1820	1.2203
BWA	3	um-ssa	506.3802	3.2739	20.4255	4892.4904	NA	329.2412	NA	64.0840	216.3175	1.5163
CAF	3	lo-ssa	1007.7694	0.1271	0.6707	342.8270	5.3961	0.2077	NA	NA	286.7296	1.0382
CAN	3	hi-nao	2705.8860	60.6499	37.9760	34201.8864	1765.3630	NA	57.0635	120.6880	NA	1.1840
CHE	3	hi-weu	6202.4140	59.3000	77.5112	52891.2724	2908.2936	122.4552	205.3378	113.3100	1858.5140	1.1553
CHL	3	hi-lac	5105.7264	22.2903	39.3636	6847.5186	257.8786	13060.7227	376.4229	99.6320	2159.0358	1.3509
CHN	3	um-eap	4899.5522	4.5023	16.0158	1326.0468	NA	NA	374.7543	79.1580	304.9932	1.1380
CIV	3	lm-ssa	1766.8060	0.5466	6.1736	1014.7244	42.4621	215.8101	29.1944	97.3720	NA	1.1510
CMR	3	lm-ssa	1667.7882	0.4907	4.4590	894.5810	25.0085	123.6538	9.6622	92.8920	319.1152	1.1510
COG	3	lm-ssa	791.4166	0.3507	6.9217	1624.1701	45.1244	8.1636	2.6510	93.0180	177.5788	1.1510
COL	3	um-lac	3378.5190	5.2339	12.8179	3142.8313	125.1048	2056.1050	318.2583	89.3080	919.3723	1.4718
COM	3	lo-ssa	1219.2896	0.6890	0.3564	627.1941	23.9260	58.7500	NA	NA	357.7151	1.0382
CPV	3	lm-ssa	468.9884	3.5341	9.2232	1748.7949	134.4075	432.9048	NA	100.0000	430.4402	1.1510
CRI	3	um-lac	3417.9930	15.2761	13.2406	4240.2778	204.7430	NA	703.6652	69.7700	958.6632	1.4718
CUB	3	um-lac	2928.5124	3.8082	0.2563	3163.9064	290.1380	NA	24.3792	30.5340	837.8592	1.4718
CUW	3	hi-sms	NA	NA	NA	NA	NA	NA	NA	NA	NA	0.9475
CYM	3	hi-sms	NA	NA	44.9095	NA	NA	NA	NA	NA	NA	0.9475
CYP	3	hi-weu	1908.7182	25.2628	43.7135	21578.5627	970.7531	1534.9962	149.7631	133.4880	1486.6650	1.1553
CZE	3	hi-weu	4425.3344	23.6415	79.0746	11649.6394	475.9609	5.8809	86.7539	112.2720	930.9132	1.1553
DEU	3	hi-weu	6572.5286	46.2635	71.5842	34138.2750	NA	96.3969	218.2993	100.1260	1011.9336	1.1553
DJI	3	lm-mea	1742.8572	0.4865	2.0009	866.4704	76.3982	3000.1000	NA	NA	115.9608	1.2075
DMA	3	um-lac	2013.7420	18.8850	24.7346	4978.1528	NA	NA	144.4667	NA	1853.7833	1.4718

DNK	3	hi-weu	6042.8430	60.7140	80.9271	46797.4383	3924.1819	72.5430	126.2477	104.4180	4044.9047	1.1553
DOM	3	um-lac	4120.2660	6.3444	18.4384	3360.9808	65.4160	2639.2059	62.4485	51.4960	667.4667	1.4718
DZA	3	um-mea	1172.6530	1.9119	4.1880	2694.6835	NA	463.3533	13.5793	93.7440	526.6890	1.1984
ECU	3	um-lac	2423.5480	3.5376	13.3608	2731.5469	31.4681	5726.0905	180.6579	97.9400	673.1674	1.4718
EGY	3	lm-mea	7379.3394	4.0316	6.3942	1175.1568	56.5316	20387.5665	539.2924	70.9160	292.3078	1.2075
ERI	3	lo-ssa	341.7732	0.1739	0.0857	244.2296	8.6529	503.6473	2.6233	66.9200	45.3826	1.0382
ESP	3	hi-weu	3333.4864	27.2207	78.6222	25249.6309	1075.8384	1761.0924	168.3751	98.4920	3600.5920	1.1553
EST	3	hi-weu	2084.0878	40.0289	65.3672	8189.0905	429.8602	46.9237	66.7426	85.4320	1065.8679	1.1553
ETH	3	lo-ssa	1190.7722	0.0772	0.0841	142.0488	5.4614	506.5722	11.0080	76.3280	70.7338	1.0382
FIN	3	hi-weu	3269.3198	56.8788	85.1660	36233.2476	2248.6899	22.7095	129.0914	108.9440	5063.0414	1.1553
FJI	3	um-eap	2410.3854	4.7292	11.7077	3436.0242	205.1788	294.1200	45.3412	71.9200	835.5072	1.1380
FRA	3	hi-weu	7023.8298	29.2208	63.4629	33881.8356	1938.4117	246.3613	215.5862	100.0560	2517.7945	1.1553
FRO	3	hi-sms	NA	50.9818	64.9150	NA	NA	NA	NA	NA	NA	0.9475
FSM	3	lm-eap	1063.8650	6.8432	3.5163	2307.9814	154.8200	NA	0.6667	NA	678.8037	1.1505
GAB	3	um-ssa	1560.5504	2.0284	20.5193	6362.2043	243.3699	124.0015	4.7662	NA	1720.2717	1.5163
GBR	3	hi-weu	6918.4076	49.4426	85.0264	37236.6893	1835.4875	227.1545	306.8582	NA	1021.9089	1.1553
GEO	3	lm-eca	1875.0264	1.9020	11.1271	1173.4749	27.0447	NA	26.2924	117.5400	406.4326	1.0692
GHA	3	lm-ssa	1322.7984	0.8188	3.1926	463.6894	29.9181	160.0039	7.9283	56.7220	NA	1.1510
GIN	3	lo-ssa	1487.6854	0.3266	0.9947	298.7610	7.0840	124.4972	0.9428	91.8140	97.1652	1.0382
GMB	3	lo-ssa	1181.3588	1.9600	7.2202	439.5893	5.6851	130.2178	8.5310	60.6220	239.7457	1.0382
GNB	3	lo-ssa	1108.5842	0.9430	0.5861	412.3095	NA	503.5227	NA	91.4900	277.0438	1.0382
GNQ	3	hi-sms	NA	0.3967	5.4874	8106.6716	60.5160	7.6921	NA	NA	NA	0.9475
GRC	3	hi-weu	3843.9304	14.7928	75.2561	20317.4196	730.5965	3278.1963	164.9616	102.9220	3504.9926	1.1553
GRD	3	um-lac	1662.0652	12.4333	20.2868	5676.7424	221.2880	NA	NA	NA	576.5934	1.4718
GRL	3	hi-sms	NA	44.4000	42.2798	29006.0191	NA	NA	NA	NA	NA	0.9475
GTM	3	lm-lac	1705.7334	3.0982	14.7048	2109.6527	NA	NA	105.4694	NA	484.0336	1.1341
GUM	3	hi-sms	2054.5454	28.5128	39.1402	NA	NA	NA	NA	NA	NA	0.9475
GUY	3	lm-lac	4040.6550	9.9092	13.3971	1089.4259	82.7442	3555.5200	33.6667	NA	484.6616	1.1341
HKG	3	hi-sms	NA	43.6363	96.3076	22935.9227	961.4230	NA	493.0000	NA	NA	0.9475
HND	3	lm-lac	1415.3100	3.1233	5.4862	1277.4227	NA	NA	73.9402	90.4340	325.4889	1.1341

HRV	3	hi-weu	4384.4874	17.9247	47.3527	8984.8118	349.2739	NA	287.4583	101.8040	945.5970	1.1553
HTI	3	lo-lac	906.6852	1.7028	2.2418	475.0372	NA	1033.3333	NA	NA	NA	0.9387
HUN	3	um-eca	4221.9260	17.5136	62.2227	9725.9100	517.5569	147.8167	96.2981	103.8440	937.1774	1.0745
IDN	3	lm-eap	4152.6744	2.0131	6.4921	1148.2369	31.8111	4300.2378	128.7669	68.1380	282.6179	1.1505
IMN	3	ot-sms	NA	NA	NA	31558.7144	NA	NA	NA	NA	NA	1.7533
IND	3	lm-sas	2330.8074	1.2776	1.9900	623.4929	23.0928	3487.7647	106.9259	73.0820	170.9702	1.2203
IRL	3	hi-weu	7476.6802	27.6279	79.8979	46468.6249	2026.3353	NA	532.4075	97.9780	1723.9774	1.1553
IRN	3	um-mea	2167.2190	4.2937	4.0601	2417.9822	113.3549	5275.7061	87.5942	63.7860	684.0153	1.1984
IRQ	3	um-mea	952.7200	0.5250	0.5079	1781.4547	NA	11791.7007	24.3627	49.2200	336.8426	1.1984
ISL	3	hi-weu	NA	68.0007	89.9885	50570.4638	3672.9632	542.5752	135.5194	NA	38193.6985	1.1553
ISR	3	hi-mea	2784.7630	19.6762	95.9561	19719.6035	1315.0859	3049.4791	285.2323	89.3020	NA	1.2879
ITA	3	hi-weu	4905.2378	28.1306	92.7558	31530.1827	1459.8512	2437.9537	176.7475	103.6760	2027.7602	1.1553
JAM	3	um-lac	1190.2924	6.1758	42.6082	NA	NA	NA	110.2713	71.8300	537.4687	1.4718
JOR	3	um-mea	1424.4000	6.6959	21.8848	2044.8048	NA	NA	994.3763	83.1940	278.7171	1.1984
JPN	3	hi-eap	5968.7068	45.1892	63.4828	34366.8413	1238.3721	12852.6776	340.7997	108.4660	2685.1110	1.0698
KAZ	3	um-eca	1053.5192	1.6001	7.5635	2917.7371	83.1121	663.4427	1.4670	87.1120	483.6771	1.0745
KEN	3	lo-ssa	1580.7602	1.6222	3.5747	501.4439	29.9438	NA	29.3636	85.8900	156.4019	1.0382
KGZ	3	lm-eca	2770.4512	3.2086	1.9583	444.4860	18.5980	7028.1124	17.8144	85.3840	209.7190	1.0692
KHM	3	lo-eap	2066.7320	0.1824	3.2509	371.0688	6.3425	NA	5.0165	78.2040	154.2990	0.8898
KIR	3	lm-eap	NA	2.6245	0.5403	1176.0746	136.0363	NA	NA	NA	469.1602	1.1505
KNA	3	hi-sms	NA	16.4875	24.7731	10200.8108	430.4279	NA	46.0000	NA	225.5462	0.9475
KOR	3	hi-eap	6261.7706	59.7800	68.2376	16580.9818	660.9661	9412.0344	468.7801	107.5120	2604.9740	1.0698
KWT	3	hi-sms	2384.2068	14.1724	55.4181	29711.9984	1878.4335	42408.6931	587.7778	NA	NA	0.9475
LAO	3	lm-eap	3146.9466	0.2512	1.4702	409.9294	8.9600	NA	NA	78.3100	205.3830	1.1505
LBN	3	um-mea	2579.3258	7.7472	22.4713	5334.6853	133.4079	7062.6900	210.8978	96.0000	1533.1566	1.1984
LBR	3	lo-ssa	1012.0202	0.0294	0.9514	187.7146	NA	31.7021	NA	NA	278.2156	1.0382
LBY	3	um-mea	602.9432	1.8291	2.8911	6835.3553	NA	1988.9517	50.3395	NA	NA	1.1984
LCA	3	um-lac	NA	14.0584	27.0433	5469.9818	290.5286	NA	NA	NA	330.2362	1.4718
LIE	3	hi-sms	NA	52.7840	48.8096	102609.9047	2509.8597	NA	NA	NA	NA	0.9475
LKA	3	lm-sas	3402.8960	1.0793	5.7947	1101.8268	NA	12995.9108	283.5857	87.6460	179.6301	1.2203

LSO	3	lm-ssa	731.5518	1.0530	5.6843	668.6967	84.2254	12.1022	NA	NA	83.5583	1.1510
LTU	3	hi-weu	2855.2780	17.6873	49.2488	6067.5609	334.0240	32.2890	143.7665	104.5140	916.2425	1.1553
LUX	3	hi-weu	5658.7490	43.8642	98.7591	74804.0265	2802.5415	3.2256	394.0753	105.0840	3261.1737	1.1553
LVA	3	hi-sms	2323.5576	20.2077	41.1764	5441.1954	293.0548	54.4508	54.7394	90.6020	666.4696	0.9475
MAC	3	hi-sms	NA	23.7056	62.8601	18291.3704	540.8745	NA	NA	NA	NA	0.9475
MAF	3	hi-sms	NA	NA	NA	NA	NA	NA	NA	NA	NA	0.9475
MAR	3	lm-mea	1055.0854	3.8800	20.3792	1763.9283	101.3060	1282.5347	56.6077	105.4740	539.2767	1.2075
MCO	3	hi-sms	NA	47.7719	45.2257	124189.0837	1552.0573	NA	NA	NA	NA	0.9475
MDA	3	lm-eca	2343.2678	4.9190	10.0497	672.2808	36.3271	NA	7.9960	98.1320	174.7394	1.0692
MDG	3	lo-ssa	2086.6394	0.3414	1.1616	273.1524	8.2833	5486.5306	2.1485	61.2580	100.7393	1.0382
MDV	3	um-sas	1935.1904	4.7468	17.2494	3234.8863	190.5849	NA	8.1111	NA	350.6588	1.9352
MEX	3	um-lac	2914.3586	10.2039	24.3018	7564.3730	350.7916	2311.9285	68.4668	87.6280	1064.1208	1.4718
MHL	3	um-eap	NA	2.3492	1.0473	2518.0403	263.2563	NA	1.5000	NA	NA	1.1380
MKD	3	um-eca	2754.6268	13.3588	23.7221	2642.8335	92.4431	550.1613	39.0487	109.1220	692.5242	1.0745
MLI	3	lo-ssa	925.7154	0.2597	1.2940	416.2535	15.7717	NA	52.0416	96.6820	204.1197	1.0382
MLT	3	hi-weu	4269.3904	25.2343	59.7097	14576.5752	663.3087	2144.4413	109.1386	101.0440	4798.0577	1.1553
MMR	3	lo-eap	3249.3422	0.0123	0.0982	NA	NA	2985.5602	11.5036	62.2980	NA	0.8898
MNE	3	um-eca	NA	25.3501	78.7034	3335.3911	NA	NA	NA	NA	664.1655	1.0745
MNG	3	lm-eap	735.2338	1.6495	10.6888	834.1204	47.5578	NA	6.6440	77.1320	428.3221	1.1505
MNP	3	hi-sms	NA	NA	21.4191	NA	NA	NA	NA	NA	NA	0.9475
MOZ	3	lo-ssa	807.4468	0.3256	1.6135	268.1180	11.9813	160.8461	2.9912	65.4120	97.9103	1.0382
MRT	3	lm-ssa	789.9978	0.3444	8.4092	563.6263	16.2310	3507.8973	NA	NA	283.4117	1.1510
MUS	3	um-ssa	7379.2204	10.4383	30.1466	4762.3125	181.5526	NA	308.5050	86.4980	498.7091	1.5163
MWI	3	lo-ssa	1225.2572	0.2264	0.9010	210.2335	9.7902	403.4602	31.7323	62.3520	82.4493	1.0382
MYS	3	um-eap	3208.3816	31.5285	38.4221	5017.1624	346.9660	1723.9071	1369.6534	103.1200	1209.1128	1.1380
NAM	3	um-ssa	383.9518	2.7720	8.6141	3161.4104	211.8842	246.4385	2.8397	80.2160	529.2687	1.5163
NCL	3	hi-sms	3831.2500	22.2546	37.5732	NA	NA	NA	342.7941	NA	NA	0.9475
NER	3	lo-ssa	378.4532	0.1228	0.5106	260.3989	7.5017	NA	0.3818	70.9080	NA	1.0382
NGA	3	lm-ssa	1268.3928	0.4638	2.1104	618.6789	NA	166.9595	5.0717	66.6160	325.5666	1.1510
NIC	3	lm-lac	1754.1700	1.6690	6.3915	1083.2070	28.2256	599.9282	31.0932	75.5560	391.1092	1.1341

NLD	3	hi-weu	7922.4164	57.5035	78.5558	39995.0832	2085.2966	55.6193	408.1427	98.0260	3406.7950	1.1553
NOR	3	hi-weu	3897.4858	68.9320	84.5139	62311.8590	4497.3257	922.9284	211.4391	105.0120	3631.9888	1.1553
NPL	3	lo-sas	2198.2046	0.3181	0.2021	304.5127	9.8235	3957.2356	9.9216	88.9260	119.1985	1.1467
NZL	3	hi-nao	6697.5700	56.5023	59.8389	25752.1075	1686.8929	4097.5469	1958.7068	100.8400	8569.1288	1.1840
OMN	3	hi-mea	3508.9794	6.0605	19.8914	13126.7641	507.4380	40195.5556	415.7508	NA	NA	1.2879
PAK	3	lm-sas	2330.2984	3.7754	1.3337	614.6372	11.6459	7584.1076	148.1554	81.4740	201.7945	1.2203
PAN	3	um-lac	1907.1980	8.6939	20.9464	4140.0529	182.5068	NA	44.5736	100.3200	760.7895	1.4718
PER	3	um-lac	3283.7736	9.0644	9.2176	2425.4983	73.9146	NA	83.6214	92.7780	NA	1.4718
PHL	3	lm-eap	2758.9824	3.7880	21.7998	1099.5822	32.8082	NA	160.1586	85.5060	276.9270	1.1505
PLW	3	um-eap	NA	22.9386	17.4296	9623.9604	701.3821	NA	NA	NA	1536.7926	1.1380
PNG	3	lm-eap	3987.6464	1.1887	0.3463	782.7273	NA	4.5877	209.8244	NA	NA	1.1505
POL	3	hi-weu	3046.9836	19.1472	37.1849	7182.8247	380.8277	84.2103	124.7340	109.9240	553.9084	1.1553
PRI	3	hi-lac	1894.7998	17.0980	43.0194	20859.0478	NA	2020.4479	NA	NA	2347.9233	1.3509
PRK	3	lo-eap	3054.3940	0.0000	0.0000	NA	NA	NA	NA	NA	NA	0.8898
PRT	3	hi-weu	2778.6518	23.0675	84.3700	18530.0619	980.3755	3904.6834	193.1026	102.5360	996.1073	1.1553
PRY	3	lm-lac	2172.9108	1.8412	25.5337	1452.9846	58.3656	109.4798	64.1257	106.6400	582.5344	1.1341
PYF	3	hi-sms	NA	10.5635	25.6678	NA	NA	NA	312.5556	NA	NA	0.9475
QAT	3	hi-mea	4027.4504	12.2408	43.3772	53019.7715	1140.0855	17212.4221	1433.0012	100.1340	2497.2142	1.2879
ROU	3	um-weu	2781.7700	7.7265	25.8355	3835.4625	125.2003	128.4365	38.6803	106.3720	809.7325	1.0283
RUS	3	hi-eca	1827.6940	6.0416	19.1293	4375.2125	149.6395	107.0749	11.9919	79.2720	817.2456	1.1337
RWA	3	lo-ssa	938.6902	0.2768	1.0078	238.9238	11.6880	97.5330	2.0286	66.8300	116.7494	1.0382
SAU	3	hi-mea	4079.9982	6.3025	22.4087	12465.0000	867.8554	NA	93.5509	100.0000	2334.9122	1.2879
SDN	3	lm-ssa	583.8888	0.3871	1.0263	606.6829	10.2709	NA	3.8590	76.2260	403.6087	1.1510
SEN	3	lm-ssa	895.9632	1.7763	5.6803	720.6492	24.8226	675.7922	11.6206	109.3060	182.8055	1.1510
SGP	3	hi-sms	NA	48.1017	79.9702	25701.2330	949.0046	NA	8975.0794	NA	NA	0.9475
SLB	3	lm-eap	4046.0094	0.5314	0.3260	862.1878	NA	NA	NA	NA	311.5483	1.1505
SLE	3	lo-ssa	1019.1032	0.1696	1.2020	289.8596	10.7400	55.3808	NA	NA	233.8152	1.0382
SLV	3	lm-lac	2300.0976	2.0555	18.1926	2638.5483	71.9247	1112.6864	78.8415	92.8220	649.0586	1.1341
SMR	3	hi-sms	NA	50.1092	57.6859	44589.7914	NA	NA	NA	NA	NA	0.9475
SOM	3	lo-ssa	716.5634	0.3289	2.4054	NA	NA	2785.4365	NA	NA	NA	1.0382

SRB	3	um-eca	3702.9394	23.5000	47.1849	2919.4550	NA	NA	NA	88.9960	720.3413	1.0745
SSD	3	lm-ssa	NA	NA	NA	NA	NA	NA	NA	NA	NA	1.1510
STP	3	lm-ssa	2157.6496	8.4030	1.9547	767.0716	23.9462	NA	NA	NA	NA	1.1510
SUR	3	um-lac	3767.4586	4.1057	25.4991	3138.9586	NA	11610.8240	114.0900	88.1340	560.1911	1.4718
SVK	3	hi-weu	3693.4082	31.6050	52.9635	9945.4356	412.0224	38.9627	81.9072	108.2500	802.4922	1.1553
SVN	3	hi-weu	5094.2826	29.1580	79.7554	16332.7491	945.7648	40.5636	387.4880	106.2080	841.9567	1.1553
SWE	3	hi-weu	4680.2842	66.2087	87.6045	39956.6094	2868.0772	50.4044	98.6596	100.6800	2625.1838	1.1553
SWZ	3	lm-ssa	1254.8896	1.9379	7.1123	2230.2885	130.7571	5651.9719	NA	NA	201.1449	1.1510
SXM	3	hi-sms	NA	NA	NA	NA	NA	NA	NA	NA	NA	0.9475
SYC	3	um-ssa	NA	14.3159	50.7566	10860.8786	574.5982	NA	17.5000	NA	723.8186	1.5163
SYR	3	lm-mea	1813.6934	2.0696	4.7714	1461.5673	77.7509	3112.0180	72.4609	93.2140	NA	1.2075
TCA	3	hi-sms	NA	NA	NA	NA	NA	NA	NA	NA	NA	0.9475
TCD	3	lo-ssa	659.1382	0.1858	0.5348	443.2704	9.9340	178.7837	NA	NA	NA	1.0382
TGO	3	lo-ssa	1117.8412	1.0800	3.3894	392.5830	16.1085	31.9325	5.3516	78.9620	216.9996	1.0382
THA	3	um-eap	2889.8436	7.3506	23.8350	2360.2448	107.4313	NA	130.4661	78.4020	411.8456	1.1380
TJK	3	lo-eca	1769.7802	0.0595	0.6012	278.1670	7.0736	14022.7021	33.9434	69.6640	82.0063	1.8677
TKM	3	um-eca	2612.7056	0.3580	0.3576	1457.1401	NA	13311.5399	NA	79.6420	424.3105	1.0745
TLS	3	lo-sas	1589.7536	0.0000	2.4045	516.0708	NA	NA	NA	NA	181.0446	1.1467
TON	3	um-eap	NA	3.0211	6.2782	2505.4883	106.8413	NA	137.5111	NA	586.3848	1.1380
TTO	3	hi-sms	1694.0874	19.6201	26.0245	10003.3359	313.3355	662.2840	344.0949	77.5900	107.5909	0.9475
TUN	3	um-mea	1407.6390	5.4643	13.6396	2918.8530	185.3477	773.7169	32.5661	97.5800	792.6023	1.1984
TUR	3	um-eca	2288.1188	9.4482	37.2315	6120.5014	173.9257	1325.0437	80.9061	66.0420	1855.0770	1.0745
TUV	3	um-eap	NA	5.2416	1.0367	2376.7880	NA	NA	NA	NA	853.9109	1.1380
TZA	3	lo-ssa	1524.5512	0.4131	2.2965	329.7034	14.9272	529.1186	4.4815	65.1880	130.2657	1.0382
UGA	3	lo-ssa	1592.9658	0.3941	2.0513	286.0174	10.6267	21.3539	1.4666	NA	91.0934	1.0382
UKR	3	lm-eca	2424.1210	2.0933	11.2888	1459.5161	73.4128	NA	16.0486	93.3740	447.8286	1.0692
URY	3	hi-lac	3754.8302	13.2160	15.2879	4845.9268	117.3991	2385.9145	107.1933	72.2580	5506.7427	1.3509
USA	3	hi-nao	6033.7940	55.4802	49.8807	41702.3300	2266.2999	1139.2646	118.2496	87.9100	2074.2039	1.1840
UZB	3	lm-eca	3177.3004	1.3340	0.9655	475.8039	NA	12204.2626	NA	NA	183.6886	1.0692
VCT	3	um-lac	14682.4602	5.5446	28.5477	4483.8960	368.2249	NA	NA	NA	520.7656	1.4718

VEN	3	um-lac	3244.9608	5.7621	26.6850	4941.1636	NA	1533.6599	157.5882	52.4240	1614.2750	1.4718
VIR	3	hi-sms	NA	22.8983	43.3293	NA	NA	NA	NA	NA	NA	0.9475
VNM	3	lm-eap	4383.6496	2.9595	2.7988	590.5971	NA	NA	350.3912	76.3960	166.7290	1.1505
VUT	3	lm-eap	510.4998	3.4198	2.3949	1879.9755	152.6790	NA	NA	80.0020	534.8508	1.1505
PSE	3	ot-sms	1948.4212	2.9160	6.6530	1280.2379	NA	1640.5639	NA	NA	364.0139	1.7533
WSM	3	lm-eap	NA	2.0753	3.8486	2295.2258	96.6530	NA	1.9829	NA	440.2600	1.1505
YEM	3	lm-mea	918.6914	0.4356	2.9381	792.9265	74.9976	2184.7780	8.7863	69.8920	NA	1.2075
ZAF	3	um-ssa	2654.1190	6.7677	30.3513	5010.0419	264.8067	575.3741	58.8809	110.8700	304.3466	1.5163
COD	3	ot-ssa	777.6880	0.0883	1.5424	207.4243	NA	10.7317	0.2417	NA	81.1242	0.9799
ZMB	3	lm-ssa	1603.9836	0.7792	1.9650	647.5603	15.5555	415.6905	27.3841	NA	182.5312	1.1510
ZWE	3	lo-ssa	997.9694	3.6309	2.7059	593.2404	NA	909.5848	32.8114	1.2400	164.9154	1.0382
ABW	4	hi-sms	NA	38.8600	113.8299	22141.9717	1124.5675	NA	NA	NA	159.7839	1.1140
AND	4	ot-sms	NA	61.1965	80.8450	33465.7473	918.3301	NA	NA	NA	NA	1.4965
AFG	4	lo-sas	1750.7044	2.1243	19.8983	285.2867	NA	NA	4.3319	77.1900	101.9137	1.3062
AGO	4	um-ssa	543.5166	3.3702	27.0839	2245.4815	63.7184	42.1452	4.5913	NA	291.7495	1.7055
ALB	4	um-eca	3837.9180	19.1500	63.6785	3158.2477	100.2569	886.5755	89.8240	109.6180	1164.1119	1.2363
ARE	4	hi-mea	36164.5112	56.0000	126.3517	35307.2277	NA	62560.3173	796.6865	NA	2241.7212	3.8829
ARG	4	um-lac	4001.3584	25.3414	97.8440	5981.5210	260.2202	NA	37.1621	143.6320	4466.8361	1.5009
ARM	4	lm-eca	2117.7574	7.6832	47.5046	1959.8986	60.5733	4184.3496	22.7374	103.3520	951.0911	1.1915
ASM	4	um-eap	NA	NA	NA	NA	NA	NA	NA	NA	NA	1.2235
ATG	4	hi-sms	1740.6058	34.2000	137.1404	13489.2459	344.7244	325.0800	5.5500	NA	290.7353	1.1140
AUS	4	hi-nao	1550.9058	68.8740	97.4924	35252.8347	1695.0070	NA	42.7968	130.3580	8081.3559	1.2896
AUT	4	hi-weu	6192.4568	67.4580	120.5583	39752.2677	2196.1491	NA	113.5644	125.5580	1487.4981	1.2020
AZE	4	um-eca	2641.6164	15.8085	55.2288	2421.5531	66.8730	5030.7144	14.3372	141.1520	316.5701	1.2363
BDI	4	lo-ssa	1308.6842	0.7219	4.7169	147.7649	7.4655	NA	2.5881	100.7300	58.8101	1.1468
BEL	4	hi-weu	8851.2546	63.1960	99.7319	37774.7383	2335.2889	43.9402	307.4890	124.2520	12906.8719	1.2020
BEN	4	lo-ssa	1158.8716	1.7378	27.6449	543.3929	21.7106	NA	1.5397	NA	297.8642	1.1468
BFA	4	lo-ssa	1061.8350	0.7805	14.2174	424.6494	19.1126	79.9805	11.5471	119.0520	111.3582	1.1468
BGD	4	lo-sas	3948.4808	1.7283	21.4966	468.0352	11.2860	NA	192.8534	141.6680	123.0884	1.3062
BGR	4	um-eca	3313.1050	33.0740	119.9593	4293.1150	181.6981	325.7923	93.2049	122.1980	901.9250	1.2363

BHR	4	hi-mea	NA	37.4815	107.5000	17646.5399	466.1999	115185.2098	3216.5835	NA	NA	3.8829
BHS	4	hi-sms	4432.3810	28.6840	91.5877	22804.0567	NA	NA	NA	NA	2386.2289	1.1140
BIH	4	um-eca	4139.5012	29.3538	64.0022	3132.0637	NA	NA	29.2009	118.6140	394.1856	1.2363
BLR	4	um-eca	3046.3254	21.5825	72.7444	3745.4241	202.2819	NA	227.3113	138.4200	1123.2095	1.2363
BLZ	4	um-lac	2665.0412	10.7024	45.4407	4120.5916	242.7641	NA	80.4648	108.1560	826.5665	1.5009
BMU	4	hi-sms	NA	75.0495	107.1766	79312.2547	1825.9009	NA	NA	NA	NA	1.1140
BOL	4	lm-lac	2030.5554	10.2455	41.1318	1086.3845	77.6991	NA	5.5944	109.8080	350.1715	1.2579
BRA	4	um-lac	3401.7150	30.6262	65.8392	5068.4306	259.5545	460.8312	133.8795	110.0840	1497.4560	1.5009
BRB	4	hi-sms	2539.4190	58.4200	95.9276	14772.0537	781.3310	4215.5846	118.7692	NA	316.5721	1.1140
BRN	4	hi-sms	724.5828	43.6665	89.4453	25624.8864	NA	NA	193.4333	101.0780	848.6396	1.1140
BTN	4	lm-sas	2287.1492	5.6011	24.9171	1458.1230	80.4280	NA	12.2582	98.2520	412.9431	1.3706
BWA	4	um-ssa	434.9098	5.0465	61.2930	5802.3679	561.5184	NA	48.6044	136.9280	259.3255	1.7055
CAF	4	lo-ssa	933.5426	0.7510	9.4790	378.0743	5.2610	0.2068	NA	NA	316.5891	1.1468
CAN	4	hi-nao	3182.3848	74.8520	61.6958	36505.0961	1746.3521	NA	60.7186	139.1580	NA	1.2896
CHE	4	hi-weu	6374.5548	76.7000	107.3603	57200.2728	3009.7244	NA	220.9235	97.3400	1786.6351	1.2020
CHL	4	hi-lac	5772.1034	36.0866	81.7156	8055.5278	282.1647	22008.5817	548.9995	134.0760	2753.9014	1.4749
CHN	4	um-eap	5392.7804	17.3093	41.7366	2177.5328	NA	3171.3125	501.6828	92.4700	415.6295	1.2235
CIV	4	lm-ssa	1753.9454	1.6528	41.2463	988.6666	43.3207	208.1401	19.6124	123.9880	415.5033	1.1709
CMR	4	lm-ssa	1731.2086	2.7203	24.8549	922.1758	29.5143	NA	7.8429	113.2640	358.6035	1.1709
COG	4	lm-ssa	771.8064	3.0037	39.1166	1745.0325	32.0504	NA	1.1605	110.6000	210.7073	1.1709
COL	4	um-lac	3569.2496	20.7498	75.6832	3677.5044	151.6856	NA	508.9348	120.5860	1024.4998	1.5009
COM	4	lo-ssa	1336.0380	2.6400	10.1830	620.3684	47.1663	NA	NA	NA	364.9529	1.1468
CPV	4	lm-ssa	212.3316	11.2332	37.6509	2397.6107	136.5180	NA	NA	149.5180	446.4519	1.1709
CRI	4	um-lac	3618.2838	28.4380	35.2317	5062.1672	262.3795	NA	823.2244	156.0020	1277.6714	1.5009
CUB	4	um-lac	2600.0618	11.9715	2.5490	4412.3286	517.7199	690.5329	29.9491	191.7780	789.4692	1.5009
CUW	4	hi-sms	NA	NA	140.2497	NA	NA	NA	NA	NA	NA	1.1140
CYM	4	hi-sms	NA	52.0069	186.9529	NA	NA	NA	NA	NA	NA	1.1140
CYP	4	hi-weu	1155.2032	40.3060	87.1116	23417.6065	1247.7617	1440.6962	124.2605	111.2840	1135.5951	1.2020
CZE	4	hi-weu	4772.7308	52.5060	124.1456	14385.8519	599.3331	9.3916	91.9559	111.3480	931.0923	1.2020
DEU	4	hi-weu	6742.1940	74.6060	112.9527	36224.9114	1679.3766	6.8047	193.2090	123.0960	1102.3781	1.2020

DJI	4	lm-mea	1549.2064	2.0207	9.9338	981.4251	82.0375	NA	NA	NA	123.0735	1.1827
DMA	4	um-lac	1418.0010	40.2793	113.5393	5794.9280	NA	NA	144.1533	NA	1839.2277	1.5009
DNK	4	hi-weu	6080.7840	85.2560	113.2144	49457.7636	4005.9042	49.5096	133.7409	127.2400	3881.7612	1.2020
DOM	4	um-lac	4176.2386	18.5056	61.1925	4090.4875	89.6080	4863.0166	78.8847	158.2980	879.5930	1.5009
DZA	4	um-mea	1389.2086	8.8162	69.0467	3072.3473	133.2722	NA	11.6435	148.3080	723.4353	1.2663
ECU	4	um-lac	2952.2864	13.4789	69.1516	3132.3676	NA	6556.0180	191.8248	108.6100	776.6135	1.5009
EGY	4	lm-mea	7413.2390	17.2280	42.1958	1380.0889	56.1251	NA	577.2425	129.9780	317.3635	1.1827
ERI	4	lo-ssa	649.4884	0.4733	1.6482	205.0149	4.3447	828.2982	2.1512	127.1240	52.8417	1.1468
ESP	4	hi-weu	3136.2882	55.0720	106.3679	27031.8131	1214.8254	1593.1932	129.1326	117.8900	3352.3507	1.2020
EST	4	hi-weu	2693.6684	66.8460	121.5320	11232.4691	596.3319	13.5998	76.5325	110.4160	1111.9947	1.2020
ETH	4	lo-ssa	1499.2044	0.3781	2.0580	190.3806	10.1646	NA	14.5872	190.5940	91.1496	1.1468
FIN	4	hi-weu	3533.7954	80.2160	119.0967	40560.7166	2539.0736	22.1968	126.1561	119.8440	5573.9236	1.2020
FJI	4	um-eap	2475.2672	11.7903	53.7856	3634.5531	182.5744	NA	30.2346	109.6960	862.0239	1.2235
FRA	4	hi-weu	7021.6792	59.6180	87.1109	35413.5552	2012.7610	212.9978	173.0652	125.6360	2660.0667	1.2020
FRO	4	hi-sms	NA	72.7984	103.4811	35211.5527	NA	NA	NA	NA	NA	1.1140
FSM	4	lm-eap	1301.9072	13.6186	21.9508	2325.3273	NA	NA	0.0800	NA	702.7081	1.2213
GAB	4	um-ssa	1622.0654	5.8119	76.1687	6232.0891	NA	123.9916	9.6800	NA	1981.2136	1.7055
GBR	4	hi-weu	7111.5464	75.1720	118.2871	40498.3311	2189.0824	222.0084	245.8217	NA	1101.8403	1.2020
GEO	4	lm-eca	1940.4504	10.3893	50.0399	1691.3924	48.4720	2219.3384	44.5865	104.6260	420.1867	1.1915
GHA	4	lm-ssa	1468.3480	3.6229	36.9531	542.1469	31.8061	NA	15.4695	139.2640	347.7647	1.1709
GIN	4	lo-ssa	1488.8128	0.7640	20.3693	306.6136	7.6684	NA	0.9897	137.1980	104.9268	1.1468
GMB	4	lo-ssa	978.5762	5.9503	50.2729	435.6848	8.9439	NA	8.0032	92.2620	236.7084	1.1468
GNB	4	lo-ssa	1533.7070	2.1646	21.3682	418.1977	NA	NA	NA	115.9400	311.1167	1.1468
GNQ	4	hi-sms	NA	1.5872	23.1429	13725.2285	NA	NA	NA	NA	NA	1.1140
GRC	4	hi-weu	4078.7546	34.5460	109.5335	23483.5621	960.8006	3558.7585	109.3232	124.3180	3208.3490	1.2020
GRD	4	um-lac	941.5434	22.2808	61.4628	6668.9349	NA	NA	NA	NA	416.6102	1.5009
GRL	4	hi-sms	NA	60.7570	97.2332	31894.6216	NA	NA	NA	NA	NA	1.1140
GTM	4	lm-lac	1913.0856	7.4200	82.6793	2242.1471	68.8633	1290.5690	119.7783	NA	515.1605	1.2579
GUM	4	hi-sms	2546.6666	45.5245	NA	NA	NA	NA	NA	NA	NA	1.1140
GUY	4	lm-lac	4219.9000	18.6333	55.8894	1082.9428	55.0853	NA	32.8771	NA	446.0978	1.2579

HKG	4	hi-sms	NA	63.7200	152.3129	28967.0133	1106.0600	NA	262.7600	NA	NA	1.1140
HND	4	lm-lac	1624.1198	8.6200	61.1719	1487.8773	NA	1135.2458	139.5463	138.8400	368.4140	1.2579
HRV	4	hi-weu	5666.2614	41.4760	102.1401	10883.6124	463.0600	NA	349.0535	115.5200	1064.8623	1.2020
HTI	4	lo-lac	967.0334	7.2144	23.0038	457.8187	NA	NA	NA	NA	NA	1.0011
HUN	4	um-eca	4926.2814	52.4660	108.0166	11403.2498	602.2500	66.4197	93.7973	130.7160	1221.5742	1.2363
IDN	4	lm-eap	4529.7728	5.7981	43.6565	1387.2208	42.8601	NA	169.9256	123.6000	333.8856	1.2213
IMN	4	ot-sms	NA	NA	NA	38762.5434	NA	NA	NA	NA	NA	1.4965
IND	4	lm-sas	2532.0254	3.7287	23.2655	846.7504	26.6741	NA	145.5321	133.6140	190.0798	1.3706
IRL	4	hi-weu	7229.1104	58.0617	110.4398	50543.1754	2673.2377	NA	434.5837	118.8860	863.7616	1.2020
IRN	4	um-mea	2302.8846	9.5280	41.1812	2961.2864	145.2827	5098.3425	91.7785	129.3060	902.5746	1.2663
IRQ	4	um-mea	1344.0390	0.9685	42.7881	1966.7622	NA	NA	50.9729	143.9280	317.4428	1.2663
ISL	4	hi-weu	NA	90.2220	103.9800	59001.4275	4470.4464	553.7421	163.8549	NA	38339.0009	1.2020
ISR	4	hi-mea	2744.8550	44.7426	124.1356	21701.2032	1250.4377	3704.6240	284.7251	131.1640	NA	3.8829
ITA	4	hi-weu	5258.2750	41.4280	141.8679	31990.7672	1448.1140	NA	160.5205	123.7580	2001.8286	1.2020
JAM	4	um-lac	1263.1068	19.6400	93.1638	4189.6559	234.0067	NA	62.2817	152.7200	509.1928	1.5009
JOR	4	um-mea	1122.8998	19.1600	82.2883	2585.5092	NA	3530.5490	643.5157	135.8040	397.1980	1.2663
JPN	4	hi-eap	6050.2254	72.6613	83.3763	36133.2734	1251.1669	NA	309.6857	93.4300	3709.4695	1.1105
KAZ	4	um-eca	1150.5628	7.8900	74.2187	4272.2974	114.3835	614.3594	1.9977	140.6780	565.9596	1.2363
KEN	4	lo-ssa	1545.3538	7.4591	30.7186	547.1333	39.3806	405.8308	33.8043	124.6480	158.7843	1.1468
KGZ	4	lm-eca	2631.1674	13.9141	45.6660	523.2840	30.4199	5815.3038	22.0644	150.0100	193.2202	1.1915
KHM	4	lo-eap	2692.4770	0.4631	22.8304	542.4596	8.6888	537.4241	8.2957	134.0440	194.2704	1.0360
KIR	4	lm-eap	NA	6.0940	2.7256	1155.7523	NA	NA	NA	NA	463.5659	1.2213
KNA	4	hi-sms	NA	52.8000	125.1279	11520.3108	472.0312	NA	16.4497	NA	193.9141	1.1140
KOR	4	hi-eap	6644.9658	78.6000	90.9210	20118.0410	843.4159	NA	479.4506	98.9200	3046.8452	1.1105
KWT	4	hi-sms	3797.9992	36.4635	62.4376	34569.7034	1464.2107	NA	1551.8180	NA	NA	1.1140
LAO	4	lm-eap	3846.9108	2.6421	27.5216	532.1581	14.3064	2715.0946	NA	131.0460	243.1929	1.2213
LBN	4	um-mea	2576.8468	19.3100	34.5698	5845.7053	139.4312	5927.7550	277.1239	117.7440	1375.8358	1.2663
LBR	4	lo-ssa	1347.4330	0.5305	16.1626	194.1261	6.3703	NA	NA	NA	238.4507	1.1468
LBY	4	um-mea	624.8552	6.5482	93.6120	8420.3170	NA	NA	46.2667	NA	873.1428	1.2663
LCA	4	um-lac	NA	28.3935	84.5785	5928.2511	298.0385	NA	47.6000	NA	249.0690	1.5009

LIE	4	hi-sms	NA	67.5331	89.0215	113569.2942	2306.9864	NA	NA	NA	NA	1.1140
LKA	4	lm-sas	3636.4396	4.5579	43.2768	1388.4388	28.5720	10376.6330	285.6440	149.1300	196.2110	1.3706
LSO	4	lm-ssa	491.8116	3.2611	23.8761	766.5606	106.4383	NA	NA	NA	72.4827	1.1709
LTU	4	hi-weu	2934.8880	49.0000	150.3689	8906.8573	442.2664	42.9911	84.1469	129.7920	1058.7153	1.2020
LUX	4	hi-weu	5748.5978	78.1940	139.5334	82378.9830	NA	NA	275.6588	117.3520	2131.8381	1.2020
LVA	4	hi-sms	2837.5442	57.8100	100.4505	8050.4127	431.1421	NA	66.0502	129.1300	809.4965	1.1140
MAC	4	hi-sms	NA	46.3660	158.0219	29423.7137	676.8013	NA	NA	NA	NA	1.1140
MAF	4	hi-sms	NA	NA	NA	NA	NA	NA	NA	NA	NA	1.1140
MAR	4	lm-mea	1175.0500	26.1511	62.7473	2129.9490	128.6716	NA	55.5355	112.8040	689.1224	1.1827
MCO	4	hi-sms	NA	63.7337	57.4729	140840.9510	1857.7988	NA	NA	NA	NA	1.1140
MDA	4	lm-eca	2390.2850	21.1182	48.5336	899.4220	73.2070	19.7504	10.0604	133.6680	179.0496	1.1915
MDG	4	lo-ssa	2645.3900	1.0211	14.9435	286.2545	9.5040	NA	3.5036	136.9760	101.3795	1.1468
MDV	4	um-sas	1919.2872	16.4412	108.3326	4128.0826	247.1711	NA	69.1333	NA	373.5210	1.9193
MEX	4	um-lac	3316.4452	21.1180	57.5110	8053.2950	393.9276	2438.8555	65.5070	134.0280	1142.4095	1.5009
MHL	4	um-eap	NA	4.3649	1.2678	2709.7780	NA	NA	0.5000	NA	NA	1.2235
MKD	4	um-eca	3199.3414	37.8360	77.2637	3138.0613	NA	291.4727	59.8936	109.9620	735.2171	1.2363
MLI	4	lo-ssa	1277.6256	1.0833	19.5226	469.9405	19.3886	871.6969	18.5629	109.8980	239.5220	1.1468
MLT	4	hi-weu	4407.0754	47.4980	88.1690	15471.9596	907.9857	NA	98.5220	119.5700	5246.9168	1.2020
MMR	4	lo-eap	3700.5910	0.1809	0.5720	NA	NA	NA	9.0313	132.0080	NA	1.0360
MNE	4	um-eca	2979.7345	30.9600	146.8723	4226.0255	NA	NA	15.1137	NA	862.4482	1.2363
MNG	4	lm-eap	1091.1634	9.6000	49.8989	1139.3968	56.1134	315.4817	8.7349	165.7580	638.9546	1.2213
MNP	4	hi-sms	NA	NA	NA	NA	NA	NA	NA	NA	NA	1.1140
MOZ	4	lo-ssa	768.5058	1.3695	15.3592	337.2015	17.2442	NA	4.9651	155.3160	123.1327	1.1468
MRT	4	lm-ssa	740.6568	1.4466	44.4171	619.7906	19.5361	3072.7764	NA	NA	278.9761	1.1709
MUS	4	um-ssa	8065.4948	19.2824	73.3634	5576.1608	197.5438	6002.0782	269.7960	110.5320	457.4129	1.7055
MWI	4	lo-ssa	1682.4880	0.7091	8.6603	226.8826	NA	355.4678	34.9502	145.5360	78.2157	1.1468
MYS	4	um-eap	3533.0134	53.5334	89.3206	5897.7323	277.2809	1391.9111	1700.0683	109.7080	1499.3134	1.2235
NAM	4	um-ssa	483.3214	5.0147	43.2438	3873.1491	241.3173	NA	1.8198	107.4360	518.4282	1.7055
NCL	4	hi-sms	3689.5094	33.8849	73.7044	NA	NA	NA	217.7941	NA	NA	1.1140
NER	4	lo-ssa	436.3494	0.4732	8.4372	264.7807	10.2964	44.8594	0.3554	143.3700	71.3783	1.1468

NGA	4	lm-ssa	1491.7226	10.3448	30.5859	878.8494	NA	195.1974	6.5158	125.5500	479.4903	1.1709
NIC	4	lm-lac	1878.2234	4.3744	42.2867	1211.0896	NA	NA	30.8021	148.6260	457.3945	1.2579
NLD	4	hi-weu	8141.8170	85.5140	113.3351	43377.4136	2397.0321	66.2029	299.7943	123.6040	4900.6642	1.2020
NOR	4	hi-weu	3891.2904	86.8240	106.7199	66481.8259	4488.7409	993.5359	209.6918	106.3740	4365.7225	1.2020
NPL	4	lo-sas	2304.7486	1.4156	11.0196	339.7188	12.8892	3957.6882	6.0775	116.5160	132.3801	1.3062
NZL	4	hi-nao	7373.8088	70.6420	98.6780	27855.2964	1690.0037	NA	2103.3402	123.2500	8432.6778	1.2896
OMN	4	hi-mea	5808.6620	15.6927	98.9040	13494.9581	524.2216	39195.5772	829.9438	NA	735.6438	3.8829
PAK	4	lm-sas	2671.5824	6.8265	35.2084	730.1848	18.7827	NA	180.4718	126.7720	227.6387	1.3706
PAN	4	um-lac	2156.2892	24.8047	95.9154	5312.9680	188.5527	NA	38.0521	122.2040	828.7282	1.5009
PER	4	um-lac	3662.9616	24.9940	53.1317	3067.3989	87.2808	NA	85.9855	115.3640	NA	1.5009
PHL	4	lm-eap	3222.5790	6.4656	62.3502	1280.4871	33.0701	12613.3788	135.6804	118.8400	291.5918	1.2213
PLW	4	um-eap	NA	NA	49.1126	9805.7018	NA	NA	NA	NA	2453.1887	1.2235
PNG	4	lm-eap	4073.5500	1.6042	8.4009	839.9357	NA	3.7308	76.1402	NA	NA	1.2213
POL	4	hi-weu	3155.1096	48.8180	102.6521	8935.2350	461.1735	90.3119	157.0827	121.1460	596.1944	1.2020
PRI	4	hi-lac	1765.1784	31.2405	63.5654	21334.7504	NA	1186.4815	NA	NA	2539.4910	1.4749
PRK	4	lo-eap	3352.7850	0.0000	0.0568	NA	NA	2824.9500	NA	NA	NA	1.0360
PRT	4	hi-weu	3091.3554	41.4980	119.4033	19136.7159	997.7677	NA	166.5668	121.2760	1045.4333	1.2020
PRY	4	lm-lac	2382.1978	12.0498	68.7454	1555.2017	55.1828	NA	74.1168	115.9160	682.4695	1.2579
PYF	4	hi-sms	NA	30.7420	64.5741	NA	NA	NA	274.5467	NA	NA	1.1140
QAT	4	hi-mea	4519.4484	37.6215	104.3626	56606.7979	1387.4318	19670.0000	1843.7069	87.2860	3491.5917	3.8829
ROU	4	um-weu	2830.2642	28.6960	90.2935	5379.2886	214.1763	124.5938	46.1423	128.6720	856.8949	1.0462
RUS	4	hi-eca	2080.9420	22.7480	121.2723	6045.6428	236.5348	NA	14.0063	134.5320	910.7507	1.2907
RWA	4	lo-ssa	1272.2224	3.7179	9.6046	308.3419	12.7676	NA	4.9964	127.6700	136.7982	1.1468
SAU	4	hi-mea	5003.5684	27.2329	109.7128	14282.7320	784.7751	6151.3201	86.5858	100.0000	2266.8932	3.8829
SDN	4	lm-ssa	606.4910	4.9760	20.4152	743.7107	18.8698	NA	4.2173	125.1700	374.5647	1.1709
SEN	4	lm-ssa	1021.2500	8.6397	34.0926	782.4203	40.0993	NA	4.5151	130.6940	181.7729	1.1709
SGP	4	hi-sms	NA	65.5800	119.4972	31380.0327	945.0265	NA	13491.6390	NA	NA	1.1140
SLB	4	lm-eap	2833.9538	2.2981	4.1233	943.9360	87.0985	NA	NA	NA	360.4947	1.2213
SLE	4	lo-ssa	1352.8186	0.2386	17.7087	339.6775	9.0027	38.3006	NA	NA	283.2635	1.1468
SLV	4	lm-lac	2736.6116	7.6000	87.6952	2940.6892	97.1160	2168.7190	127.4409	124.1480	812.3031	1.2579

SMR	4	hi-sms	NA	51.9126	70.0726	47895.1058	NA	NA	NA	NA	NA	1.1140
SOM	4	lo-ssa	510.4860	1.1206	6.5325	NA	NA	2882.9968	NA	NA	NA	1.1468
SRB	4	um-eca	4351.7484	32.0700	99.4397	3888.2115	188.5366	39.0464	132.2820	119.7640	767.4633	1.2363
SSD	4	lm-ssa	NA	NA	NA	NA	NA	NA	NA	NA	NA	1.1709
STP	4	lm-ssa	2167.8444	14.8844	22.8912	876.7453	56.7266	NA	NA	NA	329.5697	1.1709
SUR	4	um-lac	4075.3728	16.4865	91.7499	3821.2092	NA	8657.2289	229.2163	161.4980	568.3305	1.5009
SVK	4	hi-weu	4311.1362	61.8240	98.0794	13382.5989	507.8460	15.9206	83.1260	110.6280	996.3249	1.2020
SVN	4	hi-weu	5434.3870	55.9120	95.5653	19563.0025	1073.1362	28.2828	301.4842	118.6600	835.3849	1.2020
SWE	4	hi-weu	4854.9362	87.1200	107.5079	44420.8850	3038.8539	40.3935	85.3913	132.1400	3085.3566	1.2020
SWZ	4	lm-ssa	1068.4158	5.4567	35.3252	2410.4303	181.2041	NA	NA	NA	200.1647	1.1709
SXM	4	hi-sms	NA	NA	NA	NA	NA	NA	NA	NA	NA	1.1140
SYC	4	um-ssa	NA	34.7963	92.0234	12145.8131	579.7433	899.9530	32.2000	NA	684.6022	1.7055
SYR	4	lm-mea	1588.1048	11.2561	31.0606	1612.4152	79.3044	3127.9377	80.7089	115.3500	672.2202	1.1827
TCA	4	hi-sms	NA	NA	NA	NA	NA	NA	NA	NA	NA	1.1140
TCD	4	lo-ssa	783.1896	0.9035	9.9503	650.7142	13.0325	153.8193	NA	NA	428.1148	1.1468
TGO	4	lo-ssa	1154.4458	2.2000	20.4315	385.3510	14.1237	NA	5.5216	118.5120	217.7166	1.1468
THA	4	um-eap	3015.2684	18.1033	76.0951	2880.8089	116.8489	3383.0298	121.5313	129.3140	489.5161	1.2235
TJK	4	lo-eca	2404.7122	6.0237	36.2179	373.4574	13.3862	14020.7010	64.2548	117.2520	107.1602	2.5377
TKM	4	um-eca	2858.1912	1.4846	16.1012	2081.2979	NA	13946.9021	NA	115.2500	660.0388	1.2363
TLS	4	lo-sas	1615.9090	0.1411	12.1143	535.2452	52.1723	6374.8429	NA	NA	190.3624	1.3062
TON	4	um-eap	NA	7.2105	40.9703	2517.9079	NA	NA	88.5233	NA	541.0541	1.2235
TTO	4	hi-sms	1617.8624	34.0761	115.9650	14092.1447	NA	NA	462.2880	92.8880	65.3654	1.1140
TUN	4	um-mea	1530.0880	20.2683	76.2144	3514.0186	226.1755	NA	40.7308	118.3840	909.3846	1.2663
TUR	4	um-eca	2573.8096	26.6200	82.3924	7485.0456	214.2919	1325.1065	89.0952	122.3920	2081.6684	1.2363
TUV	4	um-eap	NA	15.0000	14.6204	2417.5886	NA	NA	NA	NA	1056.7396	1.2235
TZA	4	lo-ssa	1259.9740	1.6600	22.4973	401.7862	19.2000	NA	5.6850	122.7620	148.6687	1.1468
UGA	4	lo-ssa	1743.3824	5.1247	16.0931	351.3224	11.4713	NA	1.6892	NA	86.3995	1.1468
UKR	4	lm-eca	2749.8284	8.7412	105.0761	2008.3384	129.1426	36.5394	25.2951	145.0020	556.2126	1.1915
URY	4	hi-lac	4205.3672	32.9176	84.3579	5773.2729	161.5503	NA	138.3617	121.0000	7555.5064	1.4749
USA	4	hi-nao	6682.3488	71.3798	80.1016	44577.0018	2340.7975	1186.2092	117.7969	141.8780	2397.7450	1.2896

UZB	4	lm-eca	4307.7906	8.6722	27.8884	627.2943	NA	11575.5627	173.8854	NA	234.5459	1.1915
VCT	4	um-lac	13929.8250	17.8397	95.3549	5481.7655	323.5802	NA	NA	NA	588.9133	1.5009
VEN	4	um-lac	3565.4380	21.4375	79.5739	6064.0417	286.7856	6305.6574	153.8232	149.2160	1782.0747	1.5009
VIR	4	hi-sms	NA	27.3549	74.5119	NA	NA	NA	NA	NA	NA	1.1140
VNM	4	lm-eap	4859.9656	20.2440	56.4812	779.7635	38.1462	12302.6438	331.7712	145.8020	199.5049	1.2213
VUT	4	lm-eap	550.1034	6.5004	19.5772	2040.8996	110.3383	NA	NA	119.9980	547.6813	1.2213
PSE	4	ot-sms	1663.0952	22.4358	29.2738	1322.4362	NA	2216.7187	NA	NA	305.1272	1.4965
WSM	4	lm-eap	NA	4.7207	28.5524	2660.3684	153.6125	NA	3.8692	NA	393.6236	1.2213
YEM	4	lm-mea	919.4120	4.8313	22.6688	847.6158	38.6780	2510.7738	12.0628	154.7460	119.2986	1.1827
ZAF	4	um-ssa	3548.0856	8.3182	83.5057	5765.2691	304.0297	NA	57.4460	147.2580	335.6648	1.7055
COD	4	ot-ssa	771.6330	0.3808	11.4170	233.1897	NA	10.6889	0.5790	NA	79.2739	0.9722
ZMB	4	lm-ssa	2042.7150	4.7483	21.3921	806.1628	13.1268	NA	30.0859	132.7880	153.4087	1.1709
ZWE	4	lo-ssa	565.1326	10.2836	13.0586	403.3489	NA	NA	26.3926	392.9200	94.6210	1.1468
ABW	5	hi-sms	NA	70.9750	132.1529	NA	NA	NA	NA	NA	NA	1.5191
AND	5	ot-sms	NA	85.6086	82.4518	NA	NA	NA	NA	NA	NA	1.4023
AFG	5	lo-sas	1937.3008	5.0886	60.5545	391.5540	NA	2567.0820	5.0621	62.1600	112.9111	1.5014
AGO	5	um-ssa	664.6575	15.2033	57.8017	2638.0220	91.7819	33.5875	8.7758	NA	397.2738	1.3187
ALB	5	um-eca	4750.5750	52.1890	102.6509	3812.2261	NA	831.6364	89.8507	140.4967	1622.6292	1.2585
ARE	5	hi-mea	73270.1450	79.7500	145.5856	24352.4515	NA	67043.3846	679.3609	NA	1254.8778	7.0787
ARG	5	um-lac	4636.1748	52.9250	152.3915	NA	380.2881	731.4524	41.7955	279.8767	4783.7139	1.8243
ARM	5	lm-eca	2641.6063	35.6150	115.7759	2158.6088	64.3230	2606.1457	28.4253	147.0700	1029.8948	1.3129
ASM	5	um-eap	NA	NA	NA	NA	NA	NA	NA	NA	NA	1.2843
ATG	5	hi-sms	2018.7500	55.6000	165.5792	11491.6380	NA	325.0800	3.5833	NA	260.6278	1.5191
AUS	5	hi-nao	2011.1278	79.3719	104.3665	36847.1982	1968.4054	363.8536	45.4314	118.0733	9037.0743	1.3794
AUT	5	hi-weu	6496.5758	78.6397	154.2223	40968.5456	2398.9714	73.4085	104.9919	190.3867	1507.7036	1.2405
AZE	5	um-eca	2464.7523	52.2250	106.6033	3145.5814	82.0582	5347.2731	14.4999	202.7833	345.5402	1.2585
BDI	5	lo-ssa	1221.3273	1.1575	21.5050	152.7818	9.4820	226.5208	4.9872	128.5533	55.4987	1.3037
BEL	5	hi-weu	9058.9750	79.8750	111.7125	37736.8591	2476.3556	45.0458	286.7060	178.8733	13654.7771	1.2405
BEN	5	lo-ssa	1371.9138	4.1696	82.6772	563.1214	30.1199	22.6320	11.2824	NA	319.1022	1.3037
BFA	5	lo-ssa	1104.3418	3.3813	52.9354	489.9898	17.8342	71.3046	10.3762	149.9533	122.2872	1.3037

BGD	5	lo-sas	4347.0355	5.2375	59.3470	578.2285	NA	4100.9852	254.3066	180.8167	150.2099	1.5014
BGR	5	um-eca	4094.8868	49.7929	143.5510	4694.4993	185.8274	306.5148	117.3087	173.0767	848.5083	1.2585
BHR	5	hi-mea	NA	77.5000	145.8236	16887.3259	452.5699	110545.8056	1220.2083	NA	NA	7.0787
BHS	5	hi-sms	7387.6728	62.9371	89.2744	20949.5154	NA	NA	NA	NA	2135.1814	1.5191
BIH	5	um-eca	3651.3335	61.3140	85.5352	3347.3223	NA	NA	93.7464	139.3800	NA	1.2585
BLR	5	um-eca	3139.1263	43.1322	113.5857	4773.0481	244.6106	151.9058	280.6943	431.5833	1458.8354	1.2585
BLZ	5	um-lac	3255.1770	22.3500	59.7671	4107.6382	271.6659	899.9632	101.4284	112.7233	757.4621	1.8243
BMU	5	hi-sms	NA	89.7863	139.8836	73825.9835	1950.7376	NA	NA	NA	NA	1.5191
BOL	5	lm-lac	2075.9375	31.8500	84.9342	1244.4148	86.8864	484.9089	9.0894	119.3233	378.7223	1.3754
BRA	5	um-lac	4372.3193	46.6250	120.0476	5723.2268	333.2599	626.9036	173.6475	128.6733	1788.2401	1.8243
BRB	5	hi-sms	3166.6665	72.0489	119.9346	14384.5325	824.8271	4835.5235	134.9672	NA	277.7739	1.5191
BRN	5	hi-sms	876.9355	58.4433	110.9500	24695.4706	797.6651	1590.0360	254.5833	106.3900	881.3902	1.5191
BTN	5	lm-sas	2789.1423	22.4825	67.2968	1911.8532	90.2622	3277.1254	12.8100	129.2933	434.3008	1.4950
BWA	5	um-ssa	354.5865	10.1250	145.1052	6588.3632	NA	298.9001	55.5972	261.5567	294.2367	1.3187
CAF	5	lo-ssa	1592.3255	2.6750	24.9026	402.5190	4.8833	0.2222	NA	NA	379.7671	1.3037
CAN	5	hi-nao	3700.4335	83.0250	78.4200	37056.8098	1972.3413	NA	74.1254	174.0333	NA	1.3794
CHE	5	hi-weu	6200.7560	85.2483	129.8444	58560.3610	3078.7380	123.6442	213.4073	89.8967	1762.5161	1.2405
CHL	5	hi-lac	6721.5003	56.2919	129.0121	9199.6834	392.7000	22487.5582	431.2770	145.7167	3166.1277	1.5817
CHN	5	um-eap	5742.5353	40.1750	76.1782	3229.9858	NA	3265.7627	595.2981	112.5633	553.6081	1.2843
CIV	5	lm-ssa	2510.6923	2.3197	89.5815	1010.2281	NA	205.2692	25.7032	161.6700	NA	1.2545
CMR	5	lm-ssa	1649.7523	5.3497	55.5602	955.3190	30.6848	118.8672	10.1320	117.3267	405.6319	1.2545
COG	5	lm-ssa	832.7563	5.8267	96.4770	1934.0323	120.3474	7.8435	5.4697	143.7467	240.0342	1.2545
COL	5	um-lac	3350.5153	44.3827	100.2096	4181.1875	194.4668	3520.6261	691.4808	153.6400	1070.6362	1.8243
COM	5	lo-ssa	1415.5530	5.7688	35.4760	606.2777	NA	55.9524	NA	NA	357.2239	1.3037
CPV	5	lm-ssa	194.1028	33.5600	85.8038	2718.6653	144.2508	425.5362	NA	236.9400	NA	1.2545
CRI	5	um-lac	3368.3288	42.2930	103.1363	5608.9900	385.3385	5356.1074	629.4741	233.1800	1576.9014	1.8243
CUB	5	um-lac	2572.6025	20.8170	13.2972	4981.7175	639.8155	721.0579	38.9270	391.1067	906.9134	1.8243
CUW	5	hi-sms	NA	NA	133.6027	NA	NA	NA	NA	NA	NA	1.5191
CYM	5	hi-sms	NA	70.9231	172.9002	NA	NA	NA	NA	NA	NA	1.5191
CYP	5	hi-weu	1783.5415	58.9986	96.5406	22030.4706	1213.9873	1853.0816	185.0675	105.1533	NA	1.2405

CZE	5	hi-weu	4974.2823	71.7126	125.3067	14735.1944	645.0781	9.4830	100.7518	130.0533	803.3026	1.2405
DEU	5	hi-weu	6864.9138	82.3953	112.1646	38523.5253	1937.5961	6.8352	200.6685	171.8400	970.7225	1.2405
DJI	5	lm-mea	1861.1110	7.8168	23.8350	1134.8288	50.9824	1500.0500	NA	NA	NA	1.2169
DMA	5	um-lac	1537.5003	53.2351	145.8310	6120.8829	NA	NA	67.9444	NA	2029.1088	1.8243
DNK	5	hi-weu	6095.7915	91.3549	125.4323	47701.0599	4186.3060	97.3001	112.9974	160.7133	4155.9756	1.2405
DOM	5	um-lac	4534.6163	39.1250	87.6453	4716.5234	178.1616	4935.9619	94.7658	134.6033	1261.7737	1.8243
DZA	5	um-mea	1583.6855	14.5570	95.2670	3193.6403	NA	465.7406	19.5452	217.6167	942.2661	1.5149
ECU	5	um-lac	3129.3453	33.9714	104.1961	3507.7604	152.2742	6942.3158	258.2256	129.5133	838.9188	1.8243
EGY	5	lm-mea	7068.2085	41.2025	109.2517	1556.8826	NA	20717.8532	593.6574	195.6767	338.6838	1.2169
ERI	5	lo-ssa	581.1035	0.7525	4.4719	193.6712	NA	797.0870	0.8585	202.7300	NA	1.3037
ESP	5	hi-weu	3520.6720	68.6955	109.8975	25664.4715	1278.1348	1573.8313	125.8510	147.8533	3446.1305	1.2405
EST	5	hi-weu	2884.8973	77.2486	147.8201	11374.8738	615.0714	12.6439	73.6524	176.0100	1554.3309	1.2405
ETH	5	lo-ssa	2014.4805	1.3082	18.3254	266.3967	12.6497	355.9558	22.1413	284.1100	111.7718	1.3037
FIN	5	hi-weu	3471.0048	89.2486	166.5225	39766.6987	2705.6818	22.2188	154.5334	156.5667	6160.0992	1.2405
FJI	5	um-eap	2509.5865	29.7106	92.1607	3713.5491	155.8645	299.8824	35.5394	143.2367	839.8646	1.2843
FRA	5	hi-weu	6985.2395	79.6149	95.3343	35594.7612	2053.8699	213.9196	142.9139	187.4533	2785.0098	1.2405
FRO	5	hi-sms	NA	82.8168	119.3010	NA	NA	NA	NA	NA	NA	1.5191
FSM	5	lm-eap	1639.2198	24.1436	28.4371	2398.4410	NA	NA	0.0000	NA	742.1445	1.3612
GAB	5	um-ssa	1690.1740	8.2617	161.5927	6594.2050	NA	123.9916	10.1508	NA	2039.5826	1.3187
GBR	5	hi-weu	6695.1820	86.9260	124.1503	39824.7795	2441.4731	218.7617	241.6705	NA	1147.3453	1.2405
GEO	5	lm-eca	1964.5108	34.6150	103.6913	2017.5831	47.2148	2592.5956	30.9302	124.3300	413.7226	1.3129
GHA	5	lm-ssa	1716.3323	11.6275	91.5815	698.9244	47.9093	137.7566	22.3476	208.6267	NA	1.2545
GIN	5	lo-ssa	1503.8505	1.3475	48.1025	305.0584	9.3841	101.0059	2.8158	160.3733	114.0776	1.3037
GMB	5	lo-ssa	965.9418	11.6299	88.4760	448.1739	18.1661	87.7512	8.0115	92.2067	247.3587	1.3037
GNB	5	lo-ssa	1449.1680	2.7790	56.2398	443.2362	NA	480.0250	NA	126.6800	337.5677	1.3037
GNQ	5	hi-sms	NA	11.9608	64.9407	12928.4629	NA	7.8946	NA	NA	NA	1.5191
GRC	5	hi-weu	4571.9343	52.7466	114.1603	19718.4979	NA	3365.0940	114.8277	146.9867	3226.2519	1.2405
GRD	5	um-lac	980.3833	31.0000	120.0673	6348.9919	NA	NA	NA	NA	477.7386	1.8243
GRL	5	hi-sms	NA	64.4240	103.9611	NA	NA	NA	NA	NA	NA	1.5191
GTM	5	lm-lac	2008.5003	14.6250	134.1620	2307.9794	66.5256	1247.9296	158.6960	NA	545.6701	1.3754

GUM	5	hi-sms	2438.5965	59.6685	NA	NA	NA	NA	NA	NA	NA	1.5191
GUY	5	lm-lac	4471.0763	31.7250	69.0836	1251.7713	43.6014	3245.4012	30.8794	NA	468.7899	1.3754
HKG	5	hi-sms	NA	72.8250	219.4424	32549.9040	1155.6083	NA	901.3180	NA	NA	1.5191
HND	5	lm-lac	1661.0160	15.7275	104.2950	1550.7226	NA	1154.8343	83.9794	191.0067	416.8943	1.3754
HRV	5	hi-weu	5181.4070	60.7569	115.4582	10634.0998	452.6832	9.5394	308.6658	162.5233	953.8382	1.2405
HTI	5	lo-lac	972.5778	9.4425	52.8971	455.7160	NA	930.0000	NA	NA	NA	1.0069
HUN	5	um-eca	4575.5860	69.0610	117.3462	11279.0572	541.8956	69.4021	91.5854	203.7767	1084.7315	1.2585
IDN	5	lm-eap	4982.8088	13.1375	107.4573	1690.8004	55.5138	3941.5882	191.5804	310.7933	396.8101	1.3612
IMN	5	ot-sms	NA	NA	NA	NA	NA	NA	NA	NA	NA	1.4023
IND	5	lm-sas	2880.0745	11.3125	69.0734	1108.5744	40.5467	4381.7354	173.5684	172.0833	217.5848	1.4950
IRL	5	hi-weu	7610.6755	74.9769	105.9209	47126.2431	2959.7526	73.0805	426.5476	169.6800	583.9232	1.2405
IRN	5	um-mea	2317.1170	23.6500	76.8093	3268.6695	127.4696	4903.0238	35.1750	199.3667	NA	1.5149
IRQ	5	um-mea	2002.9010	5.9500	83.2564	2361.3628	NA	13652.2447	46.7356	227.9033	274.5616	1.5149
ISL	5	hi-weu	NA	95.2416	107.5625	57556.1953	4305.6787	571.8382	161.4499	NA	38640.0473	1.2405
ISR	5	hi-mea	3509.4933	69.4935	122.0735	23833.9954	1338.5047	3766.3334	305.2214	185.7167	NA	7.0787
ITA	5	hi-weu	5399.7103	55.5898	157.8470	30262.0188	1330.5810	2865.0232	135.9673	152.7900	1995.4758	1.2405
JAM	5	um-lac	1274.8873	34.1747	105.8200	NA	NA	5800.0000	72.7694	269.7000	589.4005	1.8243
JOR	5	um-mea	1502.0905	36.8250	120.9241	2834.9185	NA	3230.4896	891.9242	166.9500	472.5203	1.5149
JPN	5	hi-eap	6026.4278	82.4410	107.4052	36746.3265	1397.4609	13341.1638	262.4298	88.8933	5230.1198	1.1065
KAZ	5	um-eca	1104.7140	47.3789	162.2945	5091.5155	NA	595.6192	1.7211	192.7167	568.7463	1.2585
KEN	5	lo-ssa	1652.0860	28.2750	67.6970	608.9557	40.4620	391.2698	39.9331	168.4567	160.5998	1.3037
KGZ	5	lm-eca	2620.9415	20.8800	115.1743	587.5385	37.0668	5835.3833	21.7649	206.0067	190.8346	1.3129
KHM	5	lo-eap	3082.9828	3.8250	103.3366	655.8053	17.0960	508.9983	14.5262	189.5700	220.8921	1.1098
KIR	5	lm-eap	NA	10.3292	14.3041	1153.5712	NA	NA	NA	NA	NA	1.3612
KNA	5	hi-sms	NA	78.2372	145.5244	10740.5024	NA	NA	10.7111	NA	170.5475	1.5191
KOR	5	hi-eap	6624.0830	84.0756	108.2372	23078.8304	1122.7599	10483.3060	383.9920	104.2300	3134.8618	1.1065
KWT	5	hi-sms	8631.2575	68.2698	159.5267	30082.2511	NA	46119.4538	730.9698	NA	NA	1.5191
LAO	5	lm-eap	4026.6288	9.8119	69.8696	688.4538	19.1238	2253.8480	NA	170.8867	275.4269	1.3612
LBN	5	um-mea	3165.0628	56.8574	76.1318	7181.6573	144.3660	5403.9769	332.9304	128.5833	1562.4692	1.5149
LBR	5	lo-ssa	1139.9710	3.4235	51.3561	268.6534	7.5959	26.3581	NA	NA	300.1235	1.3037

LBY	5	um-mea	763.6565	14.8333	166.2767	6391.2714	NA	2059.8224	29.3579	NA	NA	1.5149
LCA	5	um-lac	NA	39.5800	117.0623	5772.7885	246.4639	NA	142.1111	NA	177.3183	1.8243
LIE	5	hi-sms	NA	87.0519	100.5948	NA	NA	NA	NA	NA	NA	1.5191
LKA	5	lm-sas	3792.7525	16.7964	89.5748	1805.5387	34.1989	9296.3260	229.2147	194.8200	235.0023	1.4950
LSO	5	lm-ssa	655.6810	4.4186	67.8691	916.4579	NA	12.5099	NA	NA	84.0454	1.2545
LTU	5	hi-weu	3373.0065	65.3607	159.5045	9785.4431	514.7611	37.4194	90.9339	177.0100	1172.9330	1.2405
LUX	5	hi-weu	5569.1623	91.5941	146.3240	80676.8120	NA	3.2185	308.4007	172.4700	1925.5119	1.2405
LVA	5	hi-sms	3177.1870	71.6311	159.6063	8152.1055	405.7288	45.3141	83.6635	189.5733	929.1289	1.5191
MAC	5	hi-sms	NA	60.6279	262.8727	46970.7783	1356.1231	NA	NA	NA	NA	1.5191
MAF	5	hi-sms	NA	NA	NA	NA	NA	NA	NA	NA	NA	1.5191
MAR	5	lm-mea	1501.7295	52.3809	115.8978	2443.4370	158.7822	1386.6003	38.1144	115.3967	898.9316	1.2169
MCO	5	hi-sms	NA	83.2500	82.7347	NA	NA	NA	NA	NA	NA	1.5191
MDA	5	lm-eca	2452.6568	40.6175	92.5483	1053.0227	91.3333	19.8622	14.4120	204.6300	171.9672	1.3129
MDG	5	lo-ssa	2648.4885	1.9637	38.2278	272.1935	7.5318	4608.6857	2.5242	158.1033	98.4731	1.3037
MDV	5	um-sas	2504.7343	35.8900	164.5987	4825.7542	313.3910	0.0000	114.4444	NA	349.7787	2.5047
MEX	5	um-lac	3395.0123	37.8591	81.4866	8360.9164	432.3047	2498.9343	79.8427	208.1367	1187.8472	1.8243
MHL	5	um-eap	NA	9.1900	NA	2925.9275	NA	NA	NA	NA	NA	1.2843
MKD	5	um-eca	3263.0895	56.8125	104.9938	3483.8355	NA	304.4271	62.6063	142.2533	788.7292	1.2585
MLI	5	lo-ssa	1451.6013	2.0922	88.9275	487.9058	22.2226	761.9006	22.5509	169.5867	281.0911	1.3037
MLT	5	hi-weu	5096.7565	67.0334	120.9526	16426.0924	1221.8055	2111.0833	102.4056	121.7433	5279.3198	1.2405
MMR	5	lo-eap	3615.9675	0.8748	5.8530	NA	NA	2736.6546	12.5237	154.9367	NA	1.1098
MNE	5	um-eca	3212.8735	46.6876	173.7337	4602.7048	NA	9.8879	13.1055	NA	957.5809	1.2585
MNG	5	lm-eap	1439.2380	14.2000	111.0630	1543.3971	84.0007	387.1987	22.0017	320.8600	732.7394	1.3612
MNP	5	hi-sms	NA	NA	NA	NA	NA	NA	NA	NA	NA	1.5191
MOZ	5	lo-ssa	873.8258	4.6798	36.2596	404.9264	NA	128.9775	7.1832	316.8800	141.9550	1.3037
MRT	5	lm-ssa	1327.8285	5.0173	93.7504	644.9254	26.6157	2822.2269	NA	NA	312.0428	1.2545
MUS	5	um-ssa	4337.2500	34.4250	111.1669	6577.3131	233.9485	6294.4872	210.2050	117.7600	486.3245	1.3187
MWI	5	lo-ssa	2039.2608	3.8352	26.9679	260.7017	12.6595	319.4341	34.9285	219.9200	86.5126	1.3037
MYS	5	um-eap	3798.9953	62.5175	133.3092	6660.5177	368.4988	1646.6908	1943.4462	120.7700	1768.4147	1.2843
NAM	5	um-ssa	422.3403	12.6104	100.4762	4358.8635	370.5641	251.2440	5.7171	207.4933	500.4077	1.3187

NCL	5	hi-sms	3334.9298	54.0000	91.4091	NA	NA	NA	174.5964	NA	NA	1.5191
NER	5	lo-ssa	452.6343	1.3094	30.6368	281.9870	11.6441	43.0180	0.7689	199.7000	NA	1.3037
NGA	5	lm-ssa	1451.1650	30.8075	63.1779	1024.3749	NA	197.5689	5.1469	210.6267	577.1742	1.2545
NIC	5	lm-lac	2043.8498	12.4000	89.8453	1301.3949	57.2211	670.7632	46.6639	218.5867	492.7768	1.3754
NLD	5	hi-weu	8391.9128	92.2391	116.5265	43524.2289	2591.8343	68.4380	283.4182	172.2967	6494.5122	1.2405
NOR	5	hi-weu	3573.4710	94.1458	115.6620	65014.8194	4364.2353	1032.8773	183.5508	124.2467	5238.5290	1.2405
NPL	5	lo-sas	2512.5780	10.3448	55.1826	392.2328	18.5093	4095.0597	29.3840	184.9133	147.7061	1.5014
NZL	5	hi-nao	7618.0850	81.6175	108.2911	28577.4488	2056.4180	6838.3216	1512.3497	150.6967	8135.3968	1.3794
OMN	5	hi-mea	10766.5575	52.5695	159.3087	13889.1586	NA	35792.4883	579.0815	NA	NA	7.0787
PAK	5	lm-sas	2675.1593	9.4650	64.0727	765.4587	17.4818	8282.1393	183.5828	252.4767	239.9305	1.4950
PAN	5	um-lac	2404.7125	41.5005	171.7921	6959.7931	229.5781	828.5084	67.4157	184.0967	713.5560	1.8243
PER	5	um-lac	4011.3838	37.0450	101.2976	3845.2380	112.8382	3175.6816	98.3739	149.7667	NA	1.8243
PHL	5	lm-eap	3399.2328	31.8088	99.5071	1478.9854	50.4779	12309.5971	131.6785	150.3767	246.5383	1.3612
PLW	5	um-eap	NA	NA	78.5687	9309.0356	NA	NA	NA	NA	2429.4912	1.2843
PNG	5	lm-eap	4658.0455	3.3200	35.2076	1045.2088	NA	3.3329	99.6967	NA	NA	1.3612
POL	5	hi-weu	3584.3495	62.3573	136.2085	10461.9879	529.0756	105.5435	187.3342	176.5967	592.6125	1.2405
PRI	5	hi-lac	1840.9935	59.0500	82.3171	19866.0496	NA	1229.3029	NA	NA	3966.2006	1.5817
PRK	5	lo-eap	3740.5635	0.0000	5.6021	NA	NA	2853.4027	NA	NA	NA	1.1098
PRT	5	hi-weu	3906.7743	57.7464	114.2796	18683.7275	1017.9802	5577.4812	151.2018	148.4000	1113.6257	1.2405
PRY	5	lm-lac	3414.4130	27.7009	99.0670	1785.6131	78.0311	466.1181	87.7807	150.1933	839.6048	1.3754
PYF	5	hi-sms	NA	51.9192	82.7280	NA	NA	NA	284.0000	NA	NA	1.5191
QAT	5	hi-mea	6412.4448	73.1500	131.2349	59505.2571	NA	19171.0537	9763.4432	82.5667	5057.4452	7.0787
ROU	5	um-weu	3387.0463	43.8961	107.3469	5833.9036	192.4695	130.4038	52.1540	193.6333	875.5529	1.2520
RUS	5	hi-eca	2050.0993	54.3000	151.4281	6697.3954	NA	109.6217	16.0542	177.5367	922.1923	1.2716
RWA	5	lo-ssa	2094.4013	7.9310	44.7780	380.6036	18.7323	84.4891	1.4037	177.4967	160.9857	1.3037
SAU	5	hi-mea	4923.8685	50.7500	188.8113	17202.9803	NA	6661.9190	198.9755	114.9933	2294.1979	7.0787
SDN	5	lm-ssa	519.3265	19.4260	64.3835	806.5952	NA	1364.6317	10.2535	217.7000	393.7493	1.2545
SEN	5	lm-ssa	1163.1728	18.4009	77.7711	796.9270	44.6260	560.6568	7.9267	148.2933	189.7343	1.2545
SGP	5	hi-sms	NA	71.7500	150.8898	35967.2895	1101.8692	12000.0000	3626.2897	NA	NA	1.5191
SLB	5	lm-eap	3243.1818	6.4994	46.3945	1071.1953	105.6545	NA	NA	NA	NA	1.3612

SLE	5	lo-ssa	1707.2365	1.1200	43.4569	390.0035	10.6036	34.8734	NA	NA	331.2155	1.3037
SLV	5	lm-lac	2678.2993	19.5577	132.5728	3010.5825	103.9384	2112.2265	180.0086	157.5300	901.0261	1.3754
SMR	5	hi-sms	NA	50.4275	111.3761	NA	NA	NA	NA	NA	NA	1.5191
SOM	5	lo-ssa	796.6000	1.3756	24.2091	NA	NA	2982.5913	NA	NA	NA	1.3037
SRB	5	um-eca	4402.5730	45.6750	123.1788	4195.6462	135.8355	23.4006	139.4599	217.4867	779.6866	1.2585
SSD	5	lm-ssa	NA	NA	21.2734	NA	NA	NA	NA	NA	NA	1.2545
STP	5	lm-ssa	862.0363	20.8709	62.5830	966.5674	91.6717	NA	NA	NA	NA	1.2545
SUR	5	um-lac	4305.6883	33.9178	116.8786	4411.0991	NA	7433.2759	152.0023	260.6867	706.7934	1.8243
SVK	5	hi-weu	4266.1013	76.1856	111.2120	15020.9283	622.4821	15.8081	94.4844	135.1600	1120.6671	1.2405
SVN	5	hi-weu	5678.7938	69.5914	106.7664	19055.5866	1082.6496	11.7524	277.3760	161.4667	789.0508	1.2405
SWE	5	hi-weu	4861.4395	92.6834	121.8377	45353.9456	3130.3037	40.9731	74.3579	173.6700	2993.0012	1.2405
SWZ	5	lm-ssa	1176.2063	18.6629	65.2327	2416.2859	178.7479	5748.8629	NA	NA	193.5136	1.2545
SXM	5	hi-sms	NA	NA	NA	NA	NA	NA	NA	NA	NA	1.5191
SYC	5	um-ssa	NA	45.4100	140.4928	13953.0593	506.0479	899.9530	63.3333	NA	604.6097	1.3187
SYR	5	lm-mea	1532.6678	23.4250	57.2461	NA	NA	3151.9075	37.6311	178.6600	NA	1.2169
TCA	5	hi-sms	NA	NA	NA	NA	NA	NA	NA	NA	NA	1.5191
TCD	5	lo-ssa	869.6695	2.0000	31.4514	724.6615	15.3715	141.0189	NA	NA	NA	1.3037
TGO	5	lo-ssa	1226.3050	3.7500	48.8267	408.2329	17.5328	29.8036	8.0563	128.3467	177.2879	1.3037
THA	5	um-eap	3080.7903	25.3675	122.9230	3287.3472	187.5047	3231.5545	158.9548	168.2867	581.2646	1.2843
TJK	5	lo-eca	2831.4378	13.7725	83.0371	448.3938	17.9016	12286.9525	57.4440	285.9433	137.8628	2.9880
TKM	5	um-eca	2091.3338	6.1990	99.5386	3110.0551	94.9833	13776.8179	NA	128.7567	NA	1.2585
TLS	5	lo-sas	2260.9050	0.7812	53.2392	737.0224	72.3613	6909.5071	NA	NA	169.5419	1.5014
TON	5	um-eap	NA	27.7152	53.1810	2637.0377	NA	NA	240.9167	NA	503.5519	1.2843
TTO	5	hi-sms	1597.3845	56.7541	141.3506	14216.8331	NA	800.0390	474.9867	104.9000	80.8473	1.5191
TUN	5	um-mea	1694.0778	40.2854	113.3619	3883.9012	242.3563	763.9784	49.1501	146.2400	966.3977	1.5149
TUR	5	um-eca	2967.9433	43.5664	89.8666	8363.2758	NA	1420.8874	101.7910	159.7700	2418.6776	1.2585
TUV	5	um-eap	NA	31.7500	25.1859	2581.0875	NA	NA	NA	NA	1347.5667	1.2843
TZA	5	lo-ssa	1442.7745	3.6875	53.6776	463.1868	27.8359	368.5865	6.3175	196.3733	162.3599	1.3037
UGA	5	lo-ssa	2056.9738	14.1008	43.5855	410.1943	12.3516	17.6484	1.7769	NA	83.0004	1.3037
UKR	5	lm-eca	3432.5663	32.2696	126.7130	2072.9499	132.7990	36.4931	37.6102	291.2967	677.7300	1.3129

URY	5	hi-lac	4030.2603	52.5896	143.4863	7342.5682	324.7644	1808.6303	181.5333	128.3833	10246.5149	1.5817
USA	5	hi-nao	6767.7480	76.2299	94.3229	44762.8131	2383.0900	1214.9733	127.8166	240.6300	2592.2834	1.3794
UZB	5	lm-eca	4668.7175	31.2303	77.7912	822.7121	NA	11675.6757	187.1978	NA	279.7410	1.3129
VCT	5	um-lac	24287.5313	45.2575	117.9583	5420.7466	275.5548	NA	NA	NA	580.7273	1.8243
VEN	5	um-lac	3105.7655	45.3850	99.3061	6246.9878	NA	6345.5666	169.5410	348.4000	1849.3917	1.8243
VIR	5	hi-sms	NA	38.1670	NA	NA	NA	NA	NA	NA	NA	1.5191
VNM	5	lm-eap	5361.3815	37.2775	136.3600	965.4836	60.8047	12062.0625	310.6088	245.7067	229.3738	1.3612
VUT	5	lm-eap	575.2110	9.7745	59.4956	2107.2958	NA	NA	NA	132.3000	583.7937	1.3612
PSE	5	ot-sms	1558.3445	42.1200	70.7617	1441.0524	NA	4257.1982	NA	NA	300.7661	1.4023
WSM	5	lm-eap	NA	11.5556	NA	2686.5001	NA	NA	1.6667	NA	323.9389	1.3612
YEM	5	lm-mea	1046.8533	16.1754	56.5139	769.4559	NA	2625.7151	13.8802	221.1300	NA	1.2169
ZAF	5	um-ssa	3895.2913	36.9675	124.3250	6015.6931	374.3872	642.9128	58.7073	189.5200	370.5732	1.3187
COD	5	ot-ssa	763.1083	1.4500	28.9686	268.7501	4.3131	10.4730	1.1975	NA	84.2810	0.9615
ZMB	5	lm-ssa	2621.6728	12.5921	61.8441	1004.2003	NA	317.0537	31.1466	366.3733	142.4247	1.2545
ZWE	5	lo-ssa	766.6290	15.6975	79.0025	444.4800	8.7557	815.9423	30.8652	NA	80.1389	1.3037

9 ANNEX C: Supporting material for the sub-national model

SUMMARY OF VARIABLES

simbol	Variable	Unit	Source	Comments
tr.3G.05.09	Treatment variable: 3G technology	Binary variable	ANATEL	Implementation of 3G technology in the period between 2005-09. 1=yes, 0=no.
def.10/area	Total accumulated deforestation in 2010 as a % of the municipality area	% of area	INPE	-
def.04/area	Total accumulated deforestation in 2004 as a % of the municipality area	% of area	INPE	-
pop	Population	Number of inhabitants in 2013	IBGE	-
gdp	GDP per capita	current R\$ for 2013	IBGE	-
DDD	Region	Categoric variable	ANATEL	Division of regions, as defined by ANATEL, for mobile coverage. Also serves as control for location.
agi.perc	Agricultural importance in the economy	%	IBGE	Agricultural value added as a percentage of the total value added of the economy at the municipality
agg	Index for agricultural value added growth	yr2000=1	IBGE	For the period 2000 to 2010. Values in current R\$ were deflated to 2010 using the Brazilian Extended National Consumer Price Index (IPCA) before calculating the final index
ERB.dens.07.09	Antenna density	No. of antennas / sq km	ANATEL & IBGE	Index calculated dividing the number of antennas for mobile coverage by the area of the municipality. Calculated as the average for the period between 2007 and 2009.
area	Municipality area	Sq km	IBGE	Total area of the municipality (data for 2013)
priority.mun	Amazons priority municipalities	Binary variable	MMA	List of municipalities set by government as priorities for tackling deforestation. Y=yes, N=no.

DESCRIPTIVE STATISTICS

```

> summary(avg.yr.def.10.13)
      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
0.0000  0.0000  0.2667  3.0840  2.1920 53.5000
> summary(gdp)
      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
    2067    4643    7198   10220   11770  159500
> summary(agi.perc)
      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
0.02399 0.19090 0.28580 0.30940 0.41160 0.81370
> summary(agg)
      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
-0.7403  0.4127  0.8404   1.3780   1.5700  59.9100
> summary(area)
      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
    142.8    748.6   1637.0   5622.0   4570.0 122500.0
> summary(ERB.dens.07.09)
      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
0.0000  0.0000  0.2212  0.5600  0.6278  13.3100
> summary(pop)
      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
    1024    5609   11290   14590   18810   81320
> summary(other)
tr.3G.05.09      DDD
0:424           63      :125
1: 86           98      : 80
              99      : 73
              91      : 43
              66      : 34
              69      : 30
              (Other):125

```

CODES

#treating the data

```

attach(br)
df<-data.frame(br)
Tr<-cbind(tr.3G.05.09)
Y<-cbind((def.10/area)-(def.04/area))
X<-cbind(gdp,agi.perc,agg,DDD,pop,ERB.dens.07.09,area)

```

initial probit model (step 1)

```

glm1<-glm(Tr~gdp+agi.perc+agg+DDD+pop+ERB.dens.07.09+area,family=binomial,
data=df)
summary(glm1)

```

#propensity score model

```

rr2<-Match(Y=Y,Tr=Tr,X=glm1$fitted,estimand="ATC",M=1,ties=FALSE,replace=T
RUE)
summary(rr2)

```

#note: in order to run different estimation models the command "estimand" was varied between ATC, ATT and ATE. The command "ties" was varied between TRUE and FALSE

Description on the different estimation variables, described in SEKHON, J.S. (2015). **Package Matching (Version 4.9-2)**. Descriptive text on the R software package, available on: <https://cran.r-project.org/web/packages/Matching/Matching.pdf>, retrieved on February 20th 2017.

"estimand: This determines if the standardized mean difference returned by the sdif f object is standardized by the variance of the treatment observations (which is done if the estimand is either "ATE" or "ATT") or by the variance of the control observations (which is done if the estimand is "ATC")."

replace: A logical flag for whether matching should be done with replacement. Note that if FALSE, the order of matches generally matters. Matches will be found in the same order as the data are sorted. Thus, the match(es) for the first observation will be found first, the match(es) for the second observation will be found second, etc. Matching without replacement will generally increase bias. Ties are randomly broken when replace==FALSE—see the ties option for details.

ties: A logical flag for whether ties should be handled deterministically. By default ties==TRUE. If, for example, one treated observation matches more than one control observation, the matched dataset will include the multiple matched control observations and the matched data will be weighted to reflect the multiple matches. The sum of the weighted observations will still equal the original number of observations. If ties==FALSE, ties will be randomly broken. If the dataset is large and there are many ties, setting ties=FALSE often results in a large speedup. Whether two potential matches are close enough to be considered tied, is controlled by the distance.tolerance option". (SEKHON 2015)

Checking the balance proprieties: statistics

```
MatchBalance(Tr~gdp+agi.perc+agg+DDD+pop+ERB.dens.07.09+area, match.out = rr2, nboots=0, data=df)
```

Checking the balance proprieties: graphs

```
qqplot(gdp[rr2$index.control], gdp[rr2$index.treated])
abline(coef = c(0, 1), col = 2)
```

```
qqplot(agi.perc[rr2$index.control], agi.perc[rr2$index.treated])
abline(coef = c(0, 1), col = 2)
```

```
qqplot(agg[rr2$index.control], agg[rr2$index.treated])
abline(coef = c(0, 1), col = 2)
```

```
qqplot(pop[rr2$index.control], pop[rr2$index.treated])
abline(coef = c(0, 1), col = 2)
```

```
qqplot(ERB.dens.07.09 [rr2$index.control], ERB.dens.07.09 [rr2$index.treated])
abline(coef = c(0, 1), col = 2)
```

```
qqplot(area[rr2$index.control], area[rr2$index.treated])
abline(coef = c(0, 1), col = 2)
```

RESULTS OF REGRESSIONS

Summary of the probit model (first step for calculating the propensity score matching)

```
call:
glm(formula = Tr ~ gdp + agi.perc + agg + DDD + pop + ERB.dens.07.09 +
     area, family = binomial, data = df)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-4.2317  -0.5097  -0.3209  -0.1301   2.4962

Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept)  -4.020e+00  7.533e-01  -5.337 9.47e-08 ***
gdp           -6.789e-05  3.868e-05  -1.755 0.079252 .
agi.perc      1.940e+00  1.495e+00   1.297 0.194513
agg          -2.303e-01  1.445e-01  -1.594 0.111045
DDD65         2.875e+00  8.120e-01   3.540 0.000400 ***
DDD66         2.223e+00  7.737e-01   2.873 0.004065 **
DDD68         1.267e+00  9.703e-01   1.306 0.191467
DDD69         1.914e+00  7.663e-01   2.498 0.012506 *
DDD91         1.080e+00  7.409e-01   1.458 0.144917
DDD92         4.424e+00  1.063e+00   4.161 3.16e-05 ***
DDD93         2.320e+00  9.104e-01   2.548 0.010831 *
DDD94         4.000e+00  8.950e-01   4.469 7.86e-06 ***
DDD95         2.756e+00  9.162e-01   3.008 0.002629 **
DDD96         3.128e+00  9.302e-01   3.363 0.000771 ***
DDD97        -1.458e+01  6.834e+02  -0.021 0.982981
DDD98         3.653e-01  7.047e-01   0.518 0.604161
DDD99         5.746e-01  7.016e-01   0.819 0.412802
pop           4.940e-05  1.574e-05   3.139 0.001693 **
ERB.dens.07.09 9.813e-01  1.934e-01   5.075 3.88e-07 ***
area         -7.991e-06  1.845e-05  -0.433 0.664897
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 462.78  on 509  degrees of freedom
Residual deviance: 323.05  on 490  degrees of freedom
AIC: 363.05

Number of Fisher Scoring iterations: 16
```

Summary of the propensity score matching model results

ESTIMAND = ATC, TIES = FALSE

```

Estimate... -0.0038059
SE..... 0.0016124
T-stat..... -2.3603
p.val..... 0.01826

Original number of observations..... 510
Original number of control obs..... 424
Matched number of observations..... 424
Matched number of observations (unweighted). 424

```

ESTIMAND = ATC, TIES = TRUE

```

Estimate... -0.0037134
AI SE..... 0.010461
T-stat..... -0.35498
p.val..... 0.72261

Original number of observations..... 510
Original number of control obs..... 424
Matched number of observations..... 424
Matched number of observations (unweighted). 441

```

ESTIMAND = ATT, TIES = FALSE

```

Estimate... -0.0093746
SE..... 0.0039202
T-stat..... -2.3913
p.val..... 0.016787

Original number of observations..... 510
Original number of treated obs..... 86
Matched number of observations..... 86
Matched number of observations (unweighted). 86

```

ESTIMAND = ATT, TIES = TRUE

```

Estimate... -0.0084954
AI SE..... 0.0052921
T-stat..... -1.6053
p.val..... 0.10843

Original number of observations..... 510
Original number of treated obs..... 86
Matched number of observations..... 86
Matched number of observations (unweighted). 122

```

ESTIMAND = ATE, TIES = FALSE

```

Estimate... -0.0046271
SE..... 0.0015011
T-stat..... -3.0825
p.val..... 0.0020526

```



```

Original number of observations..... 510
Original number of treated obs..... 86
Matched number of observations..... 510
Matched number of observations (unweighted). 510

```

ESTIMAND = ATE, TIES = TRUE

```

Estimate... -0.0045198
AI SE..... 0.0090095
T-stat..... -0.50167
p.val..... 0.6159

Original number of observations..... 510
Original number of treated obs..... 86
Matched number of observations..... 510
Matched number of observations (unweighted). 563

```

Checking the balance proprieties: statistics

ESTIMAND = ATC, TIES = FALSE

```

***** (V1) gdp *****

                Before Matching                After Matching
mean treatment..... 8543.5                9140.5
mean control..... 10557                10557
std mean diff..... -37.427                -39.591

mean raw eQQ diff..... 3071.1                3766
med raw eQQ diff..... 650.56                1776.3
max raw eQQ diff..... 134186                134186

mean eCDF diff..... 0.042202                0.13144
med eCDF diff..... 0.038586                0.13679
max eCDF diff..... 0.12922                0.26179

var ratio (Tr/Co)..... 0.20931                0.092567
T-test p-value..... 0.013981                0.01613
KS Naive p-value..... 0.18351                4.7962e-13
KS Statistic..... 0.12922                0.26179

***** (V2) agi.perc *****

                Before Matching                After Matching
mean treatment..... 0.27979                0.30075
mean control..... 0.31535                0.31535
std mean diff..... -23.301                -11.669

mean raw eQQ diff..... 0.036171                0.053674
med raw eQQ diff..... 0.03308                0.038474
max raw eQQ diff..... 0.14351                0.14724

mean eCDF diff..... 0.066842                0.093025
med eCDF diff..... 0.067628                0.080189
max eCDF diff..... 0.13295                0.22642

```

var ratio (Tr/Co).....	0.98947	0.66529
T-test p-value.....	0.051275	0.12656
KS Naive p-value.....	0.15961	7.2656e-10
KS Statistic.....	0.13295	0.22642

***** (V3) agg *****

	Before Matching	After Matching
mean treatment.....	0.84539	1.141
mean control.....	1.4855	1.4855
std mean diff.....	-68.479	-28.614
mean raw eQQ diff.....	1.1074	0.49901
med raw eQQ diff.....	0.24974	0.2206
max raw eQQ diff.....	54.81	54.81
mean eCDF diff.....	0.09977	0.092431
med eCDF diff.....	0.10306	0.061321
max eCDF diff.....	0.17798	0.29717
var ratio (Tr/Co).....	0.080589	0.13374
T-test p-value.....	0.0007688	0.049272
KS Naive p-value.....	0.021564	< 2.22e-16
KS Statistic.....	0.17798	0.29717

***** (V4) DDD65 *****

	Before Matching	After Matching
mean treatment.....	0.069767	0.028302
mean control.....	0.03066	0.03066
std mean diff.....	15.261	-1.4205
mean raw eQQ diff.....	0.034884	0.0023585
med raw eQQ diff.....	0	0
max raw eQQ diff.....	1	1
mean eCDF diff.....	0.019554	0.0011792
med eCDF diff.....	0.019554	0.0011792
max eCDF diff.....	0.039107	0.0023585
var ratio (Tr/Co).....	2.2042	0.92532
T-test p-value.....	0.17865	0.82736

***** (V5) DDD66 *****

	Before Matching	After Matching
mean treatment.....	0.069767	0.044811
mean control.....	0.066038	0.066038
std mean diff.....	1.4555	-10.248
mean raw eQQ diff.....	0	0.021226
med raw eQQ diff.....	0	0
max raw eQQ diff.....	0	1
mean eCDF diff.....	0.0018649	0.010613
med eCDF diff.....	0.0018649	0.010613
max eCDF diff.....	0.0037297	0.021226
var ratio (Tr/Co).....	1.0621	0.69399
T-test p-value.....	0.90177	0.17951

***** (V6) DDD68 *****

	Before Matching	After Matching
mean treatment.....	0.023256	0.049528
mean control.....	0.035377	0.035377
std mean diff.....	-7.9958	6.5144
mean raw eQQ diff.....	0.011628	0.014151
med raw eQQ diff.....	0	0
max raw eQQ diff.....	1	1
mean eCDF diff.....	0.0060608	0.0070755
med eCDF diff.....	0.0060608	0.0070755
max eCDF diff.....	0.012122	0.014151
var ratio (Tr/Co).....	0.67187	1.3795
T-test p-value.....	0.51683	0.30347

***** (V7) DDD69 *****

	Before Matching	After Matching
mean treatment.....	0.05814	0.011792
mean control.....	0.058962	0.058962
std mean diff.....	-0.34953	-43.644
mean raw eQQ diff.....	0	0.04717
med raw eQQ diff.....	0	0
max raw eQQ diff.....	0	1
mean eCDF diff.....	0.00041136	0.023585
med eCDF diff.....	0.00041136	0.023585
max eCDF diff.....	0.00082273	0.04717
var ratio (Tr/Co).....	0.99616	0.21003
T-test p-value.....	0.97648	0.00013911

***** (V8) DDD91 *****

	Before Matching	After Matching
mean treatment.....	0.16279	0.035377
mean control.....	0.068396	0.068396
std mean diff.....	25.42	-17.853
mean raw eQQ diff.....	0.093023	0.033019
med raw eQQ diff.....	0	0
max raw eQQ diff.....	1	1
mean eCDF diff.....	0.047197	0.016509
med eCDF diff.....	0.047197	0.016509
max eCDF diff.....	0.094394	0.033019
var ratio (Tr/Co).....	2.159	0.53557
T-test p-value.....	0.026354	0.026507

***** (V9) DDD92 *****

	Before Matching	After Matching
mean treatment.....	0.069767	0.009434
mean control.....	0.004717	0.004717
std mean diff.....	25.386	4.8737

mean raw eQQ diff.....	0.05814	0.004717
med raw eQQ diff.....	0	0
max raw eQQ diff.....	1	1
mean eCDF diff.....	0.032525	0.0023585
med eCDF diff.....	0.032525	0.0023585
max eCDF diff.....	0.06505	0.004717
var ratio (Tr/Co).....	13.954	1.9905
T-test p-value.....	0.02171	0.31731

***** (V10) DDD93 *****

	Before Matching	After Matching
mean treatment.....	0.081395	0.025943
mean control.....	0.018868	0.018868
std mean diff.....	22.734	4.4457
mean raw eQQ diff.....	0.05814	0.0070755
med raw eQQ diff.....	0	0
max raw eQQ diff.....	1	1
mean eCDF diff.....	0.031264	0.0035377
med eCDF diff.....	0.031264	0.0035377
max eCDF diff.....	0.062527	0.0070755
var ratio (Tr/Co).....	4.0769	1.3651
T-test p-value.....	0.042403	0.49143

***** (V11) DDD94 *****

	Before Matching	After Matching
mean treatment.....	0.10465	0.004717
mean control.....	0.0070755	0.0070755
std mean diff.....	31.691	-3.4381
mean raw eQQ diff.....	0.093023	0.0023585
med raw eQQ diff.....	0	0
max raw eQQ diff.....	1	1
mean eCDF diff.....	0.048788	0.0011792
med eCDF diff.....	0.048788	0.0011792
max eCDF diff.....	0.097576	0.0023585
var ratio (Tr/Co).....	13.462	0.66825
T-test p-value.....	0.004489	0.65487

***** (V12) DDD95 *****

	Before Matching	After Matching
mean treatment.....	0.034884	0.014151
mean control.....	0.023585	0.023585
std mean diff.....	6.122	-7.9778
mean raw eQQ diff.....	0.011628	0.009434
med raw eQQ diff.....	0	0
max raw eQQ diff.....	1	1
mean eCDF diff.....	0.0056494	0.004717
med eCDF diff.....	0.0056494	0.004717

max eCDF diff.....	0.011299	0.009434
var ratio (Tr/Co).....	1.4757	0.6058
T-test p-value.....	0.59558	0.31731
***** (V13) DDD96 *****		
	Before Matching	After Matching
mean treatment.....	0.034884	0.0070755
mean control.....	0.021226	0.021226
std mean diff.....	7.3999	-16.863
mean raw eQQ diff.....	0.011628	0.014151
med raw eQQ diff.....	0	0
max raw eQQ diff.....	1	1
mean eCDF diff.....	0.0068287	0.0070755
med eCDF diff.....	0.0068287	0.0070755
max eCDF diff.....	0.013657	0.014151
var ratio (Tr/Co).....	1.6357	0.33815
T-test p-value.....	0.51884	0.082901
***** (V14) DDD97 *****		
	Before Matching	After Matching
mean treatment.....	0	0
mean control.....	0.068396	0.068396
std mean diff.....	-Inf	-Inf
mean raw eQQ diff.....	0.069767	0.068396
med raw eQQ diff.....	0	0
max raw eQQ diff.....	1	1
mean eCDF diff.....	0.034198	0.034198
med eCDF diff.....	0.034198	0.034198
max eCDF diff.....	0.068396	0.068396
var ratio (Tr/Co).....	0	0
T-test p-value.....	4.4715e-08	4.3167e-08
***** (V15) DDD98 *****		
	Before Matching	After Matching
mean treatment.....	0.11628	0.04717
mean control.....	0.16509	0.16509
std mean diff.....	-15.139	-55.559
mean raw eQQ diff.....	0.046512	0.11792
med raw eQQ diff.....	0	0
max raw eQQ diff.....	1	1
mean eCDF diff.....	0.024408	0.058962
med eCDF diff.....	0.024408	0.058962
max eCDF diff.....	0.048815	0.11792
var ratio (Tr/Co).....	0.75249	0.32607
T-test p-value.....	0.21491	4.1534e-08
***** (V16) DDD99 *****		

	Before Matching	After Matching
mean treatment.....	0.093023	0.075472
mean control.....	0.1533	0.1533
std mean diff.....	-20.631	-29.43
mean raw eQQ diff.....	0.05814	0.07783
med raw eQQ diff.....	0	0
max raw eQQ diff.....	1	1
mean eCDF diff.....	0.030139	0.038915
med eCDF diff.....	0.030139	0.038915
max eCDF diff.....	0.060279	0.07783
var ratio (Tr/Co).....	0.65609	0.53756
T-test p-value.....	0.096675	0.00042912
***** (V17) pop *****		
	Before Matching	After Matching
mean treatment.....	20317	7311.6
mean control.....	13430	13430
std mean diff.....	45.031	-65.665
mean raw eQQ diff.....	6961.5	6118.3
med raw eQQ diff.....	6199.5	6137
max raw eQQ diff.....	19444	40759
mean eCDF diff.....	0.13692	0.25029
med eCDF diff.....	0.16383	0.26887
max eCDF diff.....	0.24375	0.5283
var ratio (Tr/Co).....	1.949	0.7233
T-test p-value.....	0.00013091	< 2.22e-16
KS Naïve p-value.....	0.00040865	< 2.22e-16
KS Statistic.....	0.24375	0.5283
***** (V18) ERB.dens.07.09 *****		
	Before Matching	After Matching
mean treatment.....	1.1652	1.1852
mean control.....	0.43728	0.43728
std mean diff.....	53.067	97.55
mean raw eQQ diff.....	0.7547	0.79126
med raw eQQ diff.....	0.49305	0.81239
max raw eQQ diff.....	5.3167	5.3167
mean eCDF diff.....	0.28454	0.42045
med eCDF diff.....	0.31809	0.48349
max eCDF diff.....	0.39623	0.63208
var ratio (Tr/Co).....	2.2713	0.70958
T-test p-value.....	7.7806e-06	< 2.22e-16
KS Naïve p-value.....	3.5583e-10	< 2.22e-16
KS Statistic.....	0.39623	0.63208
***** (V19) area *****		
	Before Matching	After Matching
mean treatment.....	5584.2	1684.2
mean control.....	5630.1	5630.1

std mean diff.....	-0.33685	-93.393
mean raw eQQ diff.....	779.71	3948.8
med raw eQQ diff.....	112.51	984.37
max raw eQQ diff.....	15438	75588
mean eCDF diff.....	0.021088	0.23364
med eCDF diff.....	0.015687	0.17099
max eCDF diff.....	0.091433	0.54481
var ratio (Tr/Co).....	1.1191	0.10784
T-test p-value.....	0.97712	4.5719e-09
KS Naive p-value.....	0.58842	< 2.22e-16
KS Statistic.....	0.091433	0.54481

Before Matching Minimum p.value: 3.5583e-10
 Variable Name(s): ERB.dens.07.09 Number(s): 18

After Matching Minimum p.value: < 2.22e-16
 Variable Name(s): pop ERB.dens.07.09 area Number(s): 17 18 19

ESTIMAND = ATT, TIES = TRUE

***** (V1) gdp *****

	Before Matching	After Matching
mean treatment.....	8543.5	8543.5
mean control.....	10557	8027.2
std mean diff.....	-37.427	9.5972
mean raw eQQ diff.....	3071.1	868.13
med raw eQQ diff.....	650.56	451.84
max raw eQQ diff.....	134186	10642
mean eCDF diff.....	0.042202	0.038336
med eCDF diff.....	0.038586	0.032787
max eCDF diff.....	0.12922	0.098361
var ratio (Tr/Co).....	0.20931	1.198
T-test p-value.....	0.013981	0.49254
KS Naive p-value.....	0.18351	0.5966
KS Statistic.....	0.12922	0.098361

***** (V2) agi.perc *****

	Before Matching	After Matching
mean treatment.....	0.27979	0.27979
mean control.....	0.31535	0.26458
std mean diff.....	-23.301	9.962
mean raw eQQ diff.....	0.036171	0.017757
med raw eQQ diff.....	0.03308	0.016017
max raw eQQ diff.....	0.14351	0.05268
mean eCDF diff.....	0.066842	0.037929
med eCDF diff.....	0.067628	0.032787
max eCDF diff.....	0.13295	0.12295
var ratio (Tr/Co).....	0.98947	1.3887
T-test p-value.....	0.051275	0.46317

KS Naïve p-value.....	0.15961	0.31505
KS Statistic.....	0.13295	0.12295
***** (V3) agg *****		
	Before Matching	After Matching
mean treatment.....	0.84539	0.84539
mean control.....	1.4855	0.93317
std mean diff.....	-68.479	-9.3898
mean raw eQQ diff.....	1.1074	0.18851
med raw eQQ diff.....	0.24974	0.13587
max raw eQQ diff.....	54.81	1.4284
mean eCDF diff.....	0.09977	0.059719
med eCDF diff.....	0.10306	0.057377
max eCDF diff.....	0.17798	0.16393
var ratio (Tr/Co).....	0.080589	1.1876
T-test p-value.....	0.0007688	0.51372
KS Naïve p-value.....	0.021564	0.075351
KS Statistic.....	0.17798	0.16393
***** (V4) DDD65 *****		
	Before Matching	After Matching
mean treatment.....	0.069767	0.069767
mean control.....	0.03066	0.046512
std mean diff.....	15.261	9.0755
mean raw eQQ diff.....	0.034884	0.032787
med raw eQQ diff.....	0	0
max raw eQQ diff.....	1	1
mean eCDF diff.....	0.019554	0.016393
med eCDF diff.....	0.019554	0.016393
max eCDF diff.....	0.039107	0.032787
var ratio (Tr/Co).....	2.2042	1.4634
T-test p-value.....	0.17865	0.48016
***** (V5) DDD66 *****		
	Before Matching	After Matching
mean treatment.....	0.069767	0.069767
mean control.....	0.066038	0.065891
std mean diff.....	1.4555	1.5126
mean raw eQQ diff.....	0	0.02459
med raw eQQ diff.....	0	0
max raw eQQ diff.....	0	1
mean eCDF diff.....	0.0018649	0.012295
med eCDF diff.....	0.0018649	0.012295
max eCDF diff.....	0.0037297	0.02459
var ratio (Tr/Co).....	1.0621	1.0544
T-test p-value.....	0.90177	0.91487
***** (V6) DDD68 *****		

	Before Matching	After Matching
mean treatment.....	0.023256	0.023256
mean control.....	0.035377	0.025194
std mean diff.....	-7.9958	-1.2784
mean raw eQQ diff.....	0.011628	0.02459
med raw eQQ diff.....	0	0
max raw eQQ diff.....	1	1
mean eCDF diff.....	0.0060608	0.012295
med eCDF diff.....	0.0060608	0.012295
max eCDF diff.....	0.012122	0.02459
var ratio (Tr/Co).....	0.67187	0.92491
T-test p-value.....	0.51683	0.93511
***** (V7) DDD69 *****		
	Before Matching	After Matching
mean treatment.....	0.05814	0.05814
mean control.....	0.058962	0.09186
std mean diff.....	-0.34953	-14.326
mean raw eQQ diff.....	0	0.04918
med raw eQQ diff.....	0	0
max raw eQQ diff.....	0	1
mean eCDF diff.....	0.00041136	0.02459
med eCDF diff.....	0.00041136	0.02459
max eCDF diff.....	0.00082273	0.04918
var ratio (Tr/Co).....	0.99616	0.65641
T-test p-value.....	0.97648	0.38008
***** (V8) DDD91 *****		
	Before Matching	After Matching
mean treatment.....	0.16279	0.16279
mean control.....	0.068396	0.19767
std mean diff.....	25.42	-9.394
mean raw eQQ diff.....	0.093023	0.016393
med raw eQQ diff.....	0	0
max raw eQQ diff.....	1	1
mean eCDF diff.....	0.047197	0.0081967
med eCDF diff.....	0.047197	0.0081967
max eCDF diff.....	0.094394	0.016393
var ratio (Tr/Co).....	2.159	0.85934
T-test p-value.....	0.026354	0.54104
***** (V9) DDD92 *****		
	Before Matching	After Matching
mean treatment.....	0.069767	0.069767
mean control.....	0.004717	0.034884
std mean diff.....	25.386	13.613
mean raw eQQ diff.....	0.05814	0.02459
med raw eQQ diff.....	0	0

max raw eQQ diff.....	1	1
mean eCDF diff.....	0.032525	0.012295
med eCDF diff.....	0.032525	0.012295
max eCDF diff.....	0.06505	0.02459
var ratio (Tr/Co).....	13.954	1.9277
T-test p-value.....	0.02171	0.25647
***** (V10) DDD93 *****		
	Before Matching	After Matching
mean treatment.....	0.081395	0.081395
mean control.....	0.018868	0.098837
std mean diff.....	22.734	-6.3415
mean raw eQQ diff.....	0.05814	0.016393
med raw eQQ diff.....	0	0
max raw eQQ diff.....	1	1
mean eCDF diff.....	0.031264	0.0081967
med eCDF diff.....	0.031264	0.0081967
max eCDF diff.....	0.062527	0.016393
var ratio (Tr/Co).....	4.0769	0.83947
T-test p-value.....	0.042403	0.65901
***** (V11) DDD94 *****		
	Before Matching	After Matching
mean treatment.....	0.10465	0.10465
mean control.....	0.0070755	0.11628
std mean diff.....	31.691	-3.7765
mean raw eQQ diff.....	0.093023	0.0081967
med raw eQQ diff.....	0	0
max raw eQQ diff.....	1	1
mean eCDF diff.....	0.048788	0.0040984
med eCDF diff.....	0.048788	0.0040984
max eCDF diff.....	0.097576	0.0081967
var ratio (Tr/Co).....	13.462	0.91184
T-test p-value.....	0.004489	0.78209
***** (V12) DDD95 *****		
	Before Matching	After Matching
mean treatment.....	0.034884	0.034884
mean control.....	0.023585	0.021318
std mean diff.....	6.122	7.3503
mean raw eQQ diff.....	0.011628	0
med raw eQQ diff.....	0	0
max raw eQQ diff.....	1	0
mean eCDF diff.....	0.0056494	0
med eCDF diff.....	0.0056494	0
max eCDF diff.....	0.011299	0
var ratio (Tr/Co).....	1.4757	1.6137

T-test p-value.....	0.59558	0.59643
***** (V13) DDD96 *****		
	Before Matching	After Matching
mean treatment.....	0.034884	0.034884
mean control.....	0.021226	0.017442
std mean diff.....	7.3999	9.4504
mean raw eQQ diff.....	0.011628	0.02459
med raw eQQ diff.....	0	0
max raw eQQ diff.....	1	1
mean eCDF diff.....	0.0068287	0.012295
med eCDF diff.....	0.0068287	0.012295
max eCDF diff.....	0.013657	0.02459
var ratio (Tr/Co).....	1.6357	1.9645
T-test p-value.....	0.51884	0.48016
***** (V14) DDD97 *****		
	Before Matching	After Matching
mean treatment.....	0	0
mean control.....	0.068396	0
std mean diff.....	-Inf	0
mean raw eQQ diff.....	0.069767	0
med raw eQQ diff.....	0	0
max raw eQQ diff.....	1	0
mean eCDF diff.....	0.034198	0
med eCDF diff.....	0.034198	0
max eCDF diff.....	0.068396	0
var ratio (Tr/Co).....	0	NaN
T-test p-value.....	4.4715e-08	1
***** (V15) DDD98 *****		
	Before Matching	After Matching
mean treatment.....	0.11628	0.11628
mean control.....	0.16509	0.096899
std mean diff.....	-15.139	6.0104
mean raw eQQ diff.....	0.046512	0.0081967
med raw eQQ diff.....	0	0
max raw eQQ diff.....	1	1
mean eCDF diff.....	0.024408	0.0040984
med eCDF diff.....	0.024408	0.0040984
max eCDF diff.....	0.048815	0.0081967
var ratio (Tr/Co).....	0.75249	1.1742
T-test p-value.....	0.21491	0.69244
***** (V16) DDD99 *****		
	Before Matching	After Matching
mean treatment.....	0.093023	0.093023
mean control.....	0.1533	0.067442

std mean diff.....	-20.631	8.7557
mean raw eQQ diff.....	0.05814	0.04918
med raw eQQ diff.....	0	0
max raw eQQ diff.....	1	1
mean eCDF diff.....	0.030139	0.02459
med eCDF diff.....	0.030139	0.02459
max eCDF diff.....	0.060279	0.04918
var ratio (Tr/Co).....	0.65609	1.3415
T-test p-value.....	0.096675	0.55447
***** (V17) pop *****		
	Before Matching	After Matching
mean treatment.....	20317	20317
mean control.....	13430	21126
std mean diff.....	45.031	-5.2875
mean raw eQQ diff.....	6961.5	2251.5
med raw eQQ diff.....	6199.5	2042
max raw eQQ diff.....	19444	8498
mean eCDF diff.....	0.13692	0.056398
med eCDF diff.....	0.16383	0.040984
max eCDF diff.....	0.24375	0.17213
var ratio (Tr/Co).....	1.949	1.0752
T-test p-value.....	0.00013091	0.69849
KS Naive p-value.....	0.00040865	0.053846
KS Statistic.....	0.24375	0.17213
***** (V18) ERB.dens.07.09 *****		
	Before Matching	After Matching
mean treatment.....	1.1652	1.1652
mean control.....	0.43728	1.3848
std mean diff.....	53.067	-16.007
mean raw eQQ diff.....	0.7547	0.47679
med raw eQQ diff.....	0.49305	0.26208
max raw eQQ diff.....	5.3167	7.4517
mean eCDF diff.....	0.28454	0.14285
med eCDF diff.....	0.31809	0.15574
max eCDF diff.....	0.39623	0.27869
var ratio (Tr/Co).....	2.2713	0.33824
T-test p-value.....	7.7806e-06	0.23539
KS Naive p-value.....	3.5583e-10	0.00015343
KS Statistic.....	0.39623	0.27869
***** (V19) area *****		
	Before Matching	After Matching
mean treatment.....	5584.2	5584.2
mean control.....	5630.1	4813.4
std mean diff.....	-0.33685	5.6635
mean raw eQQ diff.....	779.71	1085.7

med raw eQQ diff.....	112.51	131.28
max raw eQQ diff.....	15438	54300
mean eCDF diff.....	0.021088	0.029019
med eCDF diff.....	0.015687	0.02459
max eCDF diff.....	0.091433	0.098361
var ratio (Tr/Co).....	1.1191	1.9031
T-test p-value.....	0.97712	0.6683
KS Naive p-value.....	0.58842	0.5966
KS Statistic.....	0.091433	0.098361

Before Matching Minimum p.value: 3.5583e-10
 Variable Name(s): ERB.dens.07.09 Number(s): 18

After Matching Minimum p.value: 0.00015343
 Variable Name(s): ERB.dens.07.09 Number(s): 18

ESTIMAND = ATT, TIES = FALSE

***** (V1) gdp *****

	Before Matching	After Matching
mean treatment.....	8543.5	8543.5
mean control.....	10557	7991
std mean diff.....	-37.427	10.27
mean raw eQQ diff.....	3071.1	792.85
med raw eQQ diff.....	650.56	293.09
max raw eQQ diff.....	134186	6273.4
mean eCDF diff.....	0.042202	0.033101
med eCDF diff.....	0.038586	0.023256
max eCDF diff.....	0.12922	0.081395
var ratio (Tr/Co).....	0.20931	1.3129
T-test p-value.....	0.013981	0.45646
KS Naive p-value.....	0.18351	0.93819
KS Statistic.....	0.12922	0.081395

***** (V2) agi.perc *****

	Before Matching	After Matching
mean treatment.....	0.27979	0.27979
mean control.....	0.31535	0.2701
std mean diff.....	-23.301	6.3435
mean raw eQQ diff.....	0.036171	0.015711
med raw eQQ diff.....	0.03308	0.010572
max raw eQQ diff.....	0.14351	0.082256
mean eCDF diff.....	0.066842	0.026481
med eCDF diff.....	0.067628	0.023256
max eCDF diff.....	0.13295	0.081395
var ratio (Tr/Co).....	0.98947	1.216
T-test p-value.....	0.051275	0.65362
KS Naive p-value.....	0.15961	0.93819
KS Statistic.....	0.13295	0.081395

***** (V3) agg *****

	Before Matching	After Matching
mean treatment.....	0.84539	0.84539
mean control.....	1.4855	0.911
std mean diff.....	-68.479	-7.0181
mean raw eQQ diff.....	1.1074	0.15727
med raw eQQ diff.....	0.24974	0.11051
max raw eQQ diff.....	54.81	1.4284
mean eCDF diff.....	0.09977	0.051095
med eCDF diff.....	0.10306	0.046512
max eCDF diff.....	0.17798	0.12791
var ratio (Tr/Co).....	0.080589	1.4282
T-test p-value.....	0.0007688	0.62851
KS Naïve p-value.....	0.021564	0.48258
KS Statistic.....	0.17798	0.12791

***** (V4) DDD65 *****

	Before Matching	After Matching
mean treatment.....	0.069767	0.069767
mean control.....	0.03066	0.046512
std mean diff.....	15.261	9.0755
mean raw eQQ diff.....	0.034884	0.023256
med raw eQQ diff.....	0	0
max raw eQQ diff.....	1	1
mean eCDF diff.....	0.019554	0.011628
med eCDF diff.....	0.019554	0.011628
max eCDF diff.....	0.039107	0.023256
var ratio (Tr/Co).....	2.2042	1.4634
T-test p-value.....	0.17865	0.48016

***** (V5) DDD66 *****

	Before Matching	After Matching
mean treatment.....	0.069767	0.069767
mean control.....	0.066038	0.05814
std mean diff.....	1.4555	4.5377
mean raw eQQ diff.....	0	0.011628
med raw eQQ diff.....	0	0
max raw eQQ diff.....	0	1
mean eCDF diff.....	0.0018649	0.005814
med eCDF diff.....	0.0018649	0.005814
max eCDF diff.....	0.0037297	0.011628
var ratio (Tr/Co).....	1.0621	1.1852
T-test p-value.....	0.90177	0.73954

***** (V6) DDD68 *****

	Before Matching	After Matching
mean treatment.....	0.023256	0.023256

mean control.....	0.035377	0.023256
std mean diff.....	-7.9958	0
mean raw eQQ diff.....	0.011628	0
med raw eQQ diff.....	0	0
max raw eQQ diff.....	1	0
mean eCDF diff.....	0.0060608	0
med eCDF diff.....	0.0060608	0
max eCDF diff.....	0.012122	0
var ratio (Tr/Co).....	0.67187	1
T-test p-value.....	0.51683	1
***** (V7) DDD69 *****		
	Before Matching	After Matching
mean treatment.....	0.05814	0.05814
mean control.....	0.058962	0.10465
std mean diff.....	-0.34953	-19.76
mean raw eQQ diff.....	0	0.046512
med raw eQQ diff.....	0	0
max raw eQQ diff.....	0	1
mean eCDF diff.....	0.00041136	0.023256
med eCDF diff.....	0.00041136	0.023256
max eCDF diff.....	0.00082273	0.046512
var ratio (Tr/Co).....	0.99616	0.58442
T-test p-value.....	0.97648	0.24778
***** (V8) DDD91 *****		
	Before Matching	After Matching
mean treatment.....	0.16279	0.16279
mean control.....	0.068396	0.22093
std mean diff.....	25.42	-15.657
mean raw eQQ diff.....	0.093023	0.05814
med raw eQQ diff.....	0	0
max raw eQQ diff.....	1	1
mean eCDF diff.....	0.047197	0.02907
med eCDF diff.....	0.047197	0.02907
max eCDF diff.....	0.094394	0.05814
var ratio (Tr/Co).....	2.159	0.79183
T-test p-value.....	0.026354	0.31734
***** (V9) DDD92 *****		
	Before Matching	After Matching
mean treatment.....	0.069767	0.069767
mean control.....	0.004717	0.034884
std mean diff.....	25.386	13.613
mean raw eQQ diff.....	0.05814	0.034884
med raw eQQ diff.....	0	0
max raw eQQ diff.....	1	1

mean eCDF diff.....	0.032525	0.017442
med eCDF diff.....	0.032525	0.017442
max eCDF diff.....	0.06505	0.034884
var ratio (Tr/Co).....	13.954	1.9277
T-test p-value.....	0.02171	0.25647
***** (V10) DDD93 *****		
	Before Matching	After Matching
mean treatment.....	0.081395	0.081395
mean control.....	0.018868	0.10465
std mean diff.....	22.734	-8.4553
mean raw eQQ diff.....	0.05814	0.023256
med raw eQQ diff.....	0	0
max raw eQQ diff.....	1	1
mean eCDF diff.....	0.031264	0.011628
med eCDF diff.....	0.031264	0.011628
max eCDF diff.....	0.062527	0.023256
var ratio (Tr/Co).....	4.0769	0.79798
T-test p-value.....	0.042403	0.56447
***** (V11) DDD94 *****		
	Before Matching	After Matching
mean treatment.....	0.10465	0.10465
mean control.....	0.0070755	0.11628
std mean diff.....	31.691	-3.7765
mean raw eQQ diff.....	0.093023	0.011628
med raw eQQ diff.....	0	0
max raw eQQ diff.....	1	1
mean eCDF diff.....	0.048788	0.005814
med eCDF diff.....	0.048788	0.005814
max eCDF diff.....	0.097576	0.011628
var ratio (Tr/Co).....	13.462	0.91184
T-test p-value.....	0.004489	0.78209
***** (V12) DDD95 *****		
	Before Matching	After Matching
mean treatment.....	0.034884	0.034884
mean control.....	0.023585	0.011628
std mean diff.....	6.122	12.601
mean raw eQQ diff.....	0.011628	0.023256
med raw eQQ diff.....	0	0
max raw eQQ diff.....	1	1
mean eCDF diff.....	0.0056494	0.011628
med eCDF diff.....	0.0056494	0.011628
max eCDF diff.....	0.011299	0.023256
var ratio (Tr/Co).....	1.4757	2.9294
T-test p-value.....	0.59558	0.31734

***** (V13) DDD96 *****

	Before Matching	After Matching
mean treatment.....	0.034884	0.034884
mean control.....	0.021226	0.023256
std mean diff.....	7.3999	6.3003
mean raw eQQ diff.....	0.011628	0.011628
med raw eQQ diff.....	0	0
max raw eQQ diff.....	1	1
mean eCDF diff.....	0.0068287	0.005814
med eCDF diff.....	0.0068287	0.005814
max eCDF diff.....	0.013657	0.011628
var ratio (Tr/Co).....	1.6357	1.4821
T-test p-value.....	0.51884	0.65548

***** (V14) DDD97 *****

	Before Matching	After Matching
mean treatment.....	0	0
mean control.....	0.068396	0
std mean diff.....	-Inf	0
mean raw eQQ diff.....	0.069767	0
med raw eQQ diff.....	0	0
max raw eQQ diff.....	1	0
mean eCDF diff.....	0.034198	0
med eCDF diff.....	0.034198	0
max eCDF diff.....	0.068396	0
var ratio (Tr/Co).....	0	NaN
T-test p-value.....	4.4715e-08	1

***** (V15) DDD98 *****

	Before Matching	After Matching
mean treatment.....	0.11628	0.11628
mean control.....	0.16509	0.05814
std mean diff.....	-15.139	18.031
mean raw eQQ diff.....	0.046512	0.05814
med raw eQQ diff.....	0	0
max raw eQQ diff.....	1	1
mean eCDF diff.....	0.024408	0.02907
med eCDF diff.....	0.024408	0.02907
max eCDF diff.....	0.048815	0.05814
var ratio (Tr/Co).....	0.75249	1.8765
T-test p-value.....	0.21491	0.19586

***** (V16) DDD99 *****

	Before Matching	After Matching
mean treatment.....	0.093023	0.093023
mean control.....	0.1533	0.093023
std mean diff.....	-20.631	0

mean raw eQQ diff.....	0.05814	0
med raw eQQ diff.....	0	0
max raw eQQ diff.....	1	0
mean eCDF diff.....	0.030139	0
med eCDF diff.....	0.030139	0
max eCDF diff.....	0.060279	0
var ratio (Tr/Co).....	0.65609	1
T-test p-value.....	0.096675	1
***** (V17) pop *****		
	Before Matching	After Matching
mean treatment.....	20317	20317
mean control.....	13430	20762
std mean diff.....	45.031	-2.9102
mean raw eQQ diff.....	6961.5	1692.7
med raw eQQ diff.....	6199.5	1350
max raw eQQ diff.....	19444	8498
mean eCDF diff.....	0.13692	0.031438
med eCDF diff.....	0.16383	0.023256
max eCDF diff.....	0.24375	0.081395
var ratio (Tr/Co).....	1.949	1.0658
T-test p-value.....	0.00013091	0.8327
KS Naive p-value.....	0.00040865	0.93819
KS Statistic.....	0.24375	0.081395
***** (V18) ERB.dens.07.09 *****		
	Before Matching	After Matching
mean treatment.....	1.1652	1.1652
mean control.....	0.43728	1.348
std mean diff.....	53.067	-13.319
mean raw eQQ diff.....	0.7547	0.49716
med raw eQQ diff.....	0.49305	0.20318
max raw eQQ diff.....	5.3167	7.4517
mean eCDF diff.....	0.28454	0.10087
med eCDF diff.....	0.31809	0.10465
max eCDF diff.....	0.39623	0.23256
var ratio (Tr/Co).....	2.2713	0.33807
T-test p-value.....	7.7806e-06	0.32087
KS Naive p-value.....	3.5583e-10	0.019101
KS Statistic.....	0.39623	0.23256
***** (V19) area *****		
	Before Matching	After Matching
mean treatment.....	5584.2	5584.2
mean control.....	5630.1	4739.8
std mean diff.....	-0.33685	6.2044
mean raw eQQ diff.....	779.71	1486.6
med raw eQQ diff.....	112.51	121.03
max raw eQQ diff.....	15438	54300

mean eCDF diff.....	0.021088	0.02716
med eCDF diff.....	0.015687	0.023256
max eCDF diff.....	0.091433	0.10465
var ratio (Tr/Co).....	1.1191	1.8931
T-test p-value.....	0.97712	0.63836
KS Naive p-value.....	0.58842	0.734
KS Statistic.....	0.091433	0.10465

Before Matching Minimum p.value: 3.5583e-10
 Variable Name(s): ERB.dens.07.09 Number(s): 18

After Matching Minimum p.value: 0.019101
 Variable Name(s): ERB.dens.07.09 Number(s): 18

ESTIMAND = ATE, TIES = TRUE

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***** (V1) gdp *****
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	Before Matching	After Matching
mean treatment.....	8543.5	9074.5
mean control.....	10557	10130
std mean diff.....	-37.427	-26.345
mean raw eQQ diff.....	3071.1	2961
med raw eQQ diff.....	650.56	1472.5
max raw eQQ diff.....	134186	134186
mean eCDF diff.....	0.042202	0.10759
med eCDF diff.....	0.038586	0.11545
max eCDF diff.....	0.12922	0.20604
var ratio (Tr/Co).....	0.20931	0.13403
T-test p-value.....	0.013981	0.037679
KS Naive p-value.....	0.18351	8.3399e-11
KS Statistic.....	0.12922	0.20604

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***** (V2) agi.perc *****
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	Before Matching	After Matching
mean treatment.....	0.27979	0.29798
mean control.....	0.31535	0.30679
std mean diff.....	-23.301	-6.7483
mean raw eQQ diff.....	0.036171	0.040709
med raw eQQ diff.....	0.03308	0.029466
max raw eQQ diff.....	0.14351	0.14351
mean eCDF diff.....	0.066842	0.069982
med eCDF diff.....	0.067628	0.067496
max eCDF diff.....	0.13295	0.17052
var ratio (Tr/Co).....	0.98947	0.75026
T-test p-value.....	0.051275	0.31242
KS Naive p-value.....	0.15961	1.5555e-07
KS Statistic.....	0.13295	0.17052

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***** (V3) agg *****
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	Before Matching	After Matching
mean treatment.....	0.84539	1.0911
mean control.....	1.4855	1.3924
std mean diff.....	-68.479	-25.853
mean raw eQQ diff.....	1.1074	0.39518
med raw eQQ diff.....	0.24974	0.17279
max raw eQQ diff.....	54.81	54.81
mean eCDF diff.....	0.09977	0.074834
med eCDF diff.....	0.10306	0.040853
max eCDF diff.....	0.17798	0.26643
var ratio (Tr/Co).....	0.080589	0.14797
T-test p-value.....	0.0007688	0.040916
KS Naive p-value.....	0.021564	< 2.22e-16
KS Statistic.....	0.17798	0.26643
***** (V4) DDD65 *****		
	Before Matching	After Matching
mean treatment.....	0.069767	0.036275
mean control.....	0.03066	0.033333
std mean diff.....	15.261	1.5715
mean raw eQQ diff.....	0.034884	0.0071048
med raw eQQ diff.....	0	0
max raw eQQ diff.....	1	1
mean eCDF diff.....	0.019554	0.0035524
med eCDF diff.....	0.019554	0.0035524
max eCDF diff.....	0.039107	0.0071048
var ratio (Tr/Co).....	2.2042	1.0849
T-test p-value.....	0.17865	0.78251
***** (V5) DDD66 *****		
	Before Matching	After Matching
mean treatment.....	0.069767	0.05
mean control.....	0.066038	0.066013
std mean diff.....	1.4555	-7.3401
mean raw eQQ diff.....	0	0.023091
med raw eQQ diff.....	0	0
max raw eQQ diff.....	0	1
mean eCDF diff.....	0.0018649	0.011545
med eCDF diff.....	0.0018649	0.011545
max eCDF diff.....	0.0037297	0.023091
var ratio (Tr/Co).....	1.0621	0.77041
T-test p-value.....	0.90177	0.27149
***** (V6) DDD68 *****		
	Before Matching	After Matching
mean treatment.....	0.023256	0.043137
mean control.....	0.035377	0.03366
std mean diff.....	-7.9958	4.6601

mean raw eQQ diff.....	0.011628	0.01421
med raw eQQ diff.....	0	0
max raw eQQ diff.....	1	1
mean eCDF diff.....	0.0060608	0.0071048
med eCDF diff.....	0.0060608	0.0071048
max eCDF diff.....	0.012122	0.01421
var ratio (Tr/Co).....	0.67187	1.269
T-test p-value.....	0.51683	0.42797
***** (V7) DDD69 *****		
	Before Matching	After Matching
mean treatment.....	0.05814	0.020588
mean control.....	0.058962	0.06451
std mean diff.....	-0.34953	-30.9
mean raw eQQ diff.....	0	0.046181
med raw eQQ diff.....	0	0
max raw eQQ diff.....	0	1
mean eCDF diff.....	0.00041136	0.023091
med eCDF diff.....	0.00041136	0.023091
max eCDF diff.....	0.00082273	0.046181
var ratio (Tr/Co).....	0.99616	0.33413
T-test p-value.....	0.97648	0.00033144
***** (V8) DDD91 *****		
	Before Matching	After Matching
mean treatment.....	0.16279	0.054902
mean control.....	0.068396	0.090196
std mean diff.....	25.42	-15.479
mean raw eQQ diff.....	0.093023	0.028419
med raw eQQ diff.....	0	0
max raw eQQ diff.....	1	1
mean eCDF diff.....	0.047197	0.01421
med eCDF diff.....	0.047197	0.01421
max eCDF diff.....	0.094394	0.028419
var ratio (Tr/Co).....	2.159	0.63231
T-test p-value.....	0.026354	0.023062
***** (V9) DDD92 *****		
	Before Matching	After Matching
mean treatment.....	0.069767	0.019608
mean control.....	0.004717	0.0098039
std mean diff.....	25.386	7.0641
mean raw eQQ diff.....	0.05814	0.008881
med raw eQQ diff.....	0	0
max raw eQQ diff.....	1	1
mean eCDF diff.....	0.032525	0.0044405
med eCDF diff.....	0.032525	0.0044405
max eCDF diff.....	0.06505	0.008881

var ratio (Tr/Co).....	13.954	1.9802
T-test p-value.....	0.02171	0.13143
***** (V10) DDD93 *****		
	Before Matching	After Matching
mean treatment.....	0.081395	0.034314
mean control.....	0.018868	0.032353
std mean diff.....	22.734	1.0761
mean raw eQQ diff.....	0.05814	0.0017762
med raw eQQ diff.....	0	0
max raw eQQ diff.....	1	1
mean eCDF diff.....	0.031264	0.0008881
med eCDF diff.....	0.031264	0.0008881
max eCDF diff.....	0.062527	0.0017762
var ratio (Tr/Co).....	4.0769	1.0585
T-test p-value.....	0.042403	0.8552
***** (V11) DDD94 *****		
	Before Matching	After Matching
mean treatment.....	0.10465	0.021569
mean control.....	0.0070755	0.02549
std mean diff.....	31.691	-2.6969
mean raw eQQ diff.....	0.093023	0.0035524
med raw eQQ diff.....	0	0
max raw eQQ diff.....	1	1
mean eCDF diff.....	0.048788	0.0017762
med eCDF diff.....	0.048788	0.0017762
max eCDF diff.....	0.097576	0.0035524
var ratio (Tr/Co).....	13.462	0.84956
T-test p-value.....	0.004489	0.63748
***** (V12) DDD95 *****		
	Before Matching	After Matching
mean treatment.....	0.034884	0.016667
mean control.....	0.023585	0.023203
std mean diff.....	6.122	-5.1004
mean raw eQQ diff.....	0.011628	0.0071048
med raw eQQ diff.....	0	0
max raw eQQ diff.....	1	1
mean eCDF diff.....	0.0056494	0.0035524
med eCDF diff.....	0.0056494	0.0035524
max eCDF diff.....	0.011299	0.0071048
var ratio (Tr/Co).....	1.4757	0.72312
T-test p-value.....	0.59558	0.45987
***** (V13) DDD96 *****		
	Before Matching	After Matching

mean treatment.....	0.034884	0.012745
mean control.....	0.021226	0.020588
std mean diff.....	7.3999	-6.9852
mean raw eQQ diff.....	0.011628	0.0017762
med raw eQQ diff.....	0	0
max raw eQQ diff.....	1	1
mean eCDF diff.....	0.0068287	0.0008881
med eCDF diff.....	0.0068287	0.0008881
max eCDF diff.....	0.013657	0.0017762
var ratio (Tr/Co).....	1.6357	0.624
T-test p-value.....	0.51884	0.33199
***** (V14) DDD97 *****		
	Before Matching	After Matching
mean treatment.....	0	0
mean control.....	0.068396	0.056863
std mean diff.....	-Inf	-Inf
mean raw eQQ diff.....	0.069767	0.05151
med raw eQQ diff.....	0	0
max raw eQQ diff.....	1	1
mean eCDF diff.....	0.034198	0.025755
med eCDF diff.....	0.034198	0.025755
max eCDF diff.....	0.068396	0.05151
var ratio (Tr/Co).....	0	0
T-test p-value.....	4.4715e-08	4.7254e-08
***** (V15) DDD98 *****		
	Before Matching	After Matching
mean treatment.....	0.11628	0.061765
mean control.....	0.16509	0.15359
std mean diff.....	-15.139	-38.109
mean raw eQQ diff.....	0.046512	0.092362
med raw eQQ diff.....	0	0
max raw eQQ diff.....	1	1
mean eCDF diff.....	0.024408	0.046181
med eCDF diff.....	0.024408	0.046181
max eCDF diff.....	0.048815	0.092362
var ratio (Tr/Co).....	0.75249	0.44576
T-test p-value.....	0.21491	3.9835e-06
***** (V16) DDD99 *****		
	Before Matching	After Matching
mean treatment.....	0.093023	0.077451
mean control.....	0.1533	0.13882
std mean diff.....	-20.631	-22.937
mean raw eQQ diff.....	0.05814	0.071048
med raw eQQ diff.....	0	0
max raw eQQ diff.....	1	1

mean eCDF diff.....	0.030139	0.035524
med eCDF diff.....	0.030139	0.035524
max eCDF diff.....	0.060279	0.071048

var ratio (Tr/Co).....	0.65609	0.59767
T-test p-value.....	0.096675	0.0018852

***** (V17) pop *****

	Before Matching	After Matching
mean treatment.....	20317	9450.5
mean control.....	13430	14728
std mean diff.....	45.031	-45.55
mean raw eQQ diff.....	6961.5	5016.7
med raw eQQ diff.....	6199.5	5039
max raw eQQ diff.....	19444	14504
mean eCDF diff.....	0.13692	0.1998
med eCDF diff.....	0.16383	0.20959
max eCDF diff.....	0.24375	0.4405
var ratio (Tr/Co).....	1.949	0.92952
T-test p-value.....	0.00013091	8.8818e-16
KS Naive p-value.....	0.00040865	< 2.22e-16
KS Statistic.....	0.24375	0.4405

***** (V18) ERB.dens.07.09 *****

	Before Matching	After Matching
mean treatment.....	1.1652	1.1841
mean control.....	0.43728	0.59706
std mean diff.....	53.067	65.65
mean raw eQQ diff.....	0.7547	0.69236
med raw eQQ diff.....	0.49305	0.72737
max raw eQQ diff.....	5.3167	7.4517
mean eCDF diff.....	0.28454	0.34328
med eCDF diff.....	0.31809	0.39076
max eCDF diff.....	0.39623	0.51865
var ratio (Tr/Co).....	2.2713	0.45857
T-test p-value.....	7.7806e-06	< 2.22e-16
KS Naive p-value.....	3.5583e-10	< 2.22e-16
KS Statistic.....	0.39623	0.51865

***** (V19) area *****

	Before Matching	After Matching
mean treatment.....	5584.2	2293.5
mean control.....	5630.1	5492.4
std mean diff.....	-0.33685	-47.204
mean raw eQQ diff.....	779.71	2922.3
med raw eQQ diff.....	112.51	963.6
max raw eQQ diff.....	15438	61775
mean eCDF diff.....	0.021088	0.18043
med eCDF diff.....	0.015687	0.13321

max eCDF diff.....	0.091433	0.43517
var ratio (Tr/Co).....	1.1191	0.29836
T-test p-value.....	0.97712	4.7283e-07
KS Naive p-value.....	0.58842	< 2.22e-16
KS Statistic.....	0.091433	0.43517

Before Matching Minimum p.value: 3.5583e-10
Variable Name(s): ERB.dens.07.09 Number(s): 18

After Matching Minimum p.value: < 2.22e-16
Variable Name(s): agg pop ERB.dens.07.09 area Number(s): 3 17 18 19

ESTIMAND = ATC, TIES = TRUE

***** (V1) gdp *****

	Before Matching	After Matching
mean treatment.....	8543.5	9182.2
mean control.....	10557	10557
std mean diff.....	-37.427	-37.494
mean raw eQQ diff.....	3071.1	3625.9
med raw eQQ diff.....	650.56	1752.9
max raw eQQ diff.....	134186	134186
mean eCDF diff.....	0.042202	0.12721
med eCDF diff.....	0.038586	0.13379
max eCDF diff.....	0.12922	0.25397
var ratio (Tr/Co).....	0.20931	0.097224
T-test p-value.....	0.013981	0.020069
KS Naive p-value.....	0.18351	8.8662e-13
KS Statistic.....	0.12922	0.25397

***** (V2) agi.perc *****

	Before Matching	After Matching
mean treatment.....	0.27979	0.30167
mean control.....	0.31535	0.31535
std mean diff.....	-23.301	-10.901
mean raw eQQ diff.....	0.036171	0.051774
med raw eQQ diff.....	0.03308	0.037986
max raw eQQ diff.....	0.14351	0.14724
mean eCDF diff.....	0.066842	0.089779
med eCDF diff.....	0.067628	0.080499
max eCDF diff.....	0.13295	0.21315
var ratio (Tr/Co).....	0.98947	0.6693
T-test p-value.....	0.051275	0.15452
KS Naive p-value.....	0.15961	3.9754e-09
KS Statistic.....	0.13295	0.21315

***** (V3) agg *****

	Before Matching	After Matching
mean treatment.....	0.84539	1.141

mean control.....	1.4855	1.4855
std mean diff.....	-68.479	-28.678
mean raw eQQ diff.....	1.1074	0.48457
med raw eQQ diff.....	0.24974	0.21471
max raw eQQ diff.....	54.81	54.81
mean eCDF diff.....	0.09977	0.090917
med eCDF diff.....	0.10306	0.058957
max eCDF diff.....	0.17798	0.29478
var ratio (Tr/Co).....	0.080589	0.13314
T-test p-value.....	0.0007688	0.049131
KS Naive p-value.....	0.021564	< 2.22e-16
KS Statistic.....	0.17798	0.29478
***** (V4) DDD65 *****		
	Before Matching	After Matching
mean treatment.....	0.069767	0.029481
mean control.....	0.03066	0.03066
std mean diff.....	15.261	-0.69633
mean raw eQQ diff.....	0.034884	0
med raw eQQ diff.....	0	0
max raw eQQ diff.....	1	0
mean eCDF diff.....	0.019554	0
med eCDF diff.....	0.019554	0
max eCDF diff.....	0.039107	0
var ratio (Tr/Co).....	2.2042	0.96271
T-test p-value.....	0.17865	0.91418
***** (V5) DDD66 *****		
	Before Matching	After Matching
mean treatment.....	0.069767	0.045991
mean control.....	0.066038	0.066038
std mean diff.....	1.4555	-9.5594
mean raw eQQ diff.....	0	0.022676
med raw eQQ diff.....	0	0
max raw eQQ diff.....	0	1
mean eCDF diff.....	0.0018649	0.011338
med eCDF diff.....	0.0018649	0.011338
max eCDF diff.....	0.0037297	0.022676
var ratio (Tr/Co).....	1.0621	0.71138
T-test p-value.....	0.90177	0.20747
***** (V6) DDD68 *****		
	Before Matching	After Matching
mean treatment.....	0.023256	0.04717
mean control.....	0.035377	0.035377
std mean diff.....	-7.9958	5.5559
mean raw eQQ diff.....	0.011628	0.011338
med raw eQQ diff.....	0	0

max raw eQQ diff.....	1	1
mean eCDF diff.....	0.0060608	0.0056689
med eCDF diff.....	0.0060608	0.0056689
max eCDF diff.....	0.012122	0.011338
var ratio (Tr/Co).....	0.67187	1.317
T-test p-value.....	0.51683	0.38416
***** (V7) DDD69 *****		
	Before Matching	After Matching
mean treatment.....	0.05814	0.012972
mean control.....	0.058962	0.058962
std mean diff.....	-0.34953	-40.597
mean raw eQQ diff.....	0	0.045351
med raw eQQ diff.....	0	0
max raw eQQ diff.....	0	1
mean eCDF diff.....	0.00041136	0.022676
med eCDF diff.....	0.00041136	0.022676
max eCDF diff.....	0.00082273	0.045351
var ratio (Tr/Co).....	0.99616	0.23075
T-test p-value.....	0.97648	0.00023353
***** (V8) DDD91 *****		
	Before Matching	After Matching
mean treatment.....	0.16279	0.033019
mean control.....	0.068396	0.068396
std mean diff.....	25.42	-19.775
mean raw eQQ diff.....	0.093023	0.031746
med raw eQQ diff.....	0	0
max raw eQQ diff.....	1	1
mean eCDF diff.....	0.047197	0.015873
med eCDF diff.....	0.047197	0.015873
max eCDF diff.....	0.094394	0.031746
var ratio (Tr/Co).....	2.159	0.50109
T-test p-value.....	0.026354	0.016009
***** (V9) DDD92 *****		
	Before Matching	After Matching
mean treatment.....	0.069767	0.009434
mean control.....	0.004717	0.004717
std mean diff.....	25.386	4.8737
mean raw eQQ diff.....	0.05814	0.0045351
med raw eQQ diff.....	0	0
max raw eQQ diff.....	1	1
mean eCDF diff.....	0.032525	0.0022676
med eCDF diff.....	0.032525	0.0022676
max eCDF diff.....	0.06505	0.0045351
var ratio (Tr/Co).....	13.954	1.9905

T-test p-value.....	0.02171	0.31731
***** (V10) DDD93 *****		
	Before Matching	After Matching
mean treatment.....	0.081395	0.024764
mean control.....	0.018868	0.018868
std mean diff.....	22.734	3.7896
mean raw eQQ diff.....	0.05814	0.0068027
med raw eQQ diff.....	0	0
max raw eQQ diff.....	1	1
mean eCDF diff.....	0.031264	0.0034014
med eCDF diff.....	0.031264	0.0034014
max eCDF diff.....	0.062527	0.0068027
var ratio (Tr/Co).....	4.0769	1.3046
T-test p-value.....	0.042403	0.56123
***** (V11) DDD94 *****		
	Before Matching	After Matching
mean treatment.....	0.10465	0.004717
mean control.....	0.0070755	0.0070755
std mean diff.....	31.691	-3.4381
mean raw eQQ diff.....	0.093023	0.0022676
med raw eQQ diff.....	0	0
max raw eQQ diff.....	1	1
mean eCDF diff.....	0.048788	0.0011338
med eCDF diff.....	0.048788	0.0011338
max eCDF diff.....	0.097576	0.0022676
var ratio (Tr/Co).....	13.462	0.66825
T-test p-value.....	0.004489	0.65487
***** (V12) DDD95 *****		
	Before Matching	After Matching
mean treatment.....	0.034884	0.012972
mean control.....	0.023585	0.023585
std mean diff.....	6.122	-9.3685
mean raw eQQ diff.....	0.011628	0.0090703
med raw eQQ diff.....	0	0
max raw eQQ diff.....	1	1
mean eCDF diff.....	0.0056494	0.0045351
med eCDF diff.....	0.0056494	0.0045351
max eCDF diff.....	0.011299	0.0090703
var ratio (Tr/Co).....	1.4757	0.55598
T-test p-value.....	0.59558	0.25295
***** (V13) DDD96 *****		
	Before Matching	After Matching
mean treatment.....	0.034884	0.0082547
mean control.....	0.021226	0.021226

std mean diff.....	7.3999	-14.32
mean raw eQQ diff.....	0.011628	0.0090703
med raw eQQ diff.....	0	0
max raw eQQ diff.....	1	1
mean eCDF diff.....	0.0068287	0.0045351
med eCDF diff.....	0.0068287	0.0045351
max eCDF diff.....	0.013657	0.0090703
var ratio (Tr/Co).....	1.6357	0.39404
T-test p-value.....	0.51884	0.11949
***** (V14) DDD97 *****		
	Before Matching	After Matching
mean treatment.....	0	0
mean control.....	0.068396	0.068396
std mean diff.....	-Inf	-Inf
mean raw eQQ diff.....	0.069767	0.06576
med raw eQQ diff.....	0	0
max raw eQQ diff.....	1	1
mean eCDF diff.....	0.034198	0.03288
med eCDF diff.....	0.034198	0.03288
max eCDF diff.....	0.068396	0.06576
var ratio (Tr/Co).....	0	0
T-test p-value.....	4.4715e-08	4.3167e-08
***** (V15) DDD98 *****		
	Before Matching	After Matching
mean treatment.....	0.11628	0.050708
mean control.....	0.16509	0.16509
std mean diff.....	-15.139	-52.075
mean raw eQQ diff.....	0.046512	0.11565
med raw eQQ diff.....	0	0
max raw eQQ diff.....	1	1
mean eCDF diff.....	0.024408	0.057823
med eCDF diff.....	0.024408	0.057823
max eCDF diff.....	0.048815	0.11565
var ratio (Tr/Co).....	0.75249	0.34922
T-test p-value.....	0.21491	1.3889e-07
***** (V16) DDD99 *****		
	Before Matching	After Matching
mean treatment.....	0.093023	0.074292
mean control.....	0.1533	0.1533
std mean diff.....	-20.631	-30.092
mean raw eQQ diff.....	0.05814	0.077098
med raw eQQ diff.....	0	0
max raw eQQ diff.....	1	1
mean eCDF diff.....	0.030139	0.038549

med eCDF diff.....	0.030139	0.038549
max eCDF diff.....	0.060279	0.077098
var ratio (Tr/Co).....	0.65609	0.52984
T-test p-value.....	0.096675	0.00033592
***** (V17) pop *****		
	Before Matching	After Matching
mean treatment.....	20317	7246.5
mean control.....	13430	13430
std mean diff.....	45.031	-66.823
mean raw eQQ diff.....	6961.5	6006.6
med raw eQQ diff.....	6199.5	6026
max raw eQQ diff.....	19444	40759
mean eCDF diff.....	0.13692	0.24578
med eCDF diff.....	0.16383	0.26531
max eCDF diff.....	0.24375	0.51701
var ratio (Tr/Co).....	1.949	0.7134
T-test p-value.....	0.00013091	< 2.22e-16
KS Naive p-value.....	0.00040865	< 2.22e-16
KS Statistic.....	0.24375	0.51701
***** (V18) ERB.dens.07.09 *****		
	Before Matching	After Matching
mean treatment.....	1.1652	1.1879
mean control.....	0.43728	0.43728
std mean diff.....	53.067	98.232
mean raw eQQ diff.....	0.7547	0.76305
med raw eQQ diff.....	0.49305	0.80835
max raw eQQ diff.....	5.3167	5.3167
mean eCDF diff.....	0.28454	0.40621
med eCDF diff.....	0.31809	0.47052
max eCDF diff.....	0.39623	0.61451
var ratio (Tr/Co).....	2.2713	0.70483
T-test p-value.....	7.7806e-06	< 2.22e-16
KS Naive p-value.....	3.5583e-10	< 2.22e-16
KS Statistic.....	0.39623	0.61451
***** (V19) area *****		
	Before Matching	After Matching
mean treatment.....	5584.2	1626.1
mean control.....	5630.1	5630.1
std mean diff.....	-0.33685	-102.08
mean raw eQQ diff.....	779.71	3791.6
med raw eQQ diff.....	112.51	979.91
max raw eQQ diff.....	15438	75588
mean eCDF diff.....	0.021088	0.22618
med eCDF diff.....	0.015687	0.16327
max eCDF diff.....	0.091433	0.52834

var ratio (Tr/Co).....	1.1191	0.09294
T-test p-value.....	0.97712	2.0649e-09
KS Naive p-value.....	0.58842	< 2.22e-16
KS Statistic.....	0.091433	0.52834

Before Matching Minimum p.value: 3.5583e-10

Variable Name(s): ERB.dens.07.09 Number(s): 18

After Matching Minimum p.value: < 2.22e-16

Variable Name(s): agg pop ERB.dens.07.09 area Number(s): 3 17 18 19

Checking the balance proprieties: graphs

ESTIMAND = ATT, TIES = TRUE

ESTIMAND = ATE, TIES = TRUE

ESTIMAND = ATC, TIES = TRUE

COMPLETE DATABASE

cod.IBGE	DDD	area	pop	gdp	agi.perc	agg	ERB.dens.07.09	tr.3G.05.09	def.04	def.10
1200054	68	4974.176	6480	10447.53	0.284955	3.220653	0.134025548	0	220.9	253.2
1200104	68	3916.495	22899	11669.94	0.280082	0.208817	0.76599102	0	1178.4	1268
1200179	68	1702.577	9836	20407.79	0.601992	4.046067	0.391563299	0	790.8	842
1200252	68	1654.768	16099	10980.99	0.246849	0.234254	0.604314321	0	784.9	820
1200302	68	27975.4	32411	8602.542	0.275322	2.029491	0.142982743	0	1232.7	1361.5
1200328	68	5357.282	7147	8775.01	0.27519	0.39405	0	0	112.9	136.5
1200336	68	5453.073	16410	9095.186	0.254174	5.098209	0.4890209	1	368.5	395
1200344	68	10633.21	8386	9865.013	0.284411	2.486997	0.031348317	0	218.4	270.8
1200351	68	8191.694	15857	8427.824	0.289922	4.696089	0	0	177.5	230.1
1200385	68	1943.245	17795	15628.94	0.472615	0.981117	1.543809453	0	1322.8	1427.1
1200807	68	2604.856	16029	12286.61	0.443215	0.332479	0.255932254	1	1147.5	1250.1
1200393	68	6443.826	10143	8127.97	0.293706	6.872491	0	0	137.1	178.2
1200427	68	3076.95	15968	8368.362	0.306514	11.59048	0	0	444	479.6
1200435	68	6145.61	5374	7067.361	0.146955	4.689906	0.054239259	0	56.2	75.2
1200500	68	23752.87	40311	10604.15	0.324706	0.771779	0.182434102	0	1411.8	1642.8
1200609	68	20171.05	37571	8872.934	0.264002	1.370634	0.198303976	0	1286.5	1436.3
1200708	68	5347.446	17021	11537.04	0.385507	1.42824	0.748020644	0	1180.8	1270.5
1300029	97	5911.768	15166	5396.611	0.239747	-0.63316	0	0	290.8	319.7
1300060	97	4758.743	10436	5145.171	0.2119	1.429834	0	0	110.3	112.5
1300201	97	76351.79	17174	4564.167	0.17494	0.847815	0	0	227.4	237.4
1300409	97	122475.1	27110	4211.14	0.134224	-0.41916	0.005443285	0	192.5	201
1300607	97	8793.417	37564	4430.705	0.136819	0.398162	0.265350015	0	182	187.4
1300680	92	2586.847	16820	4835.434	0.240557	0.489598	0.386570988	1	196.7	203.5
1300805	92	44251.75	38073	5221.679	0.237211	3.669857	0.022597979	0	489.6	524.2
1300839	92	9456.618	12004	5532.656	0.207659	2.63098	0.070497367	1	230	239.8
1300904	97	33659.61	14754	4861.529	0.1591	0.58205	0	0	669.3	913.1

1301209	97	57921.91	81325	31878.28	0.023991	1.090275	0.063303626	0	751.1	767.2
1301308	97	18711.55	25696	6929.561	0.413833	4.54218	0.035628614	0	253.9	261.4
1301407	97	15011.77	33127	4691.521	0.182765	-0.20957	0	0	356.7	371.8
1301506	97	7499.33	18051	9298.377	0.547479	3.675773	0	0	206.7	253.4
1301605	97	12110.93	21859	6314.973	0.276964	0.443163	0	0	94.1	99.8
1301803	97	12044.63	25362	3569.947	0.109674	2.153725	0	0	189.8	213.1
1301951	97	25275.93	8232	5959.913	0.240958	1.331965	0	0	112.8	124.5
1302108	97	55791.84	6083	6990.794	0.161522	5.189844	0	0	48.1	56.4
1302207	97	19400.69	12408	5043.44	0.186245	1.903099	0	0	135	148.2
1302306	97	69551.83	17376	6122.007	0.271229	0.227338	0	0	221.1	234.1
1302702	97	48282.54	51331	9062.886	0.529962	4.411259	0.013807615	0	1206.4	1562.2
1302801	97	16910.37	18310	4944.511	0.223192	1.401581	0	0	102.3	114.4
1303007	92	14105.59	19792	5854.082	0.284452	0.509081	0.047262586	1	444.9	474.2
1303106	92	5608.565	33829	4878.98	0.186873	0.342415	0.118865818	1	399.7	415.6
1303205	92	37770.82	16719	5098.81	0.198909	1.889646	0.017650308	0	110	116.8
1303304	97	41187.69	23486	5425.956	0.324113	0.107639	0	0	651.4	897.1
1303502	97	41610.05	19149	4748.655	0.181914	2.963653	0	0	185.7	219.3
1303601	97	62846.41	20986	4155.056	0.188955	1.027651	0	0	203.8	213.1
1303700	97	12307.21	24327	4862.457	0.179649	1.353759	0	0	128.6	134.3
1303809	97	109183.4	41575	4648.563	0.093659	0.499052	0.009158899	0	1165.2	1195.4
1303908	97	19745.9	34963	4262.907	0.146622	0.194343	0	0	171.1	176.2
1303957	92	10741.08	12115	5696.822	0.280241	2.89776	0.062067005	1	185.1	202.6
1304062	97	3224.875	58314	4562.695	0.055837	3.51877	1.033631795	0	149.9	156.6
1304104	97	85488.03	18383	7673.666	0.431792	6.115927	0	0	291.7	311.5
1304203	97	23704.48	62885	8853.288	0.291027	0.687326	0.154682467	0	594.9	634.1
1304237	97	6432.659	18162	5445.711	0.267516	2.11519	0	0	77.9	82.3
1304260	97	10246.24	12801	7536.442	0.372566	2.326604	0	0	225.1	243.2
1304401	92	2906.701	20091	4877.856	0.224488	1.037879	0.573387723	1	92.1	94.6
1600105	96	9167.855	8483	12553.81	0.200286	0.557863	0	0	92.8	107.9
1600204	96	14231.32	9793	15283.47	0.099703	0.666714	0.046845031	0	132.7	181.2

1600212	96	2109.068	5173	14590.37	0.362971	1.680083	0	0	171.7	182.6
1600238	96	4969.503	6525	18739.62	0.060197	0.672108	0.134151577	1	124.6	137.2
1600253	96	1622.852	4722	10408.09	0.170741	1.532432	0	0	86.4	92
1600279	96	30971.9	43832	10650.37	0.028668	0.128599	0.032287334	1	156.6	184.7
1600402	96	13130.98	18739	9410.107	0.108401	0.299896	0.152311522	1	76.6	109.7
1600501	96	22625.29	22986	12652.57	0.130329	1.786611	0.058931115	0	165.7	199.5
1600154	96	9562.92	12828	21046.77	0.0783	0.309869	0	0	203.7	229.6
1600550	96	4950.593	4277	11758.24	0.225574	0.721092	0	0	61.5	78.2
1600055	96	7720.789	4761	21250.79	0.104913	1.364121	0	0	68.9	71.4
1600709	96	6757.618	14292	10330.88	0.159281	1.547721	0	0	253.8	309.9
2100154	98	443.267	12028	3863.402	0.169095	1.008908	0	0	0	0
2100204	98	1457.916	21644	4153.253	0.27541	-0.0802	1.14318429	1	902.2	905
2100303	99	1942.114	25177	6162.132	0.33724	4.269839	0.171634278	0	0	0
2100477	98	1932.289	31253	4246.152	0.294669	0.692944	0	0	1852.6	1863.1
2100501	99	11132.18	10904	13126.1	0.658141	3.225197	0	0	0	0
2100808	98	608.296	14815	6403.51	0.38879	1.178329	0.547978835	0	0	0
2100832	98	488.806	17474	3306.627	0.211602	0.341345	0.681933801	0	166.9	167
2100873	98	805.194	14658	3557.648	0.299613	-0.20178	0.413978909	0	749.8	757.5
2100907	98	1782.6	44317	3660.649	0.208176	1.425081	0.373985564	0	0	0
2100956	99	2976.038	31867	4484.42	0.361293	0.842229	0.112005738	0	1659	1794.9
2101004	98	1100.275	28986	4469.468	0.293756	1.006331	0.605909129	0	383.6	406.4
2101103	98	203.153	11706	6861.011	0.528692	1.28959	3.281598926	1	24.4	29.7
2101301	98	823.723	17164	2770.508	0.199198	0.426167	0.404666779	0	501	502.4
2101350	98	674.512	5440	3966.912	0.273155	0.282613	0.494184438	0	16.2	16.2
2101509	99	2208.314	18074	6722.862	0.069382	0.300462	0.150944718	0	0	0
2101772	98	142.814	10717	4224.503	0.220914	1.512507	0	0	127	127
2101731	98	569.428	7105	5673.329	0.460327	0.742296	1.170765517	1	0	0
2101806	99	1781.734	5510	4744.283	0.219368	0.065542	0	0	0	0
2101905	98	797.716	20821	3987.08	0.227787	0.023131	0.417859656	0	466.8	468.6
2101939	99	261.451	6176	7484.78	0.550227	1.59443	1.274936158	0	190.3	193

2101970	98	403.46	8626	4097.96	0.238962	1.202599	0.826186817	0	308.8	326.2
2102002	98	6590.53	40134	8286.366	0.575572	1.936049	0.252888109	1	3281.9	3531.1
2102077	99	445.976	15604	5656.691	0.481301	1.583519	0.747424376	0	451.8	451.8
2102200	98	1473.96	27697	4792.071	0.350983	0.541153	0.226148154	0	0	0
2102309	99	1582.552	23238	6418.496	0.486793	0.172528	0.210630256	0	35.6	50.6
2102358	99	818.424	15008	3884.928	0.301417	0.810342	0.40728685	0	579.2	678.3
2102374	98	705.645	8698	3776.615	0.287405	1.667894	0	0	17.4	29
2102408	98	908.729	10822	3847.348	0.230698	0.367183	0	0	84.6	84.9
2102507	98	662.066	18751	4491.494	0.372583	1.074222	0	0	51.7	58.8
2102556	99	615.384	13808	7232.329	0.34097	-0.2098	0.541667208	0	382	408.2
2102606	98	1640.756	19426	4112.993	0.301746	0.279329	0	0	888.9	929.4
2102705	98	773.01	21125	4307.645	0.257621	2.285899	0.431214775	0	214.7	244.5
2102754	99	590.529	10729	6567.061	0.376565	1.667291	1.128931292	1	208.4	221.5
2102903	98	1232.08	22811	4917.233	0.299086	0.975829	0.541090405	0	635.4	649.4
2103109	98	283.186	10414	5299.885	0.214054	0.586864	1.177082671	0	229.3	229.5
2103125	98	319.053	8255	3656.208	0.174609	0.646465	1.044758499	0	258.9	258.9
2103158	98	1167.848	12395	4630.093	0.411778	1.308227	0	0	834.2	907.6
2103174	98	8369.793	20382	4684.967	0.383721	3.284121	0	0	2017.4	2286.9
2103257	99	1464.034	14125	8381.239	0.478601	1.739162	0.227681415	0	1232.1	1297.7
2103505	99	1980.552	39915	4381.11	0.229785	2.237161	1.178122732	1	147.6	185.9
2103554	98	733.229	15313	4580.226	0.386342	0.841956	0.454610133	0	531	531
2103752	99	335.776	12646	3844.14	0.195802	0.423947	2.978175927	1	273.3	286.6
2103901	98	317.92	10942	3784.043	0.186364	0.482567	1.048481798	0	0	0
2104073	99	1473.415	8263	5042.963	0.343878	-0.11533	0	0	0	0
2104081	99	5086.584	9783	4640.499	0.411011	1.639238	0	0	27.2	36.7
2104099	99	3690.611	18087	5928.789	0.515728	1.381516	0	0	26	33.1
2104107	99	1854.01	12343	8635.421	0.568899	1.717365	0	0	0	0
2104206	99	694.997	15212	4562.319	0.310923	0.646882	0.479618377	0	213.1	272.9
2104305	98	667.325	11046	9759.008	0.097453	0.998389	0	0	286.8	294
2104404	99	883.589	17572	3965.115	0.229743	0.336888	0.377249302	0	444.1	530.4

2104503	99	445.856	10466	4089.719	0.209759	0.032612	0.747625541	0	164.3	183.2
2104552	99	615.852	17094	5379.899	0.115326	-0.05277	0.541255583	0	277.1	286.4
2104602	99	816.991	16312	3787.764	0.205414	0.659333	0.408001231	0	220.8	308.7
2104628	99	373.164	7532	3543.415	0.190514	1.345649	0.893262301	0	104.3	167.1
2104651	98	1144.069	10113	5234.253	0.464533	1.354987	0.291357718	0	1164	1165.5
2104677	98	1037.13	25262	4853.812	0.18826	3.00941	0.964199281	0	1002.8	1010.7
2104701	99	271.444	6151	5144.529	0.309133	1.096538	1.228000373	1	170.1	205.8
2104909	98	595.382	11939	4222.715	0.277337	0.610471	0	0	370	371.9
2105005	98	2131.247	27364	3859.158	0.230199	0.932686	0.469208872	1	0	0
2105104	98	1448.779	26014	3813.908	0.245306	0.887895	0.2300788	0	8	15.3
2105153	98	368.685	13347	4367.124	0.201049	1.211739	0.904114172	0	209.5	215.2
2105203	99	374.248	11431	5092.205	0.315422	1.901851	0	0	380	380
2105351	99	1066.192	14084	3402.442	0.290101	0.333956	0.312639124	0	893.3	918.8
2105450	99	591.384	9360	4623.077	0.359357	1.940929	1.127299127	1	177.5	243.1
2105476	99	1962.898	15899	3918.674	0.336295	0.597411	0.169816941	0	1075.7	1121.8
2105609	99	703.511	15755	4951.825	0.363478	1.693785	0.473813961	0	466	495.5
2105658	98	555.088	3653	8106.214	0.371053	-0.13629	0	0	543.1	546
2105708	99	1240.446	48002	4685.367	0.265571	1.016795	2.149764413	1	1552	1552.1
2105948	99	220.776	8775	6853.447	0.473871	2.773819	1.509825947	0	196.8	196.8
2105906	99	623.237	15742	5501.906	0.368684	1.200317	0.534842016	0	534.1	534.1
2105922	99	1512.985	10989	4660.388	0.249288	0.531654	0	0	0	0
2105963	99	937.714	12687	4369.197	0.32617	0.279423	0	0	704.2	712.6
2105989	99	1047.733	7211	5570.24	0.38607	0.763137	0.318147212	0	242.9	255.2
2106003	99	321.932	11580	4634.024	0.218777	2.060832	1.035415347	0	115.4	121
2106102	99	3596.84	11714	9406.864	0.554468	2.91218	0	0	0	0
2106201	98	464.06	6697	6104.226	0.413257	2.602409	0	0	301	307.5
2106300	98	433.15	18680	3883.298	0.226436	1.897641	0	0	0	0
2106326	98	635.824	20268	4397.671	0.259617	3.107923	1.572762274	0	536.5	541.6
2106359	98	1402.594	7721	6233.13	0.507559	0.739888	0	0	739.9	767.1
2106375	98	760.947	15011	4293.118	0.355322	8.402617	0.438050657	0	761.1	766.5

2106409	98	548.414	15951	5095.856	0.313377	1.216575	0	0	0	0
2106508	98	408.727	22515	4051.033	0.261511	1.180748	0.815540283	0	288.4	289.9
2106672	98	634.737	8237	5051.475	0.462782	0.790261	0	0	0	0
2106706	99	8521.084	20576	6356.435	0.506828	2.568617	0.039118654	0	0	0
2106805	98	687.748	14504	3678.296	0.132568	0.161743	0.48467365	0	681.2	681.2
2106904	98	1271.506	32180	3842.045	0.299918	0.390539	0.524312639	1	910.3	961.9
2107100	98	1715.175	18544	3725.356	0.171103	1.11429	0	0	13.7	19.1
2107209	98	572.507	13465	4467.583	0.382019	2.105607	1.164469023	1	0	0
2107258	99	743.106	5120	6787.891	0.484471	0.36249	0	0	0	0
2107357	98	2452.615	19963	4658.168	0.28935	1.095502	0.135909359	0	1144.7	1173.3
2107407	98	695.333	18934	5128.076	0.301244	0.726371	0.479386615	0	704.6	704.6
2107456	98	197.636	13911	4299.691	0.306293	0.387312	0	0	184.3	184.3
2107605	98	532.164	19133	3855.381	0.251412	-0.06109	0.626373324	0	439.7	440.4
2107704	99	530.52	20636	3563.821	0.129334	0.425597	0.628314358	0	0	0
2107803	99	3240.492	33883	4793.495	0.367579	1.516666	0.102865038	0	0	0
2107902	99	1358.327	18216	4976.175	0.347207	1.559122	0	0	0	0
2108009	99	1635.305	18687	6440.681	0.430779	0.441239	0	0	0	0
2108058	98	979.178	15234	3928.253	0.225949	1.346166	0	0	0	0
2108108	98	1098.497	20514	7525.934	0.523443	1.574226	0.303444919	0	1064	1064
2108256	98	1749.885	23874	4024.797	0.248306	0.331839	0	0	1661.8	1673.4
2108306	98	768.714	36520	3967.689	0.312572	0.518451	0.433624642	0	471.6	484.5
2108405	98	398.72	13956	3391.373	0.189868	-0.04496	0.836008561	0	243.9	245.6
2108454	99	824.722	22123	3866.157	0.168273	0.452974	0.808353199	1	232.2	253.4
2108504	98	273.526	31866	5418.157	0.086055	0.45372	3.65595958	0	202.4	202.4
2108702	98	545.14	21512	4651.776	0.216271	1.638775	1.222927444	1	479	479
2108801	98	688.761	17917	5929.676	0.471052	1.80479	0.483960813	0	253.3	285
2108900	99	990.413	18633	7081.146	0.443472	2.009347	0.336559933	0	588.9	589.8
2109056	98	218.831	5943	5951.203	0.40681	0.517983	1.523245488	0	117.9	118
2109205	98	354.696	12103	3864.001	0.191406	1.52725	0	0	33.6	59
2109239	98	437.687	6674	5003.296	0.344797	0.664154	0.761579241	0	440.1	440.1

2109403	98	1367.676	14588	3493.899	0.215408	0.25852	0	0	0	0
2109502	99	6373.017	20011	10379.94	0.488208	0.566339	0	0	0	0
2109551	99	750.553	7514	7117.381	0.51634	2.101152	0.444116982	0	417.8	435
2109700	99	2478.696	5538	23595.7	0.65174	0.608538	0	0	0	0
2109759	99	623.214	7426	4074.737	0.327202	1.002392	0	0	48.1	55.8
2110039	98	897.147	24507	6085.037	0.268783	1.310619	0.371548178	0	862.1	863.8
2110104	98	1434.898	24879	4675.55	0.214613	2.104679	0.232304549	0	0	0
2110203	98	706.385	35364	3635.392	0.091289	1.32335	2.359431	1	189.4	243
2110237	98	932.016	12761	3578.403	0.246129	1.218521	0	0	0	0
2110278	98	1601.18	15110	3192.985	0.286122	0.099039	0	0	0	0
2110401	98	931.481	18189	4386.937	0.329232	0.812436	0.357853068	0	0	0
2110609	98	1006.919	27599	4286.858	0.148332	1.449569	0.331042848	0	0	0
2110658	99	960.929	7187	17122.72	0.323785	0.742577	0	0	0	0
2110807	99	2032.364	4554	7563.022	0.497806	0.396931	0	0	0	0
2110856	99	745.606	11242	5001.957	0.45679	0.306861	0	0	700.9	714.5
2110906	99	2280.214	11961	3303.988	0.231086	0.31563	0	0	0	0
2111003	98	690.683	20195	3909.928	0.229973	0.971661	0.482614069	0	148.6	148.6
2111029	98	908.077	15558	5213.009	0.444145	0.55301	0	0	387.1	408.9
2111052	99	2053.843	10933	5929.022	0.527982	0.424466	0.162297378	0	240.8	254
2111078	99	1438.068	17956	3825.351	0.230841	0.167653	0.23179247	0	0.7	0.9
2111102	99	1482.66	25287	4845.177	0.077161	1.050944	1.348926929	0	0	0
2111250	99	353.234	7501	4116.918	0.224589	0.172028	0	0	255.8	272.1
2111409	99	968.574	18807	7246.185	0.480042	0.779719	0.344148546	0	643.5	653.3
2111532	99	720.452	12349	5039.193	0.234316	13.10865	1.388017522	0	447.3	453.9
2111573	99	979.631	4542	8640.247	0.552872	0.295348	0	0	0	0
2111607	99	3521.525	18255	17379.57	0.473521	2.27104	0	0	0	0
2111631	99	419.352	5387	4579.915	0.281848	0.988521	0.794877176	0	279.6	280
2111672	99	227.463	6432	5142.413	0.151301	1.3294	1.4654398	0	229.7	229.7
2111748	99	426.436	10763	3524.017	0.195335	0.615525	0.781672592	0	78.4	119.8
2111763	99	738.548	14195	6981.261	0.356874	0.874342	0.451336045	0	1096	1148.7

2111789	98	1165.86	10758	4034.579	0.371725	0.111362	0.285911973	0	1100.3	1101.5
2111805	99	3114.871	17559	5642.918	0.420227	0.248882	0.107013527	0	55.9	58.6
2111953	99	863.909	5519	4082.08	0.314682	0.509475	0	0	0	0
2112001	99	4382.975	8219	52748.63	0.592627	0.97616	0	0	0	0
2112100	99	1486.587	28442	3163.526	0.186415	0.131672	0.672681787	0	16.7	17.8
2112233	99	222.946	20747	5474.478	0.194318	1.758717	0	0	152.8	153.7
2112274	98	271.01	5699	4657.659	0.278946	1.486627	0	0	249	249
2112308	99	3369.123	40566	4396.169	0.30421	1.341778	0.296813147	1	1099.1	1195.2
2112506	98	1651.656	56501	3456.788	0.15241	0.906178	0.20181765	0	0	0
2112605	98	1708.294	31840	3519.975	0.322785	0.743094	0.195126444	0	0	0
2112803	98	1168.443	50976	3625.667	0.188461	0.964016	2.282239413	1	489.8	503.2
2112852	99	1188.781	12661	9210.805	0.648286	2.383594	0	0	948.5	965.6
2113009	98	1193.385	30937	5487.248	0.362051	1.283539	0.279317516	0	1166.3	1166.3
5100102	65	840.59	5431	13786.41	0.480396	0.249581	1.18964061	1	0	0
5100508	65	1846.295	10476	7439.863	0.322407	0.359726	0.541625255	0	420	423.5
5100805	66	20377.53	9094	17903.56	0.565627	6.503191	0.049073666	0	1717.2	2063.4
5101001	66	6429.386	3133	20813.92	0.58481	0.626809	0	0	811.9	830.4
5101209	66	687.973	1024	14373.05	0.334849	0.569919	0.969030277	1	0	0
5101308	65	416.785	9955	10667.2	0.194318	0.942212	7.997728645	1	364.8	367.8
5102603	66	5967.355	14827	10477.37	0.370126	0.985083	0	0	0.6	0.6
5102686	65	6801.857	5778	159492.4	0.492465	-0.02149	0.392049799	0	103.5	106.1
5102694	66	3452.684	4728	16509.52	0.541147	1.361321	0.193086499	0	1484.9	1627
5102702	66	10882.4	19681	33296.12	0.342934	0.298093	0.367565911	0	1811.5	1874.9
5102850	66	3909.537	8353	14984.32	0.537364	1.293896	0.255784764	0	2318.9	2506.7
5103106	66	16530.66	5525	22603.44	0.503012	0.946186	0.020164557	0	207.2	234.3
5103452	65	1307.188	8816	20497.84	0.641455	0.786549	2.040002407	1	1134	1141.2
5103601	66	2204.157	8101	31885.82	0.701728	1.103181	1.512293967	0	797.1	799.7
5103809	65	899.246	3651	15771.57	0.456186	0.412236	0.370680919	0	735.7	740.6
5103908	66	3794.94	5215	29903.36	0.698831	-0.05137	0.263508777	0	0	0
5103957	65	853.842	3072	15485.03	0.491714	0.759521	0.39039229	1	294.1	296.5

5104500	65	603.289	2491	25637.49	0.222681	1.496239	1.105053576	0	562.3	564.5
5105176	66	2778.961	12900	11524.34	0.289529	1.436925	0.479795626	0	925.7	1193.5
5105234	65	1763.89	5647	24229.33	0.474387	1.715587	0.377952518	1	1141.2	1174.8
5105309	66	4243.038	2148	10666.67	0.312226	0.598331	0	0	23.4	31.1
5106208	66	3281.884	4252	13048.68	0.459145	0.610505	0.203135354	0	1156.3	1165.9
5108808	66	1114.126	4731	14849.71	0.509349	0.921294	0.299188183	0	905.5	923.9
5106182	65	4735.085	5824	25272.32	0.250531	1.958789	0.422378901	0	1649	1776.6
5108857	65	1939.799	3052	36483.94	0.339139	0.087279	0.17183911	0	897.2	965.1
5108956	66	5248.543	8444	19771.44	0.562668	3.163573	0.127019378	0	2164.6	2351.3
5106257	66	5573.682	20143	15323.88	0.36685	0.297423	0.717658453	0	769.9	787.3
5106273	66	879.662	3815	12967.76	0.500127	1.264407	0.757866847	0	683.6	703.3
5106265	66	5790.968	7979	17418.1	0.575699	2.028981	0.115121801	0	2186	2475.1
5106281	66	5035.15	5611	55063.63	0.780118	-0.4616	0	0	0.8	1.1
5106307	66	24166.08	20383	24707.5	0.4731	0.725433	0.16552128	0	2224.4	2554.7
5106455	66	2455.431	2683	17937.38	0.595486	-0.18656	0.135753492	0	550.2	551.6
5106653	66	2738.777	5855	10510.5	0.367942	1.431512	0.365126478	0	0	0
5106703	66	685.987	1679	16562.84	0.499661	1.233613	0.485917858	1	0	0
5106778	66	3972.246	11336	16052.22	0.285523	1.944622	0.251746745	0	810.2	874.4
5106851	65	2062.76	3354	13318.43	0.446171	1.061038	0.323191582	1	374.4	380.5
5107008	66	6891.156	16919	25306.4	0.670213	0.908705	0.435340602	1	1840.1	1854.4
5107156	65	1337.041	2612	13111.03	0.46108	1.64499	0.498613481	0	283.6	307.7
5107180	66	11354.81	9316	16022.22	0.50853	1.02985	0.146780739	0	1495.9	1619.6
5107198	66	625.581	2259	23691.46	0.600166	0.334647	0.532838007	1	0	0
5107206	65	562.836	5063	10898.48	0.209078	0.529479	0	0	445.1	445.9
5107750	65	1752.309	3666	14041.46	0.476193	0.295695	0.380450404	0	1328.8	1345.5
5107776	66	6467.438	7709	15302.11	0.617478	1.301671	0.103080488	0	2268.2	2547.2
5107263	65	1174.18	3025	13329.26	0.504976	0.266573	0.283886059	0	906.7	955.1
5107297	66	443.876	3741	9570.168	0.393904	0.627824	1.501920957	1	27.4	27.4
5107305	65	4536.199	18339	21304.81	0.505893	0.817151	0.88179553	0	1562.8	1745.8
5107354	66	7459.645	5333	35948.43	0.588775	0.758675	0	0	4062.3	4293.3

5107404	66	342.952	4341	7962.681	0.235744	-0.03582	2.915859945	1	305.7	305.7
5107875	65	13624.37	20934	92683.67	0.520511	0.327479	0.269125554	0	158.7	184.7
5107941	66	8317.428	9678	50167.7	0.599465	4.79501	0.320611933	0	2129.6	2506.1
5108105	66	4188.092	3482	22808.44	0.679701	0.419904	0	0	0	0
5108303	66	4581.91	3639	40751.03	0.725579	3.421826	0.14549973	0	783.3	1028.7
5105507	65	13420.98	14999	21483.63	0.465723	1.553622	0.298040873	0	4368.4	4567
1500206	91	4343.805	54030	5187.877	0.299138	0.41822	0.076737637	0	2088.1	2306.8
1500347	94	7113.961	25899	10314.84	0.408613	0.261624	0.28113733	1	4428.6	4599.9
1500701	91	6921.746	26547	3254.454	0.11388	-0.31353	0	0	161.2	176.2
1500909	91	1091.541	42591	3842.619	0.189841	0.582961	0	0	720.8	728.6
1500958	91	1811.84	28441	4626.56	0.275142	0.654619	0.367950077	1	1435.9	1537.7
1501006	93	17074.05	15959	3703.929	0.193841	0.703498	0	0	990.5	1142.1
1501105	91	4397.321	26666	2640.704	0.070567	-0.60881	0.22741119	1	172.9	201.2
1501204	91	3758.297	41232	3766.201	0.164945	0.016935	0.088692653	0	1472.1	1572.4
1501451	93	4398.419	16808	5870.181	0.371514	4.317034	0.075784807	1	769.9	806.2
1501576	94	2816.476	15916	6181.013	0.336595	0.465335	0.35505362	1	1664.9	1739.7
1501600	91	586.737	14689	3615.903	0.194977	2.363055	0.568113709	0	509.8	539.3
1501907	91	1005.168	27000	3095.259	0.103538	-0.26238	0	0	608.3	652.2
1502004	91	3100.258	21740	4490.386	0.303444	0.059841	0.107517933	0	71.2	73.1
1501956	91	2461.972	29533	3127.349	0.144605	-0.06016	0.135392821	0	1109.4	1390.7
1502301	91	2899.553	52537	4410.454	0.169412	0.980966	1.264562733	1	2468.2	2557.8
1502509	91	13084.96	22029	4307.867	0.376675	0.033234	0	0	89.6	95.5
1502608	91	609.792	11600	4073.448	0.128841	0.511943	0.546634481	0	86.4	90.3
1502806	91	3617.252	30915	2625.554	0.073613	-0.02315	0.276452954	1	183	198.9
1502855	93	1431.157	13097	4807.36	0.258393	2.02273	0.698735359	1	296.2	323.6
1503044	94	3444.285	18741	20682.25	0.25313	0.742046	0.096778673	0	1686.6	1891.5
1503077	91	1599.028	25287	4205.956	0.21578	1.833342	0.208459973	0	1345.2	1418.1
1503101	91	8540.113	30727	3530.446	0.169474	-0.08654	0.03903149	0	84	105.8
1503200	91	785.983	36883	4628.501	0.170759	-0.27155	3.392779063	1	666.8	686.4
1503408	91	471.449	10693	4153.371	0.240293	0.359817	0.707040069	0	317.6	326.9

1503754	93	53303.02	41487	2066.937	0.181057	0.510302	0.012507108	0	1097.3	1339.4
1503903	93	8306.298	51483	9630.422	0.076575	0.64287	0.321041536	1	1096.3	1152.3
1504000	91	1490.186	26542	4782.307	0.305617	0.016097	0.67105717	1	58.3	61.6
1504109	91	325.265	8240	4328.641	0.159657	1.333955	1.024805415	0	154.3	161.9
1504307	91	855.664	28631	4285.355	0.183907	0.389204	0	0	310	323.3
1504406	91	795.987	27153	4390.786	0.168725	0.445259	5.862742314	1	381.3	399
1504505	91	6774.018	25860	3570.959	0.122465	0.005726	0.098415249	1	147.2	155.5
1504802	93	18152.56	56147	5534.223	0.271122	1.063569	0.12854018	1	4011.7	4156.8
1504950	91	2809.312	20528	3986.945	0.163231	1.895749	0.118653013	0	1336.5	1494.3
1504976	94	1564.184	15422	5095.902	0.233956	1.018499	0.639310976	1	1063.9	1136.3
1505007	91	489.852	14305	4317.931	0.143931	0.675499	4.763343486	1	367.5	376.6
1505106	93	28021.42	50171	5262.801	0.281737	0.793764	0.130852284	1	1601.1	1814.4
1505304	93	107603.3	66821	17574.45	0.063457	0.701481	0.074347168	1	1334.2	1481.1
1505403	91	562.387	16854	4582.414	0.09793	0.288578	1.778134985	0	472.2	496.7
1505437	94	14410.57	29547	21041.05	0.062739	-0.03912	0.208180566	1	1555.4	1666.6
1505551	94	1671.419	5743	8318.823	0.463981	-0.1222	0.199431341	1	892.1	930.6
1505601	91	450.222	7889	4235.264	0.141033	0.325292	0.740375489	0	349.5	358.2
1505635	94	3312.661	12720	10064.47	0.545475	0.010304	0.20124808	1	2715.6	2900.7
1505650	93	7173.194	26842	3935.549	0.325821	0.751893	0	0	1402.3	1747.2
1505700	91	3365.152	28025	3872.4	0.205981	0.031034	0.099054466	0	51.4	52.1
1505908	93	17423.02	36841	3892.267	0.153758	0.198673	0.01913178	0	629.8	945.3
1506005	93	14786.99	29342	5518.847	0.329688	0.753548	0.022542343	0	1308.2	1626.7
1506112	91	326.113	12838	4492.756	0.289412	0.679152	1.022140587	0	72.7	80.2
1506195	93	7021.321	44349	3682	0.197019	0.463394	0.094948894	0	1532.9	1762.5
1506351	91	278.154	18736	4629.857	0.074171	-0.46985	0	0	155.5	159.3
1506401	91	1076.652	8957	4008.038	0.21491	0.005571	0	0	0	0
1506906	91	229.51	6341	4275.509	0.132946	0.373483	0	0	133	147.9
1507003	91	537.625	28575	4843.43	0.264161	0.829212	3.100054251	1	313.7	323.8
1507102	91	743.466	17266	4791.729	0.244333	0.296112	1.345051421	1	218.7	231.4
1507151	94	1392.464	24012	6115.526	0.269278	1.385613	1.196919035	1	1223.5	1282

1507201	91	1677.249	30550	4191.26	0.249581	1.842486	0.596214396	1	1250.3	1331.2
1507409	91	479.564	15301	4976.799	0.151936	0.338705	2.085227415	0	401.8	416.4
1507458	94	3168.383	25056	8048.691	0.365244	-0.02356	0.210412272	0	2437.8	2491.9
1507466	91	195.918	5608	3978.959	0.167207	-0.05575	0	0	92.8	106.1
1507474	91	705.542	21536	4288.494	0.158533	0.625705	4.724500219	0	168.3	199.4
1507508	94	1279.889	13419	4947.686	0.258893	0.752794	0.260439252	0	801.4	906.2
1507607	91	1110.175	54417	4240.403	0.106708	0.600416	3.002529631	1	834.9	881.7
1507706	91	1632.251	24363	3573.452	0.145403	0.436588	0.612650873	1	120.5	123.5
1507755	94	1298.19	5395	9214.087	0.460894	-0.59046	0.770303268	1	1144.7	1157.8
1507961	91	206.414	10822	3308.076	0.112629	0.49753	1.614877544	0	165.4	170.6
1507979	93	1896.506	17614	4532.077	0.129697	0.27377	0.52728544	1	314.3	340.9
1508035	91	934.272	28775	3653.171	0.134966	0.234755	0.356784034	0	456.9	467.7
1508050	93	11991.09	17670	6315.224	0.340738	0.610971	0	0	819.1	1081.5
1508084	94	2512.594	36021	9446.767	0.176263	-0.12579	1.06132016	1	2217.1	2275.6
1508159	93	10791.37	44731	5995.596	0.271585	0.825567	0.154444386	0	2422	3045.5
1508308	91	4915.073	58323	4095.726	0.193899	0.585234	0.203455778	0	3322.4	3455.2
1100379	69	3958.273	13827	15071.17	0.499968	1.395792	0.25263543	0	1168.9	1287.8
1100403	69	2651.822	19459	11979.03	0.351621	1.786755	1.131297651	1	1429.1	1672.5
1100452	69	3265.809	36555	12140.91	0.354948	9.343735	1.224811371	0	1777.9	2206.4
1100031	69	1314.351	6495	25016.47	0.634446	0.778973	0	0	942.3	971.4
1100601	69	1961.778	6268	21638.16	0.614042	1.441676	0.169913891	0	1366.2	1456.6
1100700	69	3442.005	13939	14396.15	0.46796	4.642725	0	0	1549.8	1878.7
1100908	69	892.842	3689	17622.93	0.544844	0.856478	0	0	700.3	717.2
1100056	69	2783.3	18041	24597.58	0.43197	0.495363	1.43714296	0	770.3	799.9
1100924	69	5126.723	9636	36305.31	0.58003	2.361069	0	0	2500.5	2634.8
1100072	69	3060.321	9036	35349.71	0.727506	2.393143	0	0	2092.8	2145.2
1100080	69	4987.177	15853	10508.04	0.321164	11.96795	0.401028478	0	1260.5	1645.7
1100940	69	3863.943	19410	11395.21	0.297147	7.684933	0.172535326	0	1055.8	1431
1101005	69	5067.384	10534	14809.09	0.5012	1.50757	0.131560321	1	1265.9	1351.2
1101104	69	4081.583	9661	12925.06	0.274483	1.695591	0.24500298	0	737	863.5

1101203	69	798.083	10899	13550.23	0.385614	0.651751	1.253002507	1	697.3	710.3
1101302	69	1191.875	12469	12338.2	0.323854	0.672846	1.678028317	0	604.5	631.1
1101401	69	1931.378	15541	13855.48	0.378071	2.133162	1.553295108	0	1220.2	1357.7
1101435	69	807.126	7883	11928.71	0.428314	0.337517	0.412987976	0	683.1	695.6
1101450	69	2548.683	5477	15915.65	0.533487	2.413946	0.130786502	0	988	1126.4
1101468	69	6014.733	2440	74469.67	0.813727	2.757528	0.055419473	0	1183.6	1256.7
1101476	69	605.692	3597	14944.12	0.458547	0.159729	0.550334714	0	410.5	421.8
1100262	69	1717.64	3666	25954.45	0.646077	2.012455	0.194064724	0	985.4	1060.5
1100296	69	1197.796	8887	19891.53	0.543017	0.380209	1.66973341	1	944.7	974.4
1101484	69	541.647	6219	13952.56	0.462666	0.880881	0.615406959	0	478	485.2
1101492	69	10959.77	18265	14548.48	0.434478	8.15457	0.182485631	0	2125	2451
1101500	69	3773.505	12505	13405.76	0.383582	1.608351	0.265005611	0	1074.2	1234.2
1101559	69	459.978	5080	14215.94	0.428129	0.252416	0.724672339	0	439	441.5
1101708	69	831.857	13491	11251.2	0.342439	0.797994	1.202129693	1	673	687.6
1101757	69	3135.211	10518	17068.36	0.585328	2.7794	0	0	1067.8	1195.3
1101807	69	965.676	8425	12841.19	0.427198	0.697479	0	0	860.8	868.2
1400050	95	25567.01	16428	11048.15	0.18533	-0.12626	0.013037633	0	669.9	743.2
1400027	95	28472.33	10432	10697.57	0.195455	-0.01345	0	0	241.6	307.3
1400159	95	8095.421	11525	13046.33	0.278191	-0.08753	0	0	323.7	374.3
1400175	95	7664.831	15393	11498.34	0.190665	-0.09882	0.086977347	1	1231.5	1478.5
1400209	95	47408.9	19696	11109.21	0.062836	-0.23102	0.042186169	1	868.9	984.4
1400233	95	12066.05	8826	11640.15	0.192575	1.263635	0	0	733.6	923.1
1400282	95	14412.69	9762	10536.26	0.159966	0.548605	0	0	546.8	726.2
1400407	95	6966.811	9754	10472.22	0.227928	0.011578	0	0	18	19.5
1400456	95	8028.483	11423	10440.86	0.075942	-0.74025	0.124556532	0	62.3	75.2
1400472	95	33595.46	26326	11682.98	0.092325	-0.07174	0.019843953	1	975.5	1083.1
1400506	95	4284.507	7284	11504.94	0.067162	0.107006	0	0	429.6	511.6
1400605	95	1526.888	7210	10303.05	0.090473	0.042791	0	0	481.2	550.9
1400704	95	8065.564	9127	8344.034	0.048798	-0.15137	0	0	24.8	45.5
1700251	63	1895.212	2506	9086.193	0.35777	0.646179	0	0	3.9	7.4

1700301	63	235.394	5820	13125.95	0.064735	1.464998	4.248196641	0	104.3	107.6
1700350	63	1579.751	5686	9472.388	0.27003	0.6861	1.899033455	0	0	0
1700400	63	4013.243	7553	7469.88	0.182515	0.265795	0.41529174	0	0	0
1700707	63	1212.167	8557	24334.81	0.223313	1.004082	3.299875347	0	0	0
1701002	63	1576.973	9952	7785.169	0.209026	0.035441	1.902378798	0	1146.8	1157.4
1701051	63	451.733	3332	7365.546	0.206594	1.124119	1.475798019	0	189.3	199.6
1701101	63	1160.368	4504	12337.03	0.491352	2.622049	0.287265189	0	0	0
1701309	63	1173.058	5958	8403.659	0.373831	0.901007	0.568315179	0	901.1	1006.4
1701903	63	2778.475	6716	8212.775	0.313001	0.67721	0.239939775	0	41.6	53.2
1702000	63	5167.797	8868	14407.98	0.431697	0.849759	0.516016141	0	0	0
1702158	63	836.03	5379	8886.596	0.327153	0.682658	0.79741955	0	733.7	742.9
1702307	63	1552.221	6844	11078.9	0.343435	0.626643	0.644238159	0	1462.4	1464
1702406	63	5786.871	10833	12076.34	0.336727	2.646691	0.518414874	0	0	0
1702703	63	752.83	3625	8635.586	0.346458	1.12094	0.885547423	0	0	0
1702901	63	150.213	9632	6474.875	0.110169	1.477019	13.31442685	0	138.3	139.6
1703008	63	1788.461	10720	6191.698	0.192504	0.433364	0	0	3.5	3.5
1703057	63	1541.842	3336	18657.07	0.391167	0.440209	0.216191629	0	1496.8	1500.3
1703073	63	1106.345	4371	9394.418	0.392806	3.603493	0.602584787	0	0	0
1703107	63	713.3	5557	8549.937	0.267746	0.912355	2.336557783	0	0	0
1703206	63	926.888	4547	11776.56	0.387064	0.484124	0	0	891	894.9
1703602	63	641.467	2154	12620.71	0.335716	2.038248	0	0	218.9	218.9
1703701	63	1724.45	5400	13017.59	0.497711	1.794932	0	0	0	0
1703800	63	251.919	10522	5433.473	0.078719	1.104025	2.646353259	0	213.7	214
1703826	63	352.345	2236	6650.268	0.121116	1.982227	1.892084936	0	104.2	108.7
1703842	63	3240.177	9000	38938.33	0.467023	3.458857	0	0	0.1	0.1
1703867	63	1128.601	4053	24138.17	0.302271	2.128228	0	0	0	0
1703883	63	339.405	2457	10446.07	0.348366	1.394237	1.964221702	0	305.7	307.3
1703891	63	192.939	3906	6182.796	0.141453	0.335275	3.455323531	1	130.5	131.3
1703909	63	1691.614	4965	9078.55	0.351333	0.434895	0	0	241.3	269.1
1704105	63	1954.699	2737	7844.355	0.271896	2.502181	0.170529239	0	0	0

1705102	63	1646.472	3362	12574.06	0.50006	3.327627	0.404906167	0	0	0
1704600	63	659.249	1386	10466.81	0.372383	0.509866	1.011251692	1	0.8	1.7
1716703	63	990.72	8581	9705.046	0.199194	0.921195	1.682278208	0	748.8	753.3
1705557	63	209.572	4827	9138.388	0.220837	0.871336	3.181086532	0	0	0
1705607	63	2500.74	4240	7313.679	0.19075	0.041178	0.266587757	0	0	0
1706001	63	1585.787	5314	9025.969	0.305142	1.215583	0	0	222.5	232.2
1706100	63	1848.241	7399	9501.554	0.25688	0.534703	1.082109963	0	0	0
1706258	63	986.693	1651	15969.11	0.484127	1.319393	0	0	0	0
1706506	63	1639.162	5670	10293.12	0.390678	5.625173	0.406711885	0	103.5	108.3
1707009	63	3217.313	20566	12953.52	0.31279	3.360004	1.346879627	0	0	0
1707108	63	2347.434	6681	10101.48	0.277075	0.772256	0.283998045	0	17.4	18.4
1707207	63	3757.036	7319	9269.846	0.417688	0.460943	0	0	60	64.9
1707306	63	3424.852	4718	16901.23	0.591984	0.615384	0.194655613	0	31.3	34.6
1707405	63	504.023	10203	5587.18	0.100724	2.518804	0.661345481	0	211.8	217.3
1707553	63	382.908	3892	10204.01	0.261578	1.639789	1.741062257	0	0	0
1707652	63	1930.072	5421	19807.23	0.3538	0.458786	1.554346159	0	0	0
1707702	63	1988.081	8800	8286.364	0.245187	1.405509	0.335331743	0	0	0
1708205	63	13423.38	18804	16714.79	0.514233	0.253034	0.297987475	0	173	186.8
1708254	63	621.562	2527	27988.92	0.204572	1.435225	0	0	402.6	402.6
1708304	63	1800.983	5115	9330.205	0.397242	1.041631	0	0	98.2	102.2
1709005	63	6408.602	12644	9651.693	0.43791	6.146642	0.104026848	0	0	0
1709807	63	815.254	1804	14356.43	0.522176	2.607788	0	0	0	0
1710508	63	3051.36	7388	8298.457	0.293445	2.440124	0	0	0	0
1710706	63	739.849	6063	6952.829	0.207481	1.506307	0	0	335.8	358.8
1710904	63	1243.961	3711	10765.29	0.433396	3.117198	0.535922482	0	0	0
1711100	63	972.977	2482	13276.79	0.492747	0.55401	0	0	925.6	928.1
1711506	63	2173.047	3730	10102.41	0.391298	0.621692	0	0	0	0
1711803	63	481.048	2253	8572.126	0.284546	0.558997	0	0	210.9	210.9
1711902	63	10564.66	11859	26454.34	0.467869	3.243928	0.189310381	0	187.2	239.3
1711951	63	911.342	3957	6193.328	0.168774	1.855757	0.365760969	0	0	0

1712009	63	322.485	2991	9817.118	0.063744	0.838844	0	0	0	0
1712157	63	519.614	1782	8586.42	0.332465	0.902036	1.283003666	0	0	0
1712405	63	5723.234	3801	6072.086	0.164876	0.390925	0.058242129	0	0	0
1712454	63	279.563	2896	7622.238	0.172782	1.415779	2.384674176	0	152.2	156.4
1712504	63	2091.374	4814	10489.61	0.410204	0.496407	0	0	119.6	143
1712702	63	9681.657	2478	33959.24	0.736893	59.90851	0.034429368	0	0	0
1712801	63	738.105	3338	6468.544	0.174762	1.798709	0.45160693	0	138.1	143.5
1713601	63	3616.674	7412	14267.4	0.499476	3.272565	0.184331423	0	0	0
1713700	63	1091.553	2213	10795.75	0.422036	0.529187	0	0	0.4	0.7
1713957	63	1186.647	3395	9665.685	0.38993	0.832317	0.561807064	0	941.1	953.5
1714203	63	3240.715	9279	8651.148	0.162589	0.918533	1.028579598	0	0	0
1714302	63	395.907	4239	7116.065	0.141887	1.104967	1.683897144	0	268.8	282.5
1714880	63	1566.184	11408	15200.65	0.089538	1.94825	1.064157638	0	798.2	798.9
1715002	63	516.308	4066	7164.535	0.190009	0.22917	1.291218937	1	0	0
1715101	63	2674.682	4101	7030.237	0.143138	1.510919	0	0	0	0
1715150	63	200.105	2350	8001.277	0.22129	0.902465	3.331584252	0	0	0
1715259	63	1309.665	2625	10454.86	0.249482	5.745442	0.509036026	0	0	0
1715507	63	205.85	1091	12309.81	0.356406	0.533296	3.238604162	1	0	0
1715705	63	2640.816	5543	8596.969	0.3777	2.353116	0.252447223	0	103.2	103.6
1713809	63	747.898	6272	6782.366	0.226873	1.591639	0.445693575	0	57.3	58.2
1715754	63	1703.944	7623	9794.307	0.261516	0.817574	0.978122912	0	0	0
1716208	63	11260.22	10579	19266.28	0.095362	0.328086	0	0	0	0
1716307	63	1377.406	4793	9736.282	0.38976	0.738753	0.48400157	0	1112.5	1129.9
1716505	63	2010.902	12698	29982.36	0.390217	-0.05385	1.989157105	0	19.7	20.8
1716604	63	5291.208	11209	32841.73	0.146496	1.216634	0.377985519	0	0	0
1716653	63	1209.8	5344	9031.25	0.343138	0.647739	0	0	837.8	844.2
1717008	63	1559.086	4562	8333.406	0.324868	-0.00665	0.427600958	0	0	0
1717206	63	1367.613	3024	11590.61	0.476576	1.073079	0.487467337	0	1075.9	1096.6
1717503	63	10013.79	7264	14562.5	0.578164	0.440981	0	0	29	34.6
1717800	63	1806.141	4652	7101.247	0.245023	0.878371	0	0	0	0

1717909	63	6491.125	7712	7437.5	0.272524	0.732729	0	0	0	0
1718006	63	501.862	3007	6987.695	0.160954	0.942211	1.328386422	0	0	0
1718303	63	289.054	8158	5525.864	0.074244	1.861276	0	0	208.8	222.9
1718402	63	770.423	3750	20241.87	0.143684	0.95061	1.297988248	0	337.5	340
1718451	63	401.834	2561	10765.72	0.165811	0.194776	1.659059877	1	0	0
1718501	63	2216.663	4081	6922.568	0.198827	1.32224	0.150376189	0	32.8	37.7
1718550	63	517.478	4478	6937.919	0.184472	0.47705	1.288299535	0	437.4	442.4
1718659	63	787.116	1938	6621.259	0.092793	6.344084	0.423486924	0	0	0
1718709	63	845.065	2740	9900.365	0.364826	3.725572	0	0	17.8	17.8
1718758	63	6354.367	6473	6640.97	0.231449	0.567209	0.052457363	0	0	0
1718808	63	222.29	4329	5514.438	0.074933	0.905755	2.999085279	1	73.5	75.3
1718840	63	3528.621	3411	14708	0.525082	0.716248	0.188931219	0	4.1	4.1
1718865	63	1678.091	7144	9756.859	0.359965	1.104884	0.397276826	0	1226.7	1264.5
1718881	63	1410.457	3198	8301.438	0.286873	1.735481	0	0	0	0
1718899	63	3274.947	2278	15821.77	0.580427	0.204953	0	0	17.3	20.7
1718907	63	1796.257	4773	13905.72	0.523217	2.753821	0.37114214	0	0	0
1719004	63	539.912	2729	7892.635	0.250827	1.334318	1.234769123	0	0	0
1720002	63	269.677	2545	6555.599	0.159931	1.385894	0	0	71.8	73.3
1720101	63	1105.901	5026	6243.733	0.135891	1.352283	0.602826715	0	341.5	349.5
1720150	63	1908.678	1532	6795.692	0.130575	0.980539	0	0	0	0
1720200	63	398.82	11436	4960.563	0.071727	0.587347	0	0	325	337.9
1720259	63	1422.032	3044	7852.825	0.212002	0.791648	0.468812704	0	0	0
1720309	63	287.275	4604	6052.563	0.131488	2.302116	2.320656746	1	135.4	135.6
1720499	63	2519.585	4267	10070.78	0.323338	2.207475	0.264593839	0	0	0
1720655	63	1258.831	5318	15568.82	0.525059	2.601039	0	0	0	0
1720804	63	324.106	9270	6051.025	0.114387	0.895162	2.056940219	0	289.1	295.9
1720853	63	1025.519	1878	20813.1	0.611814	1.266994	0	0	0	0
1720903	63	2437.399	16086	10998.38	0.152542	0.41417	1.504335838	0	0	0
1720937	63	1116.202	2075	7450.602	0.225858	0.111317	0	0	0	0
1720978	63	2156.902	2716	16736.38	0.509412	0.595892	0	0	0	0

1721109	63	2601.603	7236	5750.138	0.069316	0.142991	0	0	0	0
1721307	63	895.308	2402	8972.107	0.314073	3.201592	0	0	2.1	2.2
1722081	63	1373.061	11509	7960.726	0.155621	0.898601	1.9421327	0	297	315.1
1722107	63	1186.428	11722	15319.74	0.133775	0.612333	3.371464598	0	949.9	987.3