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Article abstract

To study the role of Information and Communication Technology (ICT) on countries' socioeconomic development, the paper investigates the case of Facebook penetration on improving their standing as measured via GNI per capita PPP (Gross National Income per capita based on purchasing power parity). We use four macro factors categories (political, economic, demographic, and technological) in addition to Facebook penetration per capita in order to measure the potential influence of various factors on the socioeconomic level of countries. While the analyses of ICT effect on development has been the focus of many papers in the past, the specific analysis of social media is scarce. Compared to previous studies investigating social media role, we use a large dataset covering all classes of countries and examine holistically many types of determinants using different models. In addition, we distinguish our paper using the economic classification of countries according to the World Bank. Our study indicates that Facebook penetration has a significant positive role on the socioeconomic level of countries, but such role varies depending on the countries' classification level. Besides, there is a decreasing marginal effect showing the importance for policy makers to assess the complex dynamic behind the characteristic of each country.

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Role of Social Media in Socioeconomic Development: Case of Facebook

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To study the role of Information and Communication Technology (ICT) on countries' socioeconomic development, the paper investigates the case of Facebook penetration on improving their standing as measured via GNI per capita PPP (Gross National Income per capita based on purchasing power parity). We use four macro factors categories (political, economic, demographic, and technological) in addition to Facebook penetration per capita in order to measure the potential influence of various factors on the socioeconomic level of countries. While the analyses of ICT effect on development has been the focus of many papers in the past, the specific analysis of social media is scarce. Compared to previous studies investigating social media role, we use a large dataset covering all classes of countries and examine holistically many types of determinants using different models. In addition, we distinguish our paper using the economic classification of countries according to the World Bank. Our study indicates that Facebook penetration has a significant positive role on the socioeconomic level of countries, but such role varies depending on the countries' classification level. Besides, there is a decreasing marginal effect showing the importance for policy makers to assess the complex dynamic behind the characteristic of each country.

Keywords: Facebook penetration; Country level analysis; Socioeconomic development; World Bank classification.

JEL Classification: F63.

1 Introduction

Information and Communication Technology (ICT) changed our lives on many levels such as social, political, educational, medical, and business levels (Roztocki et al. 2019). The impact of ICT on social standing (i.e., society wellbeing) and economic standing has attracted the

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attention of many researchers and practitioners. Many conceptual frameworks (e.g., Madon 2000; Roztocki and Weistroffer 2016) have been proposed to link the power of ICT to the social (e.g., education, health, democracy) and economic development (e.g., income, economic productivity, alleviation of poverty).

Following Brown and Grant (2010), we adopt the same definition as Von Braun and Torero's (2006) about ICT. It is any technology infrastructure or digital ecosystem enabling the creation, collection, distribution, usage and storage of information. Hence, ICT encompasses for example various social media platforms, emails, intranets, extranets, etc. Brown and Grant (2010) reviewed 184 journal articles and proceedings linking ICT to development and explained that there are two stream of research: 1/ studies focusing on the effect of ICT on development and 2/ studies focusing on the impact of ICT in developing countries. In addition, we adopt the definition of OECD about social capital as "networks together with shared norms, values and understandings that facilitate cooperation within or among groups" (OECD, 2001). Another project from OECD (based on the work of Scrivens and Smith, 2013), detailed four interpretations of the social capital concept: 1/ Personal relationships which is exchanging information via social networks, 2/ Social network support which is the outcome of the social network, 3/ Civic engagement which is about activities such as community actions, and 4/ Trust and cooperative norms which is composed of shared values fostering mutual benefit and cooperation.

Some studies focused on specific case analyses such as Ashraf et al. (2017) who examined a community level case of Bangladesh, and Palvia et al. (2018) who focused on Pakistan socioeconomic development related to the application of ICT tools and programs. The previous frameworks are descriptive and conceptual. In addition, a number of empirical studies (e.g., Cronin et al. 1991; Colecchia and Schreyer 2002) are very limited to specific economies and disregard other types of regions or countries.

In our paper, we offer an empirical analysis of a special type of social media (i.e., the case of Facebook as a digital ecosystem and an enhancer of social capital) in order to investigate the interplay of ICT (via Facebook platform) on the socioeconomic development of the majority of countries in the world. For that purpose, we stratify these countries into all four economic levels according to the World Bank classification (developed or high income, upper middle income, low middle income, and low income). Hence, our paper joins the first stream of research according to Brown and Grant (2010) and focus on examining the effect of ICT (via Facebook as a digital ecosystem case) on socioeconomic development of countries across the globe.

As of the fourth quarter of 2020, Facebook users reached exceeded by far 2500 million users (Statista, 2020), making it the largest network connecting the world. However, does this social networking system generate economic growth? Mark Zuckerberg, co-founder of Facebook, envisioned that global poverty could be reduced through Internet connectivity (see Zuckerberg

2014). However, the question is still debatable as some studies showed contradicting results. Economists are also arguing about its real effect.

A 2015 Deloitte Report found empirically that Facebook has a global economic impact. The study focused on companies' sales and included marketing effects (facilitating marketing efforts and entrepreneurship), platform effects (offering platforms for apps' developers and fostering innovation) and connectivity effects (stimulating products' purchase and spilling over data consumption). According to the report, United States is the largest beneficiary in terms of economic influence (with $100 billion revenues and 1076 thousands jobs created), followed by United Kingdom ($11 billion revenues and 154 thousand jobs created), then Brazil ($10 billion revenues and 231 thousand jobs created). The study received controversial feedback from economists. As reported by Albergotti (2015), some economists questioned the study assumptions. Others affirm that Facebook is just the result of using and accessing the Internet with no reciprocal effect. Finally, another group of economists approves Facebook impact but disagrees about the magnitude reported by Deloitte. Indeed, the central question that consulting companies and economists are debating is whether Facebook is significantly boosting the economic well-being of countries.

Florida (2010) examined the case of US and performed different correlation analyses between social media metrics (Netrospex social index or NPSI provided by NetProspex 2010) and various macro factors of each US state. The study found that social media is highly and positively correlated with economic output, income, high tech industry, human capital (measured via education level), artistic and culturally creative jobs, and openness to diversity. However, social media has a modest positive correlation with innovation (measured via the number of patents as a proxy variable).

To our knowledge, only one academic study looked empirically at the effect of social media on the economic development at the country level. Dell'Anno et al. (2016) used a growth regression model and included social media penetration index (combination of Facebook and other types of social networks' users) to test its impact on GDP per capita. They found unexpectedly, in the majority of tested models, that social media has significant negative effect on economic growth. Their rationale is that social media augments information cost and possible distraction due to switching between labor and entertainment. Other studies focused only on the influence of social media on business performance or government workability and task enhancement, and did not take a macro look at the country level.

In our paper, we explore the effect of Facebook penetration, among other macro-factors, on countries' socioeconomic development via national income level. The research question is important as it could help many countries suffering from low socioeconomic standing to implement effective solutions. It is also beneficial for high-income countries as it contributes to further enhancing their socioeconomic development. Our paper explore this central question by assessing the determinants of the socioeconomic level of 160 countries and incorporate

Facebook penetration as one of the potential determinants. We use different approaches in order to look for results' convergence and support our conclusions. Our study is among the first works to explore such question. Hence, we propose our findings as initial ground that needs further confirmation in future research by utilizing larger dataset, longer data frame, and additional models.

We contribute to the literature on many novel points. First, as suggested by Sein et al. (2018), we offer a holistic approach to study the ICT effect by investigating the impact of various factors (political, technological, economic and demographic) on the socioeconomic level of 160 countries across all economic classes (as defined by the World Bank). Moreover, by utilizing GNI per capita PPP as proxy, our study explores the broader impact of ICT on the socioeconomic development of countries, rather than on its domestic economic output (as measured by GDP per capita). Second, we focus on Facebook, which is the most popular social-network platform in the World in 151 countries out of 167 countries as of January 2020 (Vincos Blog, 2020), rather than a combination of social media sites as did Dell'Anno et al. (2016). The purpose of focusing only on Facebook is to isolate the effect of one specific social networking site. Third, we assess the effect of Facebook penetration on countries' socioeconomic level using various methods and models in order to investigate the possible convergence of our results and reach findings that are more robust. Fourth, we examine the potential differential effect of Facebook penetration on different classes of countries to: 1/ verify if the results in the whole sample could be replicated to each class of countries, 2/ verify if the result is characteristic to each World Bank class. Qureshi (2015) proposed different levels of analysis for the effect of ICT on development such as region, institution, individual, and country. Fifth, we use a larger dataset, over multiple years and a larger number of countries, which provides more validity to the empirical findings of the study. Finally, we investigate various types of effect of Facebook, which was not the concern of previous studies.

Our findings show via different models that Facebook has consistently a significant positive effect on the socioeconomic development of countries. In addition, it could have different shapes of effect reflecting a more complex relationship between social media usage and the economic standing than simply a significant positive effect. The type of effect also depends on the characteristics of the country based on the World Bank classification. We tried several statistical techniques namely the Ordinary Least Squares (OLS) model, the fixed effect model, and the random effect model. All models confirmed the potential positive effect of Facebook as well as its diminishing effect over time. The issue of causality here should be emphasized as it is debatable whether more social media penetration in a country leads to better economy or better economy in a country leads to higher usage of social media. As we will discuss later in the paper, we have introduced some mitigants in the research design to address possible reverse causality.

The paper is organized as follows for the remaining parts. Section 2 explains the previous studies that looked at the relationship between social media and businesses, government agencies, individuals, or the economic standing of countries. Section 3 provides a description of the methodology and a summary for the data operationalization. Section 4 explains the econometric analyses via different models. Section 5 presents a discussion of the results. Section 6 offers practical and managerial implications of our research. Finally, Section 7 concludes by offering perspectives to explore in future studies.

2 Literature Review

Following the holistic framework of Sein et al. (2018) to study ICT effect, our paper touches at three levels of the framework: the first level is the digital ecosystem by focusing on Facebook penetration as a special case of social media platforms to study. At the second level, the socioeconomic development is measured by the GNI per capita PPP (purchasing power parity) of each country. The GNI is defined by OECD as "gross domestic product, plus net receipts from abroad of compensation of employees, property income and net taxes less subsidies on production." OECD, 2020). Hence, GNI per capita is considered a good proxy for the social and economic wellbeing of a country, as it provides a more complete picture of a country's total economic income, regardless of its source. Compared to GDP per capita measuring the value of domestic production and output, GNI per capita PPP is the value of domestic and foreign production taking into account the purchasing power parity as a measure of socioeconomic development. Hence, our study will focus on the broader impact of ICT on the socioeconomic development of countries, rather than on their domestic economic output (as measured by GDP per capita). At the third level, the transformative process is based on the variety of factors used in our study in order to uncover the interrelationship between politics, technology, demography and economic context on the overall development standing of each country.

A number of studies investigated the effect of ICT on the economic standing. Lee et al. (2017) provided a literature review of these papers. To illustrate, Cronin et al. (1991) used time series analysis for US data and found that telecommunication infrastructure positively influenced economic growth. Analyzing OECD countries, Colecchia and Schreyer (2002) found that ICT had contributed positively to economic growth and the magnitude of the positive effect is idiosyncratic to the country. Analyzing developed and developing countries, Papaioannou and Dimelis (2007) also found a positive impact of ICT on labor productivity growth with stronger impact for developed countries. However, there are papers that showed a controversial effect such as Lee et al. (2005) who found that ICT investments improved productivity levels for developed and newly industrialized economies, but that was not the result for developing countries.

Previous research that specifically examined the social media effect on socioeconomic development used different units of study such as government, individual, as well as a narrower list of countries. For example, some studies examined the benefit of social media on businesses (e.g., Aghakhani et al. 2018; Chen et al. 2012; Goh et al. 2013; Pentina et al. 2013; Rishika et al. 2013). Other studies focused on the effect on E-government (e.g., Graham 2014; Landsbergen 2010; Verdegem and Verleye 2009). However, the benefit of social media on countries' economic level is still an open question. Different papers examined also the effect of social capital (Ellison et al. 2007; Munzel et al. 2018; Steinfield et al. 2008) through involvement in social networks on people welfare (Groot et al. 2007; Helliwell and Putnam 2005; Winkelmann 2009; Allcott et al. 2020). They argued that participating in social activities and being part of a greater network have a positive influence on people in terms of their well-being and self-worth. Nevertheless, Winkelmann (2009) did not find significant moderating effect of social capital on people welfare when they are unemployed. Allcott et al. (2020) found that, by studying the case of Facebook using an experiment, deactivating social media improved offline activities, reduced political polarization, and boosted social welfare. . It affected also post de-activation by reducing online persistence and Facebook valuation. Other studies provided either descriptive or empirical evidence that social capital and networks have an added value in terms of job creation and other economic benefits (Afridi 2011; Calvo-Armengol and Jackson 2004; Fernandez et al. 2000; Hann et al. 2011; Waldinger 1997;). For instance, Hann et al. (2011) showed empirically that networking on Facebook create ties between apps' developers which helps improve firms' employment and create significant benefit to the industry. Choudhury (2018) described the role of multiple languages and mobile technology in enhancing the spread of Facebook in developed and developing countries. Other studies focused on the effect of social media on a particular economic variable such as Ozturk and Ciftci (2014) who studied the effect of number of tweets and Twitter sentiment on the movement of exchange rate.

Dell'Anno et al. (2016) studied the relationship between social media (measured as a combination of social media sites' users depending on the available data for Facebook, Linkedin, Twitter and Google +) and the country output (GDP per capita). They used a growth regression model (between 2007 and 2012) and studied the case of 83 countries. One data limitation in the paper is its representativeness for certain geographies. For instance, the study only included 9 out of 54 African countries. They found that social media has a significant negative effect on economic growth. They explained that social media could augment information and transaction costs due to the content clutter, and could lead to labor distraction due to inclination to leisure and entertainment. They proposed though an opposing hypothesis that social media could induce the diffusion of knowledge, which ultimately helps the economic growth. However, they were not able to find evidence for such a positive effect.

Vitenu-Sackey (2020) examined the effect of various social media (i.e., Facebook, YouTube, Twitter and Pinterest) on economic growth. They focused on GDP as a response variable and studied the case of 198 countries on a span of time between 2009 and 2017. They found that social media could have positive or negative economic effect and fixed broadband, internet users and technology infrastructure are the major determinants. Particularly, Facebook has negative effect on economic growth due to probably the clutter of content and high transaction cost to search for information, substitution effect between leisure and labor, and the non-monetary type of social media that accounts partially for GDP. The limitation of the paper is that it focuses on GDP instead of GNI, which as discussed earlier does not fully capture the economic income of a country. Moreover, the regressors are limited to fixed broadband, internet users, investments, education at the tertiary level only, labor rate, and trade. Other potential determinants such as network readiness, mobile subscription, innovation, all levels of education, tourism, life expectancy, peace index, and urbanism are omitted. In addition, the study did not cluster the countries into classes of various economic levels to examine the effect based on the idiosyncrasy and economic specificities of the countries.

Other studies investigated the role of Internet and broadband on global economic status (e.g., Audretsch 2007; Choi 2003; DePrince et al. 1999; Romer 1990). Following such literature, we hypothesize and conjecture that, while Internet could play a role in boosting economic productivity and countries development, social media (and specifically Facebook as the largest global network) should create ties that could in turn be economically beneficial to countries. Our paper differs from Dell'Anno et al. (2016) on many aspects. First, we consider a much larger sample including 160 countries. Second, we only focus on Facebook users instead of combining different social media sites in order to isolate the specific effect of that digital ecosystem platform. Third, we use a panel spanning over 3 years instead of just considering a growth rate between two distant years. The panel study offers more insight into the transformative process from ICT (in our paper Facebook platform) to economic development. Fourth, we do not include data from financial crisis (2008-2011) , and we rather used the phase after the crisis 2011 to 2013, for the following reasons: 1/ first, we were unable to procure research data prior to 2010, 2/ second, the inclusion of the peak of the financial crisis (Great Recession) could have disturbed the results and conclusions of our analysis as economic growth were largely influenced by major extraordinary economic policies decisions, 3/ third, the number of Facebook users did not materialized until 2011. For instance, the global number of FB users as of 2008 Q3 was only 100 million users compared to 680 million users as of 2011 Q1 (Statista, 2020), and 4/ lastly, we examine the variation of social media effect by classes of countries, which was not part of Dell'Anno et al. (2016) study.

We include many variables as potential covariates in terms of political, technological, economic, and demographic factors. Dell'Anno et al. (2016) used patent applications, technological index, propensity to capital accumulation, labor force rate, school enrollment, trade openness, and technological infrastructure (such as broadband subscribers, servers' usage and Internet users). We use similar factors but different proxies (see Table 2 in the next section *Description of data*). These factors are widely recognized as reflecting socioeconomic standing (e.g., Castelló-Climent and Doménech 2008; Coulombe and McKay 1996; Czernich et al. 2011; Jordan 2004; He et al. 2010; Hoynes et al. 2006; Woolard and Klasen 2007). For example, on the technological effect, Czernich et al. 2011 showed that 10% increase of broadband penetration contributes to the increase of per capita growth by 0.9 to 1.5% for a sample of OECD countries between 1996–2007. On the political effect, Costalli et al. (2017) showed the economic cost of ethnic fractionalization of 20 war countries that experienced an average annual loss of GDP per capita exceeding 17%. Cebula and Ekstrom (2009) investigated the effect of economic factors OECD countries between 2004 and 2007. Their findings indicated that economic growth increases for higher levels of trade, business and monetary freedom, and protection of property rights. They examined also the effect of political factors and found that the economic growth is influenced positively by the political stability of a country and its control of corruption. On the demographic effect, a number of studies showed the positive effect of education on the economic standing of countries. To illustrate, Mankiw et al. (1992) and Barro (1991) examined the educational effect for both the industrialized and the less-developed countries. They found that schooling has a significant positive influence on GDP growth.

We consider GNI per capita PPP (value of domestic and foreign production taking into account the purchasing power parity) as a measure of socioeconomic development instead of GDP per capita (value of domestic production and output). Indeed, the GNI is appropriate in our study because it includes the additional economic input of countries across borders facilitated via the Internet usage and the globalization of Facebook as the largest social media site. The GNI variable has been used in different economic studies such as Dao (2008), Dao (2014) and Asabere et al. (2016). Our paper differs also from Vitenu-Sackey (2020) by focusing on a broader response variable GNI instead of GDP. We also include many omitted explanatory variables such as network readiness, mobile subscription, innovation, all levels of education, tourism, life expectancy, peace index, urbanism, etc. We examine the effect of Facebook on group of countries based on their economic standing (high, middle and low-income levels).

Contrary to Dell'Anno et al. (2016) and Vitenu-Sackey (2020) studies, our findings show via different models that Facebook (when it is isolated from other social media platforms) has consistently a significant positive effect on socioeconomic development of countries. In addition, it could have different effect shapes such as a positive and a decreasing influence reflecting a more complex relationship between social media usage and the economic standing of countries. The type of effect depends on the characteristics of the country and its World Bank classification. We note that Dell'Anno et al. (2016) study was not focusing only on the effect of Facebook but rather on a combination of many social media tools. That could be the reason for diluting the net effect of Facebook on the economic standing of countries.

3 Data and Method

We compare our methodology to two types of research stream. The first research stream includes the papers that studied the effect of ICT in general on countries' economic development. The second stream of research includes the papers that studied the effect of specifically social media on the countries' economic standing. To illustrate the first stream of research, Qureshi and Najjar (2015) used linear regression and showed a positive effect of ICT on the economic development of 32 island states for 2010-2012. Sağlam (2016) focused on 34 OECD countries for 1990-2012, used Time stationary VAR model (Vector Autoregressive model), and showed the positive effect of investing in Internet and mobile phones on the human capital and economic growth. To illustrate the second stream of research, Dell'Anno et al. (2016) is the only paper that studied the relationship between social media on countries development. They used a growth regression model for 2007-2012 and studied the case of 83 countries.

Our paper focuses on 160 countries for the period 2011-2013. Our dataset is much larger dataset compared to the previous research of Dell'Anno et al. (2016) who used a dataset of 83 countries. In addition, our paper includes a more comprehensive set of macro factors for countries from four World Bank economic classes instead of specific regions or some countries. Moreover, our paper focus on one specific ICT tool, which is the case of Facebook platform, instead of studying ICT in general or social media as an aggregate index. We also examine the effect on countries' socioeconomic development of additional technological factors separate from Facebook platform (i.e., Internet usage, mobile subscription, network readiness index and innovation index). Finally, our methodological difference stems from the use of two phases of analyses in order to validate our findings and performs various statistical models in each phase instead of focusing on one model. The first phase is to apply predictive regression models for the whole sample of data by using various statistical models (OLS, fixed effect model, and random effect model). The second phase divides the sample into classes of countries (four separate samples) and applies the best statistical model for the whole sample on the different classes to examine the consistency of the findings to separate contexts. Contrary to previous studies that investigated the impact of social media on countries' development, our paper methodology uses a much larger dataset, includes all types of countries (at all levels of economic development), proposes various phases to validate the models, and uses a temporal effect in order to enhance our understanding of the transformative process on development.

3.1 Description of Data

From the original dataset of 182 countries, we retain 160 countries for which we have complete Facebook usage data and GNI data (22 countries are removed because they are missing these two important variables). Refer to Table 9 and 10 (appendices) for details about the sources of the data and the selected countries. Table 1 reports the grouping of these countries using the World Bank country classification by income level. Table 2 summarizes the operationalization of our explanatory and dependent variables. We also removed some explanatory variables due to the missing data for various countries that are not suitable for imputation (e.g., cultural dimensions). Imputing such missing data will not reflect the real cultural specificity of each country. In addition, we removed the age variable, as it is reflected already in the variable life expectancy and it would be redundant to include it as a separate proxy. Similarly, we removed technological usage by individuals, government and businesses is already captured in the variable network readiness as a single index. We focus on the main drivers of economic drivers avoiding a clutter of determinants that could create multicollinearity issues and a large increase of explanatory variables at the expense of model's quality.

We use a panel of data spanned over three years for each country (2011 to 2013) that we call a diffusion phase for Facebook. Though Facebook was launched around 2004, it became public and started its worldwide diffusion only in late 2006. Between 2004 and late 2006, Facebook was used only by universities and international student networks. For this reason, we consider the period 2011-2013 as a large diffusion period after the early diffusion standing between 2007 and 2011. A larger diffusion period is more suitable to untangle a potential effect on the socioeconomic standing.

Table 1. World Bank classification of countries by income level

WB Classification	Classes	Frequency	Percent
High Income	Class 1	51	31.88
Upper Middle Income	Class 2	47	29.38
Low Middle Income	Class 3	40	25.0
Low Income	Class 4	22	13.75
Total		160	100

WB Classification based on the GNI level

Table 2. Variable Definition

Variables	**Description**
Dependent variable	
LogGNI	GNI per capita PPP (based on purchasing power parity) measured in current international $
Dummy independent variables	
Year11	Year 2011 is used as reference for the time effect over the phase 2011-2012-2013 – Diffusion phase
Year12	Dummy for 2012 – Diffusion phase
Year13	Dummy for 2013 – Diffusion phase
Metric independent variables by type	
Technological factors	
FB	Facebook penetration (percent of Facebook users in the country per capita)
FBsq	Square of FB to include the possibility of non-linear effect of FB (diminishing or enhancing marginal effect)
IU	Internet usage (percent of Internet users in the country per capita)
Mobile	Mobile subscription (percent of mobile subscribers in the country per capita)
NetRead	Network Readiness index (Technology Readiness) as proxy for information and communication technology usage in the country
Innov	Innovation index as average of Innovation Input (drivers are institutions, human capital and research, infrastructure, market sophistication, and business sophistication) and Innovation Output (drivers are knowledge and technology outputs, and creative outputs) in the country
Political factors	
Peace	Peace Index (higher index in the country means lower peace level)
Demographic factors	
Educ	Education Index (mean years of schooling and expected years of schooling in the country)
LifeExp	Life Expectancy (life expectancy at birth in the country derived from different sources and aggregated in World Bank data)
Urban	Urbanism percentage (percentage of the population living in urban area of the country)
Unemp	Unemployment rate (percentage of unemployment as total labor force of the country)
Economic factors	
Tourism	Percent of tourism per capita (number of arrivals or tourists per capita in the country)
Trade	Percentage of trade by GDP (aggregate value of imports and exports of the country by its GDP)
Classification variable	
ClassWB	Classification of countries by GNI based on World Bank (Class 1 coded 1 for High GNI to Class 4 coded 4 for Low GNI)

Our goal is to examine the role of Facebook penetration on countries' socioeconomic standing, and test its potential decreasing marginal effect by including the variable *FBsq* (square of Facebook penetration). We classify the independent variables into technological, demographic, political and economic factors. All variables are measured either as percentage per capita or as an index variable. The majority of the variables are collected from the World Bank database. However, other variables are collected from other reliable sources such as the Global Innovation Index (GII) released by Cornell University, INSEAD, and WIPO (partnership with other organizations). The Network Readiness index published by the World Economic Forum in partnership with INSEAD. The peace index measured by the Institute for Economics and Peace. The education index published by the United Nations. The estimation of Facebook penetration by country is reported by Facebook in the advertising page and provided (as a courtesy) by Lee (2015). Refer to Table 9 (in the appendix) for the sources of the data. We use the logarithm of GNI instead of the real GNI, which is widely used in economic papers, as the GNI grows proportionally while the *logGNI* grows linearly. *LogGNI* captures diminishing returns and normalizes the data.

We use the imputation method Amelia II package using R software to replace the missing data of the independent variables. Refer to Table 10 (in the appendix) for detailed statistics on data imputation. The technique has many benefits: 1/ it uses multiple imputations for the same missing value instead of only one imputation using Bootstarp-based EM (expectation-maximization) algorithm, 2/ it has been shown very efficient by reducing bias, and 3/ it is quite appropriate for small sample sizes, time series as well as cross-sectional datasets. An additional important benefit of the Amelia Package is that it includes Bayesian priors and bound arguments for missing values, which implies a valuable information to base the imputation. For more details about the technique, interested readers could refer to Honaker, King and Blackwell (2011). Then, we test different regression models (OLS, fixed effect and random effect models) in order to check the economic impact of Facebook penetration and ensure some robustness check by performing different prediction approaches.

3.2 Descriptive Analyses

We start by providing some descriptive statistics to explore the data. The summary Table 3-a and Table 3-b shows the different levels of FB penetration. The percentage could be as low as 0.038% up to as high as 71%. It is interesting to see that the mobile penetration could exceed the 100%, and this is caused by the fact that some people have more than one smartphone. This also explains the importance of mobile marketing in helping businesses generate more sales and decrease the digital divide between countries or areas (urban versus rural) within countries. Indeed, according to ComScore recent study in 2016 (www.comscore.com) comparing nine markets (USA, Canada, Brazil, Spain, China, Mexico, UK, Indonesia, and Italy), mobile phone accounts for the main digital platform that people check daily (more than 60% of all minutes spent on digital devices).

Table 3-a. Descriptive Statistics

	All Sample				By Class			
Variables	**Mean Obs. 480**	**StdDev Obs. 480**	**Minimum Obs. 480**	**Maximum Obs. 480**	**Mean Class 1 Obs. 153**	**Mean Class 2 Obs. 141**	**Mean Class 3 Obs. 120**	**Mean Class 4 Obs. 66**
LogGNI	9.17	1.15	6.36	11.34	10.41	9.36	8.45	7.18
FB	23.01	18.01	0.038	70.77	39.26	26.37	9.85	2.07
IU	40.63	27.88	0.9	100.57	72.28	38.06	23.13	4.56
Mobile	101.99	37.67	13.17	217.52	124.61	113.52	87.83	50.73
NetRead	3.83	0.82	2.19	5.98	4.74	3.69	3.34	2.94
Innov	35.58	11.11	16.8	68.2	47.86	33.47	28.89	23.82
Peace	1.99	0.39	1.11	3.29	1.68	2.08	2.17	2.23
Educ	0.63	0.16	0.19	0.92	0.79	0.65	0.54	0.38
LifeExp	71.01	8.38	48.21	83.33	78.41	72.39	66.58	58.94
Urban	57.28	22.66	8.66	100	76.26	60.51	44.7	29.31
Unemp	9.12	6.16	0.2	31.39	8.6	11.16	9.34	5.57
Tourism	59.01	82.88	0.08	679.02	117.07	53.45	20.57	6.19
Trade	71.76	30.45	19.8	158	76.02	74.93	71.84	54.97

* Obs. means number of observations

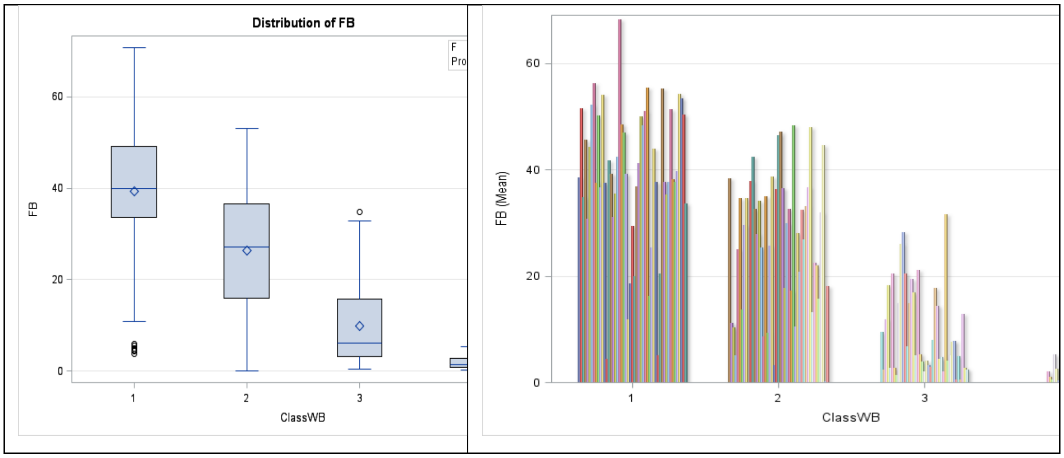
Table 3-b. Minimum and maximum Facebook penetration by class

Classes	Minimum Average* Penetration of Facebook	Maximum Average* Penetration of Facebook
Class 1	Equatorial Guinea 4.5%	Iceland 68.2%
Class 2	China 0.04%	Montenegro 48%
Class 3	Tajikistan 0.5%	Philippines 31.5%
Class 4	Chad 0.4%	Nepal 7.6%

* Average penetration of Facebook over 3 years (2011 to 2013)

Next, we perform the Welch's ANOVA tests to investigate the relationship between Facebook penetration and the economic classification of countries according to the World Bank (Fig. 1). All pairwise comparisons are significantly different at 5% level performing the Welch's Anova test (F value = 491.54 and p-value <.0001) knowing that the Levene's test for homogeneity of variances is statistically significant at 5% (F value = 18.88 and p-value <.0001). We further obtain the above graphs that reflects the significant differences between the economic groups and their Facebook usage.

Fig. 1. Relationship between Facebook usage and WB classification



From the Fig. 1 above (across the World Bank classification), it is straightforward that there are enough variations of average Facebook penetration within each income classification. Besides, the graphs show that the Facebook usage includes a clear consistent decreasing pattern of Facebook usage across categories moving from Class 1 to Class 4.

The correlation analysis shows that all variables are significantly correlated to the GNI level except the unemployment proxy (Table 4). The Peace index has a negative correlation because the lower is the index, the higher is the peace level. Hence, this translates into a higher economic standing. The highest correlation with the GNI level are with the Internet usage, the education index, the network readiness index, the life expectancy, and the innovation index where the Pearson correlation exceeds 0.8. The correlation between explanatory variables is listed in Table 12 in the appendix. The correlation varies from 0.02 to 0.95. High correlations indicates potential for multicollinearity issues (e.g., correlation between FB and NetRead 0.77 with p-value 0% and correlation between Educ and Innov 0.81 with p-value 0%). To avoid multicollinearity issues, we use VIF as the best indicator for variables selection (Table 11 in appendix).

Table 4. Correlation analysis

	FB	IU	Mobile	NetRead	Innov	Peace	Educ	LifeExp	Urban	Unemp	Tourism	Trade
LogGNI	0.768 <.0001	0.870 <.0001	0.718 <.0001	0.823 <.0001	0.801 <.0001	-0.522 <.0001	0.842 <.0001	0.810 <.0001	0.748 <.0001	0.045 0.3229	0.464 <.0001	0.181 <.0001

4 Models and Econometric Analyses

In designing the research (for all models below), we chose to approximate the countries' economic development with the GNI per capita PPP instead of the GDP. The GNI per capita PPP expresses the socioeconomic standing of countries uniformly and better captures the economic output of nations by also taking into account the contribution of nationals living abroad. Knowing that we are investigating the socioeconomic effect of Facebook as a social networking site for each country, the Internet effect transcends the borders and could bring economic input or economic harm due to international exchange, accessibility (enhanced via mobile devices if the infrastructure for broadband is archaic or limited) and interactivity. We also observed a very strong correlation between log GDP and log GNI (correlation coefficient = 0.99), which indicates that this study's finding are still valid if we used log GDP as dependent variable.

A major and common theoretical issue in economics is reverse causality. Within the context of our study, the question is whether social media leads to a better economy or if a better economy leads to more social media usage. The World Bank classifies countries according to their GNI, which yields to countries grouped in the same cluster for similar economic characteristics. This mitigates the concern with reverse causality as the economic models are estimated for countries with comparable economic standing. We also observe that better economies (as categorized by the World Bank classification) do not necessarily translate into higher social media penetration (see Fig. 1). We also prefer calibrating the economic models by World Bank classification as not only it controls for the current economic standing of countries but also better estimates the distinctive drivers within each class.

To confirm the research conclusions, we investigate numerous econometric techniques, including the pooled OLS model with time effect, the fixed effect model with / without time effect, and the random effect model with time effect. Besides, we investigated the OLS model by controlling for the GNI at a constant date.

4.1 The Pooled OLS Model with Time Effect

This model is used as a reference to other models. We include in equation (1) various proxy of macro variables (technological, political, demographic, and economic variables) as well as the Facebook positive and quadratic effect.

$$Log\ GNI_{it} = \alpha + \lambda FB_{it} + \gamma FBsq_{it} + \beta X_{it} + \delta_1 Year12 + \delta_2 Year13 + e_{it} \qquad (1)$$

where $Log\ GNI_{it}$ represents the dependent variable GNI for each country *i* and time *t* (panel of 3 years from 2011 to 2013). The estimator α is the overall intercept term for the whole model. The vector X_{it} includes the metric independent variables listed in Table 2 (except the

Facebook penetration as linear and quadratic term). The β = ($\beta_1, \ldots, \beta_k$)′ is a vector of estimators corresponding to the effect of each independent variable (1 to k). The independent variables control for observed heterogeneity between countries. λ is the linear effect of Facebook penetration on Log GNI, and γ denotes the decreasing or enhancing marginal effect (depending on the sign of the estimator) of Facebook penetration. The estimators δ correspond to the time effect (as dummy variables where 2011 is taken as a reference year) and reflects the dynamic evolution of a country's socioeconomic development over time. We assume that e_{it} is normally distributed with mean zero and variance σ2 for all (*i*, *t*).

4.2 The Fixed Effect Model with Time Effect

Using the within estimator, this model controls for unobserved heterogeneity that pooled OLS cannot handle. Indeed, there are fixed characteristics between countries and systematic country-level differences such as regulations, geographic size, etc. that are probably correlated with the included independent variables and that pooled OLS does not take into account. We replicate the same independent variables as the OLS model and take into account a time effect (as dummy variables) that could reflect a variation over time of the country socioeconomic development. In the fixed effect model, the intercept is time-invariant and is specific to each observation (in our paper each country). The model is written as follows in equation (2):

$$Log\ GNI_{it} = \alpha_i + \lambda FB_{it} + \gamma FBsq_{it} + \beta X_{it} + \delta_1 Year12 + \delta_2 Year13 + e_{it} \quad (2)$$

where α_i represents the fixed effect that summarizes the unobserved, time-invariant, country specific-effect. Their distribution is assumed to be not too far from normality. This model assumes that unobservable fixed country characteristics are invariant over time and could be correlated to the independent variables.

4.3 The Random Effect Model with Time Effect

This model, also called a variance components model or error-component model, takes into account a specific error structure and controls for the unobserved heterogeneity of the data. While the fixed effect model assumes that the individual specific effect is correlated with the independent variables, the random effect model assumes that these effects are uncorrelated to the independent variables (see Wooldridge 2005) and that the variation across countries is random. However, the important difference between both models is the correlation or not with the independent variables rather than the stochastic effects (Greene 2008). The model is written as follows in equation (3):

$$Log\ GNI_{it} = \alpha_i + \lambda FB_{it} + \gamma FBsq_{it} + \beta X_{it} + \delta_1 Year12 + \delta_2 Year13 + u_{it} \qquad (3)$$

The estimators α_i represent the random individual unobserved heterogeneity, and u_{it} is an independent term called "idiosyncratic error" or "idiosyncratic disturbance" changing across *i* and *t* (see Wooldridge 2010). This term is a combined error composed of the within entity error and the between entity error (see Torres-Reyna 2007).

5 Results and Discussion

We study two phases in order to investigate the role played by Facebook penetration on the socioeconomic development of countries. The first phase includes the whole sample with all classes. Hence, we perform different regression analyses for the whole sample. The second phase uses the best type of regression model for phase 1, and apply it to each class separately in order to examine the idiosyncratic characteristics of each class in terms of Facebook effect on their socioeconomic standing. We eliminate two variables from the independent variables list namely the innovation index and the Internet use due to their high multicollinearity (VIF exceeding 5 when they are present in the OLS model). The remaining variables VIF are listed in Table 11 in the appendix. We use the software R for generating Tables 5 to 8.

5.1 Results of Phase 1

We report below the results of phase 1 using different statistical models. First, we compare the OLS model to the fixed effect model and the random effect model. It is clear from Table 5 that there are some overlap of significant variables between the three models. The technological factor is predominantly significant such as mobile penetration and Facebook penetration. We notice that Facebook does not only have a positive effect but has also a significant decreasing effect. The result highlights the decreasing marginal effect of Facebook. Based on Table 6, the fixed effect model is the preferred technique over the random (based on the Hausman test) and the OLS models (based on the F test for individual effect).

Similar to Dell'Anno et al. (2016), we control for the GNI at a constant date in order to have convergence of the OLS (we chose 2001 as a control date). The year 2001 noticed a slowdown as part of the early 2000 major contraction in global economic growth (see Tapia 2013). The choice of the year is then appropriate to use as a control year in order to detangle the economic standing in later years. The results of the new model controlling for GNI2001 and the first OLS model have many similarities in terms of values' estimates and significance of variables (except for life expectancy). Facebook penetration is again confirmed as an important significant variable and the decreasing effect is highlighted in this model.

Table 5. Comparing different models for the whole sample (all classes included)

	OLS model		Fixed effect model		Random effect model		OLS model with control GNI2001	
Variable	**Estimate**	**Standard Error**	**Estimate**	**Standard Error**	**Estimate**	**Standard Error**	**Estimate**	**Standard Error**
Intercept	4.65485	0.35783***					5.104	0.31803***
FB	0.02359	0.00501***	0.00465	0.00159***	0.00568	0.00176***	0.02359	0.00442***
FBsq	-0.00034	0.00008***	-0.00006	0.00002***	-0.00007	0.00002***	-0.00034	0.00007***
Urban	0.00967	0.00130***	0.00662	0.00678	0.02021	0.00213***	0.00541	0.00120***
Mobile	0.00581	0.00077***	0.00052	0.00024**	0.00054	0.00026**	0.00572	0.00068***
Trade	0.00019	0.00074	-0.00030	0.00061	-0.00009	0.00062	-0.00016	0.00066
Unemp	0.00038	0.00362	-0.00822	0.00202***	-0.00846	0.00214***	0.00039	0.00321
Tourism	0.00052	0.00029*	-0.000006	0.00020	0.00033	0.00021	0.00007	0.00026
LifeExp	0.00690	0.00511	0.00345	0.00702	0.03035	0.00545***	0.00874	0.00451*
Educ	1.83780	0.23951***	0.03697	0.26528	1.2892	0.02417***	2.0491	0.02121***
NetRead	0.37178	0.05441***	-0.00197	0.01561	0.04146	0.01694**	0.15665	0.05148***
Peace	0.01237	0.06745	-0.06197	0.02568**	-0.07543	0.02821***	0.06366	0.05967
Year12	-0.03669	0.04887	0.02902	0.00560***	0.00949	0.00547*	-0.01517	0.04315
Year13	-0.05084	0.05006	0.05582	0.00839***	0.02082	0.00720***	-0.02208	0.04423
GNI2001							0.00002	0.000002***
R^2	**0.862**		**0.529**		**0.656**		**0.891**	

***Significant at 0.01; **Significant at 0.05; * Significant at 0.1

Table 6. Comparison tests between models

Tests	P-Value	Alternative Hypothesis	Decision
Lagrange Multiplier Test OLS (null) versus Random	< 2.2e-16	Significant effects	Preference for the random effect model
F Test for individual effect OLS (null) versus Fixed	< 2.2e-16	Significant effects	More support for the fixed effect model
Hausman Test Random (null) versus Fixed	0.0001314	One model is inconsistent	More support for the fixed effect model for consistent estimates

5.2 Results of Phase 2

As the fixed effect model was the preferred one in the overall sample, we choose to apply that type of model for each class. We compare all classes with the total sample in the detailed Table 7 and the summary Table 8. We perform the regression on all variables including the time effect. Next, we eliminate the time effect as we notice that it dilutes the significance of many other independent variables. We add one final model for Class 1 where we eliminate the quadratic effect of Facebook (*FBsq*). Finally, we eliminate Trade because it is constantly non-significant in all models. This finding is consistent with the World Bank Group (2015) analysis. The low elasticity of Trade to the economic standing has been analyzed between 1970 and 2013 by World Bank Group (2015) and many reasons were put forth in order to explain such decreasing effect in recent years compared to previous decades. The first reason is the revolution of communication technology and just-in-time production processes, which affected the structure of the global value chain. The second reason reflected in the changes of aggregate demand is mainly due to the global investment level. The third reason is the decrease of trade finance due to the financial regulations such as the Base III regulations. Finally, the higher trade protection could have some damping effect on the relationship between Trade and the economic standing, and mainly the slower speed of liberalization during the 2000s. Besides, various academic studies showed opposing results concerning the Trade-economy relationship while some studies found positive association (e.g., Chang et al. 2009; Jouini 2015; Tekin 2012), others found a U shaped relationship (e.g., Zahonogo 2016), and another group found negative or even no association (e.g., Musila and Yiheyis 2015; Singh and Tarlok 2011; Ulaşan 2015).

Our Model 1 (with time effect) shows that only the total sample, Classes 2 and 4 incur a significant positive effect of Facebook as well as it is decreasing marginal effect (see Table 7). However, focusing on Model 2 (without time effect), all classes as well as the total sample incur a significant effect of Facebook as well as additional variables appear to have a significant influence (positive and decreasing effect or either one of the effect). It seems that the time variables suppress some other factors' influence on the economy. This is partly due to the strong correlation with time variables, or the short time panel (only 3 years).

Focusing on Model 2 for the total sample (without time effect), the result shows the positive significant effect of Facebook penetration, mobile, life expectancy, urbanism, network readiness on economic development. The result sheds light on the growing importance of technological factors on the economic standing of countries. At the opposite, Unemployment and Peace have significant negative effect on the socioeconomic development. The lower the unemployment level and the higher the political stability of a country, the higher the wellbeing and development of its economy. Besides, we obtain again the negative effect of Facebook square highlighting a quadratic relationship with the economic development and the decreasing effect.

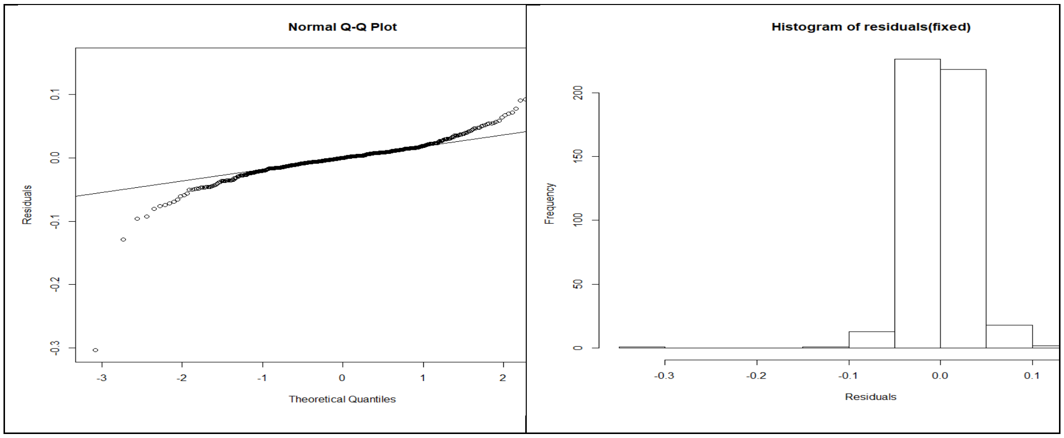
Following the steps of Models 2 to 4, we conclude that the effect of Facebook is consistent on each class except Class 1 where the positive effect appears only when we eliminate the time effect, the trade variable and the quadratic effect. The reason could be that this class is composed of highly developed countries and the effect of Facebook reached a maturity. In other words, Facebook influence is diluted in recent years compared to probably earlier diffusion of Facebook (2007 to 2010). Hence, it becomes more difficult to capture its influence on developed countries. Focusing on Model 3 and (Model 4 for Class 1), we notice that the positive Facebook effect is stronger in Class 4 as $exp(0.09707)=1.1019$, followed by Class 2 as $exp(0.01009)=1.0101$, then Class 3 as $exp(0.00992)=1.0099$, and Class 1 as $exp(0.00286)=1.0028$. This means that an increase in Facebook use of 1% in each class respectively lead to a higher GNI in Class 4 by 10.19%, by 1.01% in Class 2, by 0.99% in Class 3, and by 0.28% in Class 1. It seems that the effect of Facebook in Classes 2 and 3 are very similar in magnitude.

The difference between classes in terms of combination of factors affecting their economies is not counterintuitive because each class has specific characteristics and the factors influencing their economic development vary across classes. Focusing on Model 3, while some variables have a major influence on the economy of one class of countries, others might have more influence on other classes. For example, while mobile penetration seems to have significant and positive effect on Class 1, it does not seem to have any effect on other classes. The explanation could be that in advanced economies, businesses strongly leverage smartphone devices as an additional channel of distribution and payment. However, this might not be the case in less developed countries where the technological infrastructure and payment methods through smartphone devices are not as sophisticated as developed countries. The Peace index seem to be prevalent in Class 3 and Class 4 and not significant in Class 1 and Class 2. The result is intuitive as most advanced countries already enjoy political stability. However, political destabilization has a distinct and more differentiated effect in less developed countries. The network readiness has a significant positive impact only in Class 1 and Class 3, which suggests that advances in research and development, and the sophisticated use of information and communication technologies matter for high income-level countries, but it is less intuitive for Class 3. A possible rationale for a non-significant effect in certain classes could be due to the lack of technological infrastructure and tech skills in Class 4 and the significance of other variables that overshadow the network readiness for Class 2.

We tested the effect of the response lag by adding “LogLagGNI” in Model 3 and we found the the expected positive effect of the previous year GNI on the following year. This dynamic effect of GNI over time is expected as measures of economic output tend to be positively autocorrelated over short horizons and negatively autocorrelated over longer horizons (Cogley and Nason 1995).

Considering the Model 3 with the lag effect as the best model, we tested a number of residuals and potential model issues. First, we do not deem that there is a need to test for cross-sectional dependence given that we have a panel of few years and large number of cases. Baltagi (2012) explained that cross-sectional dependence is a problem for panel data with long time series. However, it is not a problem for small panel data with few years and large number of cases. Serial correlation testing also applies to macro panels not small time-series data similar to our dataset. A number of residual tests have been performed, namely test of normality, heteroscedasticity, and serial correlations. According to Fig. 2, the normality is not violated.

Fig. 2. Test of Normality



We measured the Durbin Watson (DW) using the package lmtest. This DW does not take into account the structure of residuals into consideration. In this case, DW = 2.2887 with p-value = 0.9995 (serially uncorrelated under the null of no serial correlation in idiosyncratic errors). We also measured the generalized Bhargava et al. (1982) Panel Durbin-Watson Test using BNF statistic and LBI. The values are respectively DW = 1.4288 and LBI = 2.2859. The values of DW seem to potentially have serial correlation based on the generalized DW. However, we should note that the generalized DW is more appropriate for longer time series data (Bhargava et al. 1982) while our data includes only 3 years. We applied the generalized DW for additional scrutiny of any potential issue.

Moreover, we checked for heteroscedasticity by measuring the Breusch-Pagan test and we found BP = 3633.6 and p-value < 0.001 which suggests that there is a heteroscedasticity issue. To fix heteroscedasticity issue, we run the fixed model with Robust Covariance Matrix Estimators. In addition, to fix the heteroscedasticity and the potential serial correlation issues, we applied the Arellano method. We obtain the results in Tables 7 Model 3. The results remain unchanged compared to the complete sample with lag effect before applying the Arellano method.

Overall, the results indicate that Facebook penetration plays a positive role as an economic enabler and enhancer of the socioeconomic development. They also point to numerous drivers of economic development including superior technological infrastructure, network interactivity and innovation, reducing barriers and censorship of social media, assuring political stability, investing in urbanism, and finally, educating individuals, businesses and government officials to create stronger and more effective ties through social media.

Tables 7. Summary results for fixed effect models by class and all sample

Model 1: Fixed effect models with time effect										
Samples	**Class 1**		**Class 2**		**Class 3**		**Class 4**		**All sample**	
Variables	**Estimate**	**P value**	**Estimate**	**P value**	**Estimate**	**P value**	**Estimate**	**P value**	**Estimate**	**P value**
FB	-0.00071	0.7131	0.00694	0.005 **	-0.00212	0.5222	0.09324	0.0029 **	0.00466	0.0037 **
FBsq	0.00003	0.154	-0.0001	0.0064 **	-0.00005	0.5165	-0.00473	0.0116 *	-0.00007	0.0036 **
Urban	-0.01219	0.3253	0.01396	0.1334	-0.00559	0.5891	-0.03507	0.3629	0.00662	0.33
Mobile	0.00071	0.0304 *	0.00010	0.7445	-0.00096	0.0811 ‘’	0.00066	0.6379	0.00052	0.031 *
Trade	-0.00034	0.5044	0.00048	0.6715	0.00115	0.308	-0.00405	0.3202	-0.0003	0.6184
Unemp	-0.01	<.0001***	0.00056	0.8847	-0.00598	0.1772	-0.22252	0.0105 *	-0.00822	<.0001***
Tourism	0.00003	0.8301	-0.00113	0.1114	0.00044	0.3675	-0.00237	0.567	-0.000006	0.9747
LifeExp	0.01484	0.3558	0.00692	0.4811	-0.00881	0.6049	-0.01979	0.5442	0.00345	0.6228
Educ	0.11938	0.6985	-0.084	0.8378	-1.98829	0.1994	1.26840	0.1411	0.03697	0.8892
NetRead	0.05902	0.0269 *	0.01286	0.5886	-0.00173	0.9429	-0.05225	0.4537	-0.00195	0.9006
Peace	-0.01858	0.6306	0.01339	0.7275	-0.06816	0.0455 *	-0.12946	0.2467	-0.06197	0.0164 *
Year12	0.00617	0.4844	0.02271	0.0114 *	0.06642	<.0001***	0.01187	0.7613	0.02902	<.0001***
Year13	0.01599	0.1974	0.05922	<.0001***	0.13924	<.0001***	0.00106	0.9867	0.05582	<.0001***
R^2	**0.66229**		**0.6735**		**0.85333**		**0.69796**		**0.529**	

Significance :: >0.0001 ‘***’; >0.01 ‘**’ ; >0.05 ‘*’ ; >0.1 ‘ ’

Model 2: Fixed effect models without time effect										
Samples	**Class 1**		**Class 2**		**Class 3**		**Class 4**		**All sample**	
Variables	**Estimate**	**P value**	**Estimate**	**P value**	**Estimate**	**P value**	**Estimate**	**P value**	**Estimate**	**P value**
FB	-0.000004	0.9983	0.01005	0.0001***	0.00973	0.0419 *	0.09213	0.0016 **	0.00709	<.0001***
FBsq	0.00004	0.0829 ‘’	-0.0001	0.008 **	-0.00017	0.1245	-0.00472	0.0088 **	-0.00006	0.0137 *
Urban	-0.01249	0.3049	0.03653	<.0001***	0.00276	0.8613	-0.03626	0.2086	0.02792	<.0001***
Mobile	0.00054	0.0753 ‘’	-0.00011	0.7338	-0.00013	0.873	0.00074	0.5784	0.00042	0.1006 ‘’
Trade	-0.00036	0.4815	-0.00071	0.5251	0.00052	0.735	-0.00277	0.4109	-0.00037	0.5508
Unemp	-0.00934	<.0001***	-0.00628	0.1039 ‘’	-0.00798	0.2366	-0.21962	0.0067 **	-0.01067	<.0001***
Tourism	0.00005	0.7289	-0.00126	0.1044 ‘’	0.00129	0.0858 ‘’	-0.00241	0.5356	0.00007	0.741
LifeExp	0.02642	0.0597 ‘’	0.01992	0.0547 ‘’	0.08846	<.0001***	-0.01811	0.3579	0.02483	0.0002***
Educ	0.12312	0.6899	-0.46571	0.2912	-0.97084	0.6781	1.43185	0.0692 ‘’	-0.11232	0.6905
NetRead	0.06706	0.0006***	0.03413	0.1789	0.06289	0.0769 ‘’	-0.06692	0.2957	0.02534	0.113
Peace	-0.02005	0.5933	0.01673	0.6889	-0.09585	0.0548 ‘’	-0.16108	0.0805 ‘’	-0.07202	0.0083 **
R^2	**0.65395**		**0.59706**		**0.64568**		**0.69419**		**0.4608**	

Model 3: Fixed effect models without time effect and Trade variable												
Samples	**Class 1**		**Class 2**		**Class 3**		**Class 4**		**All sample**		**All sample with Lag effect**	
Variables	**Estimate**	**P value**	**Estimate**	**P value**	**Estimate**	**P value**	**Estimate**	**P value**	**Estimate**	**P value**	**Estimate**	**P value**
FB	-0.00017	0.927	0.01009	0.0001***	0.00992	0.0358 *	0.09707	0.0007***	0.00706	<.0001***	0.00686	<.0001***
FBsq	0.00004	0.0592 ‘’	-0.0001	0.0077 **	-0.00018	0.0965 ‘’	-0.00492	0.0058**	-0.00006	0.015*	-0.00006	0.01203*
Urban	-0.01227	0.3122	0.03644	<.0001***	0.00273	0.862	-0.03498	0.2218	0.027951	<.0001***	0.02693	<.0001***
Mobile	0.00054	0.0753 ‘’	-0.00011	0.7486	-0.00012	0.8843	0.00053	0.6858	0.00041	0.1051 ‘’	0.00041	0.10729
Unemp	-0.00931	<.0001***	-0.00613	0.1104	-0.00804	0.2298	-0.20648	0.0085**	-0.01066	<.0001***	-0.01033	<.0001***
Tourism	0.00004	0.7576	-0.00123	0.1116	0.00133	0.0708 ‘’	-0.00256	0.5087	0.00007	0.7503	0.00012	0.56890
LifeExp	0.02832	0.0394 *	0.01947	0.0588 ‘’	0.08803	<.0001***	-0.02017	0.3003	0.02504	0.0002***	0.02539	0.00015***
Educ	0.04034	0.8872	-0.4781	0.2765	-0.96668	0.6774	1.31314	0.0872 ‘’	-0.14677	0.5947	-0.1408	0.60810
NetRead	0.06522	0.0007 ***	0.03320	0.1886	0.06228	0.0775 ‘’	-0.05845	0.3515	0.02517	0.1151	0.02368	0.13659
Peace	-0.02145	0.5663	0.01705	0.6822	-0.09519	0.0547 ‘’	-0.14452	0.1047 ‘’	-0.07162	0.0085**	-0.07212	0.00779**
LagLogGNI											0.05684	0.04533*
R^2	**0.65205**		**0.59508**		**0.64508**		**0.68776**		**0.46018**		**0.46715**	

Model 3: Fixed effect models with Arellano method			Model 3: Fixed effect models with Robust Covariance Matrix Estimators		
All sample with Lag effect			**All sample with Lag effect**		
Variable	**Estimate**	**P value**	**Variable**	**Estimate**	**P value**
FB	0.00686	0.000932***	**FB**	0.00686	0.000932***
FBsq	-0.00006	0.012221 *	**FBsq**	-0.00006	0.012221 *
Urban	0.02693	<.0001***	**Urban**	0.02693	<.0001***
Mobile	0.00041	0.109107	**Mobile**	0.00041	0.109107
Unemp	-0.01033	<.0001***	**Unemp**	-0.01033	<.0001***
Tourism	0.00012	0.550242	**Tourism**	0.00012	0.550242
LifeExp	0.02539	0.019829 *	**LifeExp**	0.02539	0.019829 *
Educ	-0.14078	0.519745	**Educ**	-0.14078	0.519745
NetRead	0.02368	0.175505	**NetRead**	0.02368	0.175505
Peace	-0.07212	0.017551 *	**Peace**	-0.07212	0.017551 *
LagLogGNI	0.05684	0.074404 ‘’	**LagLogGNI**	0.05684	0.074404 ‘’

Model 4: Fixed effect models without time effect, Trade variable and FBsq		
Class 1		
Variable	**Estimate**	**P value**
FB	0.00286	0.0037 **
Urban	-0.01284	0.2968
Mobile	0.00048	0.1175
Unemp	-0.00911	<.0001***
Tourism	0.00006	0.6621
LifeExp	0.02599	0.0607 ‘’
Educ	0.04714	0.8702
NetRead	0.06691	0.0006 ***
Peace	-0.02165	0.568
R^2	**0.63825**	

Table 8. Summary results of fixed effect models across different samples

Variables	FB	FBsq	Urban	Mobile	Trade	Unemp	Tourism	LifeExp	Educ	NetRead	Peace	Year12	Year13
Model 1: Fixed effect model with time effect													
Class1				+		-		-		+			
Class2	+	-										+	+
Class3				-							-	+	+
Class4	+	-				-							

All classes	+	-		+		-					-	+	+
Model 2: Fixed effect model without time effect													
Class1		+		+		-		+		+			
Class2	+	-	+			-	-	+					
Class3	+	-					+	+	+	-			
Class4	+	-				-			+		-		
All classes	+	-	+	+		-		+		+	-		
Model 3: Fixed effect model without time effect and Trade variable													
Class 1		+		+		-		+		+			
Class 2	+	-	+			-		+					
Class 3	+	-					+	+		+	-		
Class 4	+	-				-			+		-		
All classes	+	-	+	+		-		+		+	-		
Model 4: Fixed effect model without time effect and Trade variable and FBsq													
Class 1	+			+		-		+		+			

6 Practical and Managerial Implications

Our paper tackles an important and timely topic about the major role played by social media in countries' socioeconomic standing. While the analyses of ICT effect on development has been the focus of many papers in the past, the specific analysis of social media as one digital ecosystem of ICT is scarce. In addition, compared to previous studies, we use a larger dataset covering all types of countries and examine holistically many factors namely technological, demographical, economic and political factors. We study a cross-sectional time series analysis for 160 countries spanning over the period 2011-2013 which is a period reflecting a large diffusion of Facebook on many countries.

Previous academic and business studies disagree on the effect of social media on economic standing of countries, so we triangulate many models in order to propose conclusive findings. Via various robustness checks and using different research designs, our exploratory study indicates that Facebook penetration plays a positive role in improving the socioeconomic development of countries but the effect is more complex than just a positive effect. There is a more complex relationship between Facebook penetration and socioeconomic development. Our study also indicates that Facebook penetration does no impact countries the same way. Besides, the remaining independent variables do not affect in a similar manner the socioeconomic level of countries. The World Bank classification seems to be a good categorization in order to separate the main effect from the insignificant ones. Hence, we propose the following practical implications:

- Decision makers should first assess the country's characteristics in order to understand the specificities of the ICT effect on their country. In other words, decision makers should avoid replicating any action taken by other countries in different economic class directly to their own country without considering its specificity. Our results suggest that the classification of the World Bank is an avenue for comparability and replication of appropriate actions.
- Countries should take into account the power of social media as an enhancer of social capital in their infrastructure and socioeconomic planning. These influences should be as critical as other measures usually studied in economic research, even more for developing countries (as defined within our study by countries in World Bank classification 2 and 3). For instance, Paraguay and Ecuador could mirror the social capital of Brazil and Colombia (all in World Bank Class 2). By mirroring more successful social capital models in peer and comparable countries, countries that are lagging behind can positively affect their socioeconomic development.
- Our study shows that ICT effect on development is a holistic dynamic that requires the inclusion of many factors including the technological side. Decision makers should implement appropriate technological infrastructure enhancements along with health benefits and services (to improve life expectancy), urban development, employment opportunities with strong added value to the economy, and educational capabilities (to improve network readiness, quality of social interaction, creativity and entrepreneurial spirit via digital ecosystem). For instance, per our study, ICT sophistication leads to more competitive industry and velocity in economic transactions. Hence, investment in infrastructure and technological enhancement should be prioritized accordingly. To illustrate, mobile payment in Kenya via M-PESA revolutionized the purchasing behavior of Kenyans. In 2007, Safaricom launched the world-leading mobile system in Kenya. With 93% of Kenyans having access to mobile payments, 1.7 Billion

transactions were processed using M-PESA between July 2016 and July 2017. As a result, close to 49% of GDP share was generated via the use of M-PESA (McGath, 2018).

- Countries should solve the digital divide issue (especially for developing and emerging countries) by building better infrastructure for mobile penetration. Such technological factor is an enhancer for the social media ecosystem, which in turn improves countries' development. While its positive effect on socioeconomic development mainly appeared in developed countries, the improvement of its penetration in emerging and developing countries is crucial in order to benefit also from such positive effect.
- Decision makers should foster the usage of Facebook and implement the appropriate infrastructure that helps its diffusion in order to make the citizens benefit from its economic effect and take advantage of some of its features (such as Facebook market and games). This recommendation requires, however, the implementation of conjoint policies from politicians to regulate the manipulation, censorship and negative spillover effect of social interaction that could harm the economic benefit of Facebook. Recent political scandals and social manipulations that was the subject of many headlines shed light on the potential harmful effect off misusing social media.

7 Conclusion

There is a scarce number of studies investigating the role of social media on countries economic standing. The reason could be the complexity of proving such effect. Our paper explores the conjecture that there is a positive effect of social media on the socioeconomic development of countries. Our paper tests the conjecture using various models and a large dataset. However, we have a number of limitations to be addressed in future research. First and foremost, reverse causality is a legitimate and common concern in economic studies. Does higher widespread usage of social media result in higher economic growth, or does higher economic growth yield to higher usage of social media? We attempted to mitigate this concern by segmenting the countries according to their World Bank classification. Second, the choice of the data imputation technique may not be optimal because missing data in the context of countries could be due to lack of transparency of some countries or archaic technological infrastructure resulting in data omission instead of random occurrence. With that in mind, we selected the methodology Amelia II package for the major benefits presented previously such as the multiple imputations for the same missing value and the Bayesian prior and the bound arguments as a valuable information. We also selected this method for its wide usage in different fields (where missing data could be not random) as a powerful imputation tool (e.g., Pampaka et al. (2013) in educational research and Clavel et al. (2014) in biological sciences).

We offer a variety of theoretical implications for academicians to explore in future research in order to improve our understanding of ICT role (specifically social media tools) in influencing countries' socioeconomic development levels.

- For theoretical papers, researchers should design a structural framework explaining the role of ICT on countries' socioeconomic development by incorporating various conjectures and hypotheses and showing the distinctive power of social media in comparison to other ICT mechanisms.

- In addition, researchers should look at the benefit of social media sites at different levels either individuals, businesses, or governmental institutions in order to delineate the most beneficiary from these sites' influence.
- For empirical papers, it will be interesting to replicate the work on other social media sites (e.g., micro-blogging sites such as Twitter; video-sharing sites such as YouTube) and compare their influence on countries' socioeconomic development. Along the same line, it will be of interest to assess the spillover effect between social media sites in shaping countries' socioeconomic development. Studying social media from different angles will help broaden our understanding of ICT effect on countries' development as related to newly growing platforms beyond the usual ICT factors largely studied in the past (e.g., Internet penetration, mobile subscription, telecommunication infrastructure, and fixed-line broadband subscription).
- It is also important to study and empirically confirm the specific features of each social media platform that drive socioeconomic development.
- In addition, it will be critical to examine and measure the magnitude of the network effect over time, and propose a new construct or metric that could help governments and businesses evaluate such factor. A potential social media index effect could be a valuable research direction in the future.
- Finally, forecasting models should include social media variable as a key component in their future economic projections to enhance the decision-making in terms of socioeconomic development. A number of studies investigated the media sentiment on financial markets (e.g., Nisar and Yeung 2018). As a parallel, economists should replicate such forecasting investigations for a complete analysis of the socioeconomic standing of a country, and advance our understanding of a new trendy component of ICT on human, economic and social development. The progress toward variety of technological tools (e.g., artificial intelligence, machine learning, and deep learning) and the increasing role of social media as a growing basis of analysis and source of information orient our attention to this ICT parameter (i.e., social media platforms) as a key factor to understand future development.

Appendices

Table 9. Sources of data

Dependent variable	
LogGNI	https://data.worldbank.org/indicator/NY.GNP.PCAP.PP.CD
Metric independent variables by type	
Technological factors	
FB	https://www.facebook.com/business/a/online-sales/ad-targeting-details*
IU	https://www.itu.int/en/ITU-D/Statistics/Pages/stat/default.aspx
Mobile	https://www.itu.int/en/ITU-D/Statistics/Pages/stat/default.aspx
NetRead	http://reports.weforum.org/global-information-technology-2011/
Innov	https://www.globalinnovationindex.org/

Political factors	
Peace	http://visionofhumanity.org/indexes/global-peace-index/
Demographic factors	
Educ	http://hdr.undp.org/en/content/education-index
LifeExp	https://data.worldbank.org/indicator/SP.DYN.LE00.IN
Urb	https://data.worldbank.org/indicator/SP.URB.TOTL.IN.ZS
Unemp	https://data.worldbank.org/indicator/SL.UEM.TOTL.ZS
Economic factors	
Tourism	https://data.worldbank.org/indicator/ST.INT.ARVL
Trade	http://wits.worldbank.org/visualization/openness-to-trade-visualization.html

**Facebook data: provided by Dr. Shin Haeng Lee (2015) and used in his paper "Can regimes really discourage social networking? Urbanization, mobile phone use, and the dictator's plight" published in First Monday (2015). The data is an estimate of Facebook users per country based on the advertising page of Facebook.*

Table 10. Missing data statistics

Variables	**Mobile**	**IU**	**Peace**	**Pop**	**Educ**	**Life.Exp**
Count / 480 observation	**0**	**51**	**63**	**0**	**9**	**3**
Percentage	**0**	**10.625**	**13.125**	**0**	**1.875**	**0.625**

Variables	**Unemp**	**Tourism**	**Urban**	**Innov**	**NetwRead**	**Trade**
Count / 480 observations	**30**	**24**	**0**	**81**	**93**	**27**
Percentage	**6.25**	**5**	**0**	**16.875**	**19.375**	**5.625**

From 182 countries, we eliminated 22 countries due to missing values for GNI level or Facebook penetration data (FB) or because of many independent variables that are missing for the same country. Our final data includes 160 countries (160*3 years = 480 observations) which are: *Albania, Algeria, Antigua & Barbuda, Armenia, Australia, Austria, Azerbaijan, Bahamas, Bahrain, Bangladesh, Belarus, Belgium, Belize, Benin, Buthan, Bolivia, Bosnia & Herzegovana, Botswana, Brazil, Bulgaria, Burkina Faso, Burundi, Cambodia, Cameroon, Cape Verde, Canada, Central African Republic, Chad, Chile, China, Colombia, Comoros, Congo Republic, Congo Democratic, Costa Rica, Croatia, Cyprus, Czech Republic, Denmark, Dominica, Dominican Republic, Ecuador, Egypt, El Salvador, Estonia, Equatorial Guinea, Ethiopia, Fiji, Finland, France, Gabon, Gambia, Gaza Strip, Georgia, Germany, Ghana, Greece, Grenada, Guatemala, Guyana, Guinea, Honduras, Hungary, Iceland, India, Indonesia, Iraq, Ireland, Israel, Italy, Jamaica, Japan, Jordan, Kazakhstan, Kenya, Kiribati, South Korea, Kuwait, Kyrgyzstan, Laos, Latvia, Lebanon, Lesotho, Lithuania, Luxembourg, Macedonia, Madagascar, Malawi, Malaysia, Maldives, Mali, Malta, Marshal Islands, Mauritania, Mauritius, Mexico, Moldova, Mongolia, Montenegro, Morocco, Mozambique, Namibia, Nepal, Netherlands, New Zealand, Nicaragua, Niger, Nigeria, Norway, Oman, Pakistan, Panama, Papua New guinea, Paraguay, Peru, Philippines, Poland, Portugal, Puerto Rico, Romania, Russia, Rwanda, St. Lucia, St. Vincent, St. Sao Tome, Saudi Arabia, Senegal, Serbia, Sierra Leone, Singapore, Slovakia, Slovenia, South Africa, Spain, Sri Lanka, Suriname, Swaziland, Sweden, Switzerland, Tajikistan, Tanzania, Thailand, Togo, Tonga, Trinidad & Tobago, Tunisia, Turkey, Turkmenistan, Tuvalu, Uganda, Ukraine, UAE, UK, USA, Uruguay, Uzbekistan, Venezuela, Vietnam, Yemen, Zambia.*

Table 11. VIF score for explanatory variables

Variable	Variance Inflation
FB	20.70965
fb_sq	16.14352
Urban	2.20975
Mobile	2.13654
Trade	1.31665
Unemp	1.26436
Tourism	1.46348
LifeExp	4.65896
Educ	4.06356
NetRead	5.08238
Peace	1.84059

Table 12. Correlation between explanatory variables

Coeff.	Urban	Unemp	LifeExp	Educ	FB	IU	Mobile	Peace	Tourism	Innov	NetRead	Trade
Urban	1.00	0.02	0.67	0.64	0.65	0.70	0.55	-0.36	0.32	0.65	0.65	0.06
Unemp	0.02	1.00	-0.04	0.11	0.11	0.02	0.06	0.01	0.13	-0.03	-0.10	0.10
LifeExp	0.67	-0.04	1.00	0.79	0.78	0.82	0.60	-0.50	0.40	0.77	0.78	0.08
Educ	0.64	0.11	0.79	1.00	0.72	0.84	0.60	-0.53	0.38	0.81	0.79	0.19
FB	0.65	0.11	0.78	0.72	1.00	0.81	0.53	-0.53	0.49	0.77	0.77	0.08
IU	0.70	0.02	0.82	0.84	0.81	1.00	0.58	-0.57	0.48	0.88	0.90	0.14
Mobile	0.55	0.06	0.60	0.60	0.53	0.58	1.00	-0.38	0.40	0.49	0.56	0.31
Peace	-0.36	0.01	-0.50	-0.53	-0.53	-0.57	-0.38	1.00	-0.34	-0.64	-0.61	-0.29
Tourism	0.32	0.13	0.40	0.38	0.49	0.48	0.40	-0.34	1.00	0.43	0.46	0.20
Innov	0.65	-0.03	0.77	0.81	0.77	0.88	0.49	-0.64	0.43	1.00	0.94	0.13
NetRead	0.65	-0.10	0.78	0.79	0.77	0.90	0.56	-0.61	0.46	0.94	1.00	0.09
Trade	0.06	0.10	0.08	0.19	0.08	0.14	0.31	-0.29	0.20	0.13	0.09	1.00

P-values	Urban	Unemp	LifeExp	Educ	FB	IU	Mobile	Peace	Tourism	Innov	NetRead	Trade
Urban		0.6296	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.2150
Unemp	0.6296		0.3804	0.0168	0.0123	0.6451	0.1989	0.7570	0.0042	0.4779	0.0329	0.0253
LifeExp	0.0000	0.3804		0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0735
Educ	0.0000	0.0168	0.0000		0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
FB	0.0000	0.0123	0.0000	0.0000		0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0827
IU	0.0000	0.6451	0.0000	0.0000	0.0000		0.0000	0.0000	0.0000	0.0000	0.0000	0.0028
Mobile	0.0000	0.1989	0.0000	0.0000	0.0000	0.0000		0.0000	0.0000	0.0000	0.0000	0.0000
Peace	0.0000	0.7570	0.0000	0.0000	0.0000	0.0000	0.0000		0.0000	0.0000	0.0000	0.0000
Tourism	0.0000	0.0042	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000		0.0000	0.0000	0.0000
Innov	0.0000	0.4779	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000		0.0000	0.0034
NetRead	0.0000	0.0329	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000		0.0508
Trade	0.2150	0.0253	0.0735	0.0000	0.0827	0.0028	0.0000	0.0000	0.0000	0.0034	0.0508	

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Notes:

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