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An Inquiry on the 21st century Productivity Paradox:
The impact of social media and internet usage on Total Factor Productivity

António Carlos Duarte Lopes de Amaral Dias

Master's in Economics

Supervisor:

PhD Sofia Vale, Associate Professor, Department of Economics
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BUSINESS
SCHOOL

Department of Economics

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Em homenagem às minhas avós Teresa, Maria e Nazaré,
aos meus avôs Carlos e António,
às minhas tias e tios, aos meus primos e primas,
aos meus Irmãos, Irmãs, à minha namorada Jin, e por fim, e mais importante,
aos meus Pais, Henrique e Vanda.

"Today's real borders are not between nations, but between powerful and powerless, free and fettered, privileged and humiliated" – Kofi Anna

"Perhaps humankind cannot bear too much reality, but neither can it bear too much unreality, too much abuse of the truth" – Saul Bellow

"It is clear that global challenges must be met with an emphasis on peace, in harmony with other, with strong alliances and international consensus"- Jimmy Carter

"If we want to reap the harvest of peace and justice in the future, we will have to sow seeds of nonviolence, here and now, in the present"; "We need radical thinking, creative ideas and imagination- Mairead Maquire

"Today, with globalization bringing us ever closer together, if we choose to ignore the insecurities of some, they will soon become the insecurities of all" – Mohamed ElBaradei

"According to the American Psychological Association, the most effective stress-relief strategies are exercising or playing sports, praying or attending a religious service, reading, listening to music, spending time with friends or family, getting a massage, going outside for a walk, meditating or doing yoga, and spending time with a creative hobby. The least effective strategies are gambling, shopping, smoking, drinking, eating, playing video games, surfing the Internet, and watching TV or movies for more than two hours".

Kelly McGonigal - Psychologist

Agradecimento

Quero agradecer a todos aqueles com os quais tive a oportunidade de privar com, aprender, amadurecer e crescer, durante o meu tempo de vida. Um especial agradecimento à minha família, amigos e à Professora Doutora Sofia Vale, pela perseverança e paciência com a qual construímos esta tese de Mestrado. Quero também agradecer à minha Namorada pelo apoio incondicional ao longo destes meses que antecederam a submissão da tese. Finalmente, quero expressar o meu sentido de gratidão a todos os economistas e cientistas dos quais tive o privilégio de aprender e sem os quais seria impossível elaborar esta tese; de facto todos nós caminhamos nos ombros de Gigantes que abriram caminhos onde antes se supunha que eles não existissem.

“As scientists, we have to hold ourselves to a standard that requires us to reach a consensus about which model is right, and then to move on to other questions.”

My Paper "Mathiness in the Theory of Economic Growth"

May 15, 2015

Paul Romer

Resumo

Esta tese utiliza um modelo dinâmico do Método Generalizado dos Momentos, com desvios ortogonais avançados, para obter resultados de regressão para a UE27, de 2013 a 2021. Estes mesmos indicam uma relação negativa entre o consumo de redes sociais e da internet e a produtividade total dos fatores (PTF). Em parte, fá-lo para responder parcialmente ao Paradoxo da Produtividade Moderna, segundo o qual não existem retornos equitativos para a PTF, apesar dos investimentos maciços em serviços de TI, Internet e redes sociais. A improdutividade gerada pela má utilização destas tecnologias ultrapassa os seus benefícios produtivos, o que é indicativo de má instrução tecnológica.

"True happiness is to enjoy the present, without anxious dependence upon the future, not to amuse ourselves with either hopes or fears but to rest satisfied with what we have, which is sufficient, for he that is so wants nothing. The greatest blessings of mankind are within us and within our reach. A wise man is content with his lot, whatever it may be, without wishing for what he has not."

Senenca

Abstract

This thesis leverages a Generalized Method of Moments dynamic model, with forward orthogonal deviations, to obtain regression results, for the EU27, from 2013 to 2021. These results indicate a negative relationship between social media/internet consumption and Total Factor productivity (TFP). In part, it does so to partially answer the Modern Productivity Paradox, one in which there are not equi-proportionate returns to TFP despite massive investments in IT, internet and social media services. The unproductiveness generated by the misuse of these technologies outweighs their productive benefits, which is indicative of technological mis instruction.

JEL Type: I10, F63, O11

"You cannot teach a man anything; you can only find it within yourself."

Galileo Galilei

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"All progress is precarious, and the solution of one problem brings us face to face with another problems" – Martin Luther King

"All theory depends on assumptions which are not quite true. That is what makes is theory. The art of successful theorizing is to make the inevitable simplifying assumptions in such a way that the final results are not very sensitive…" – Robert Solow

Disclaimer

The author of this thesis aims to further the answers to a complex and dynamic paradox. Its assumptions are not quite true, in the words of Solow. Although some of the assumptions about the variables used hold truth in their economic dynamical genesis, in some cases, they are not generalizable at all. It is not, in any intent or purpose, to culprit either internet founders, social media founders, or its users. The crux of the argument at hand is that, collectively, there is a strong possibility to maximize current and future technologies' use, if technological instruction is at the heart of the policy maker's decision making. The slowdown of productivity and economic growth (Gordon, R (2018)) is worrisome and is a major challenge that must be tackled.

That is, first and foremost, the assumption that this thesis wishes to stronghold at its core. Utopic scenarios are just that, utopic. But with the advent of AI, there has never been such a strong necessity (technologically wise) to instruct general populations on its positive use, whilst mitigating harmful derivative ideas of it.

Finally, I want to credit all the economic and scientific minds that I have read about for helping me construct this piece. It would be meaningless and worthless without the contribution of their invaluable minds to it, to which I owe them the upmost respect and gratitude.

Section 1 - Introduction

Is the exponential progress of digital and computer industries a positive precursor or harmful catalyzer for economic, political, scientifical and existential ethics, morality, prosperity, development, growth and abundance? What if the generation of ideas is not the sole crux driver of capital accumulation and economic growth? What if today´s Modern Productivity Paradox, a derivative of the original Solow Productivity Paradox, is linked to the concept that creating and outputting ideas, without their proper implementation, is not the sole factor of capital accumulation? This question is at the genesis of what the ensuing thesis aims to put into question. Robert Solow (which supported Exogenous Economic growth theory) was the pioneer in identifying what was later coined as the “Solow Productivity Paradox”. The modern version of the Paradox states that computerization (and implicitly digital technologies) was and is reflected in a plethora of socio-political-economic statistics but one, productivity.

Productivity has increased due to these technologies but not in the incremental and proportional amounts that their originators intended. This paper utilizes (Through the application of a Dynamic Generalized Method of Moments estimation) three main variables associated with social media and Internet use to study their impact on Total Factor Productivity (TFP). The econometric results produced (subjected to endogenous constructive criticism), albeit far from being mathematically perfect (Sir Paul Romer´s coined term of “mathiness” underlines the fragilities of the results obtained; his view of economics was of an endogenous nuclei), indicate that there is a negative impact of these technologies on TFP. This paper is fundamentally a steppingstone to continue paving the work of Robert Solow, Paul Romer and other illustrious economists.

Technological advancement and innovation have tremendous upsides, but perhaps only up to a certain point. From that point onwards, there is a loss of efficiency and efficacy in its use due to **lagging poor technological instruction**. Social media, the Internet and computerization have brought a panoply of benefits to society but, concomitantly, have negatively accommodated a relevant quantity of its status quo constituents, mainly due to mental health disturbances and cognitive disruptions. The hypothesis that this paper aims to develop is that technological advancement, efficiency and, perhaps even more importantly, technological instruction are the fundamental aspects to be considered by policymakers. Finally, it aims to forward the discussion regarding the Productivity Paradox of the 21st century.

On a final note, it's imperative to debate the OECD report on the impact of AI on the labor market. Published in 2021, the report does not thoroughly interpret, analyze and dissect any of the more indirect effects of AI and the Internet. The effects are the ones associated with the use of AI and Internet products for leisure, entertainment and social networking. The 21st century Productivity Paradox assumes a mitochondrial position in this study. AI and IT systems are not only applied to the production chain of the economy, but they also enhance end products for consumers. A glaring example of this is the application of machine and deep learning algorithms and neural networks to social networks[3].

This AI application allows for social networks and social media outlets to suggest material that corresponds to user preferences in a more personalized fashion. It appears to utilize, with the users' consent, content suggestion algorithms that are more efficient in detecting and matching user preferences. The impact of these new features is evident.

At this moment, progressively more people are on social media, and they spend substantially more time utilizing it than ever. Referenced from official Statista data (https://www.statista.com/statistics/433871/daily-social-media-usage-worldwide/;), minutes spent on social media increased from around 90 minutes in 2013 to 150 minutes in 2023 worldwide. As seen from the data collected for 27 EU countries, the percentage of individuals of total population that use social media has increased as well. In this plot, a point represents for each country the percentage of individuals of its population that utilize social media.

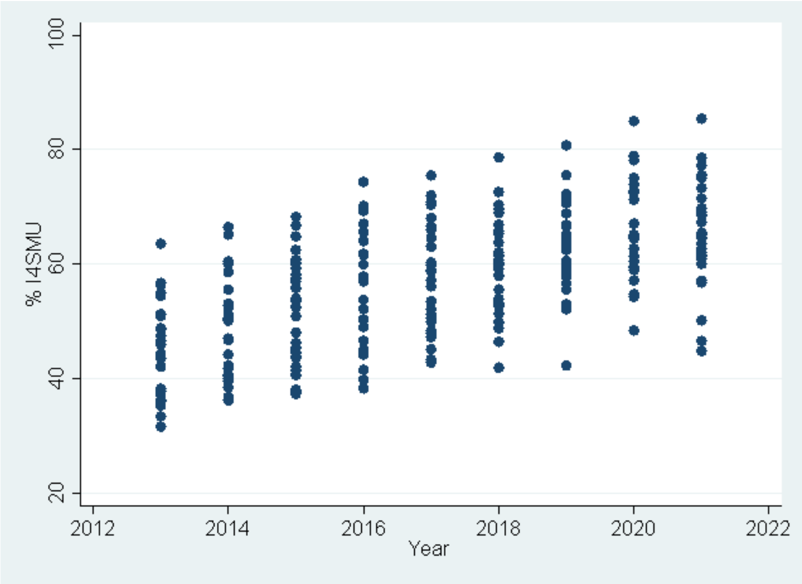

Figure 1- Percentage of Individuals of total population utilizing social media(Y-axis)

Most countries had between 40% and 60% of their population consuming social media in 2013, while in 2021 they had between 60% and 80% of their population consuming social media.
Overall, social media and the internet´s impact on society is a double-edge sword. Some of its benefits are that it helps individuals to belong to and be included in certain communities that match their interests, facilitates user interactions and communication flow (whether professional or personal) and increases access to information. It also allows users to creatively enhance the status quo boundaries and format. Social media and the Internet also benefit firms by having employees more connected with one another; by easing communications between company and current/potential customers. It also is a more cost-result effective method of marketing and advertising, and it overall allows for personal branding and self-promotion of the company´s perimeter of action. However social media and the internet do not only have positive benefits. Several studies have analyzed the impact of social media and of the internet on mental health and a great deal of these studies point towards the fact that their use impacts mental health negatively.

Its nature can be quite addictive, and with enhanced content-suggestion algorithms, it can potentially be able to cause depression, anxiety and other mental disorders. It stimulates the dopamine driven feedback loops in an unhealthy manner in line with the effects of the abuse of substances like alcohol, tobacco, and other psychotropic substances. Social media also promotes social comparison and rivalry which most of the times is an upward comparison (when one compares himself to people with a more glamorous/superior lifestyle), something which has been found to have negative effects on the user´s self-esteem, self-image and self-concept.

In addition, cell phone notifications were studied in the context of harming attention. In the studies collected (Cary Stothart et al (2015)) it was found that cell phone notifications, some of which will inherently come from social media, harm attention in tasks, diverting the focus of the user from the current task they have at hand. Equally, it has been stated that notifications can prompt task-irrelevant perceptions or even mind wandering in the user, which has been stated to hurt task performance.

There also exists the phenomenon of information overload. In an article by Charlotte Huff (https://www.apa.org/monitor/2022/11/strain-media-overload,), for the American Psychological Association, it is confirmed that information and media overload, perpetrated also by social media and the internet, may cause anxiety, stress, and overall compromise cognitive and emotional resources for a lot of users. The spread of fake news is also a phenomenon that seeds division, hate and discrimination across several demographics. A study quantifying information overload[12] also states that humans have limited cognitive capacity of processing abilities and that when they are overloaded with information, the standard of their decision making is negatively affected.

A general simple association can be made that social-media utilization, for its general purposes, is a way of investing time in digital social networks rather than investing in other, perhaps more productive and fruitful activities. In an article by the Guardian, former vice-president of user growth of Facebook Chamath Palihapitiya said that the "short-term, dopamine-driven feedback loops that we have created are destroying on how society works. No civil discourse, no cooperation, misinformation, mistruth". Facebook´s founding president Sean Parker also criticized the way of how the underlying appealing nature of social media "exploits a vulnerability in human psychology" by creating what he mentioned to be a "social-validation feedback loop". As mentioned hitherto, social media has both positive and negative impacts on society and individuals as whole, with its effects being amplified by the application of enhanced AI, IT and Internet-interconnected systems to its baseline functioning structure.

In summary, this paper uses data from 2013 until 2021 to produce results (through Stata 18) utilizing a Dynamic GMM methodology to estimate the coefficients impact of social media and internet metrics on TFP.

Section 2 – Literature Review

(A) “Endogenous Technical Change” - an Overview

This paper will now critically analyze Dr. Paul Romer´s “Endogenous Technical Change” (1989). The main notions one aims to build upon this paper will be the concepts that hold true to today’s status quo format. Despite it, some concepts will be critically reviewed and deconstructed. There are three main premises that serve as the theoretical and practical basis of the investigation conducted by Romer. They are correct and nearly complete at the time Romer elaborated them, but since times have changed, their foundational basis, and its core genesis, haven’t kept up with a constantly evolving, exponentially and ex(im)plosive dynamic socio-political-technological-military-economic world. Firstly, Romer affirmed that technological change is at the heart of economic growth. This statement holds true today, but it is incomplete when applied to the current technological world status quo. This paper aims to assert that technological instruction and mis instruction are as important as technological change and innovation in enabling economic growth, development and prosperity. Take the following example. Social Media Networks were created with the purpose of connecting friends and co-workers, enabling the sharing of ideas and thoughts, and to help companies disperse their brand name and activity while also connecting employers to employees, businesses and personal live at like.

However, many negative and positive derivative ideas and practices have flowered from the original positive idea that its creators had in mind. Some users utilize them to bully other users, other users share information that may be false or inaccurate; and some companies, which are built on scam-based business models, utilize social networks to take advantage of users that may not have awareness to realize that they are being involved in a scam. From this example it is possible to deduce the fact that the positive idea that social media (which is a ramification of the “www” internet structure) originally was, is trampled by the negative intentions that some of its users apply to it, whether they are consciously or unconsciously purposeful in their use. Hence, it is possible to deduce from this example that despite technological change/innovation being a main driver of economic growth, technological instruction is also key in enabling the correct application of a given technology to enable true economic prosperity. Think of this constant derivation of positive ideas and negative ideas as a decision circle diagram.

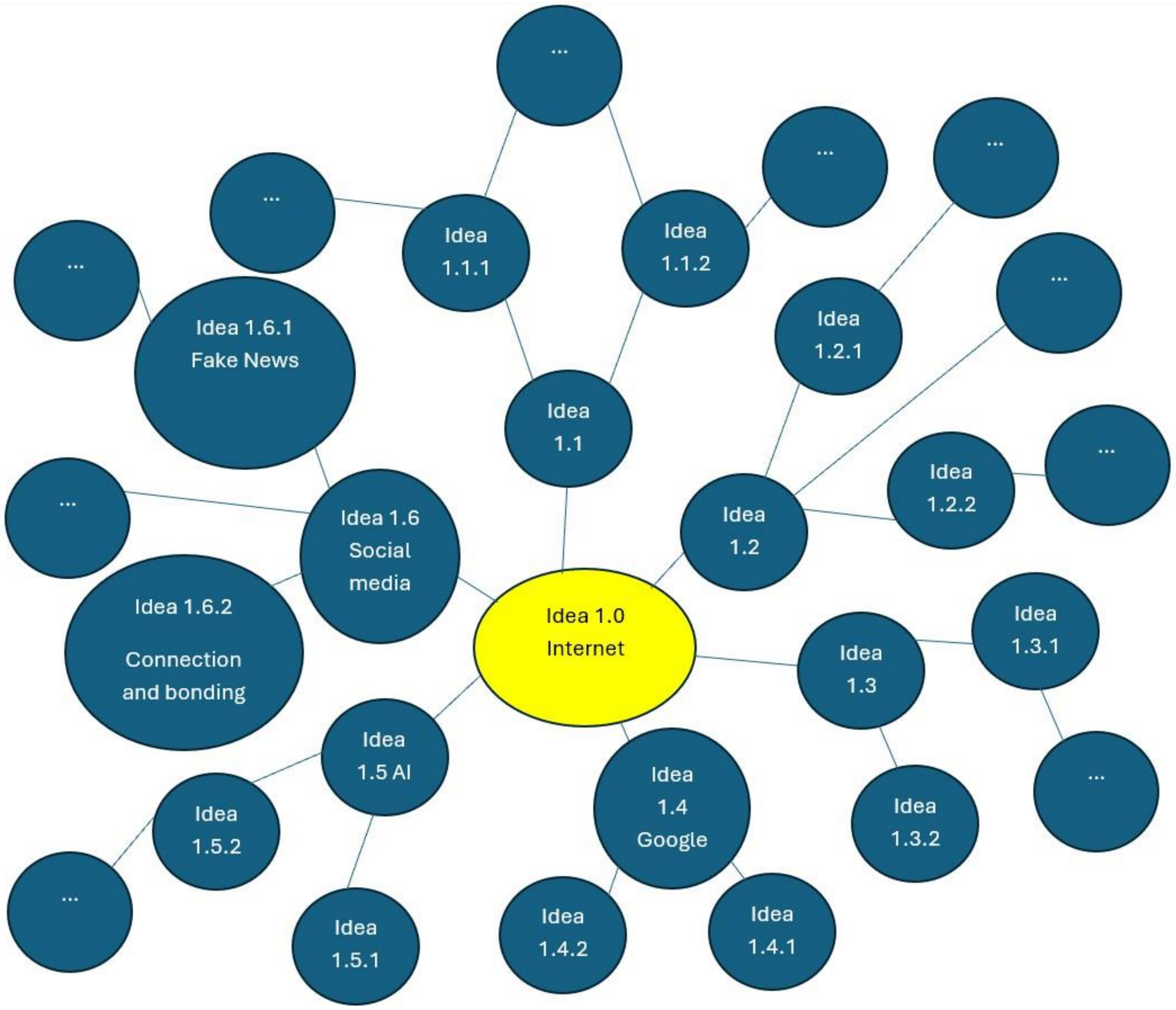

Diagram 1

In this example let's imagine the decision circle has 1000 nodes, with the internet being at the center as idea 1.0. From this It would be possible to suppose that a positive idea equilibrium would exist if there were more positive idea nodes derived from the original idea than negative idea nodes and their latter connections. Therefore, a positive economic-product based equilibrium would fundamentally come into fruition if there were more processes of technological instruction than processes of technological mis instruction. Instruction and mis instructions comes from the lines that connect the nodes.

Again, it is important to stress that the success and wealth of a given economy depends on its technological instruction, which can be assumed to be the lines connecting the positive or negative nodes or the lines connecting negative nodes to positive nodes. The same occurs in abstract socio-economical terms. If in a given economy, with X amount of goods, with each one derived from each other, there are more positive applied goods (X-n) than negative applied goods(X-n-1), then that economy is in a state of prosperous economic growth. In a situation where technological change occurs, new positive ideas don´t necessarily translate into other positive ideas embryonating.

That is when technological instruction comes into play. It fundamentally must be recognized to be an important component to economic growth, just as technological change and innovation are.
Returning to Romer´s work, the focus is now on the second premise that was elaborated. The following is stated: “technological change arises in large part because of intentional actions taken by people who respond to market incentives”.

This premise is correct, even in today´s world, although one can consider that an individual´s passion is incentive too, albeit in a small minute minority of the existing cases. The third premise states that “once the cost of creating a new set of instructions has been incurred, the instructions can be used over and over again at no additional cost”. This statement may have been correct in 1989, associated with the level of technology existing at that time, but it no longer holds true today. Take the following example. OpenAI needed electricity, IT engineers and internet access to construct ChatGPT and other applications. After these were created, OpenAI still required electricity and internet access, and a part of its engineers, to maintain their new set of instructions, or design, functionally active. The fixed costs incurred in creating a new set of instructions will, in a relevant number of cases, be present, even after the design or product has been built.

At a certain point in “Endogenous Technical Change” there is the mention that “one should expect that fixed costs lead to gains from increases in the size of the market and therefore to gains from trade between countries”. This affirmation is correct, but an additional concept can be added to it.

One could assume that fixed costs not only lead to increases in the size of the market and to gains from trade between countries, but they also increase the probability of new markets being developed, originating from the starting market where fixed costs were increased (again the circle decision model is connotated here in its essence). Take the following example. Fixed costs were incurred in creating Chat GPT, and the investments made in it increased the market size due to an increase in the need for competition, concomitant with an increase in the popularity of LLM's (large language models). But with time, the need for complementary services also appeared, in this case, Chat GPT plug-ins and other complementary services and goods. Therefore, one can assert that new markets increase the audience that desires the intrinsic good supplied (Supply creates demand, Say´s Law) but new markets also increase supply again because of the need to complement the always present imperfections of the existing markets with the creation of complementary goods and services. To quote and enunciate the intrinsic premise proposed by Lionel Robbins, economics is about managing unlimited needs with limited resources. This is tied to the previous line of thought, where complementary goods sprung from the increase of the original market, to continuously satisfy unlimited needs.

In a first note about the attributes of any economic good, Romer identifies two of them, the degree to which they are rivalrous and the degree to which they are excludable. This paper aims to introduce two more attributes: appropriability and positivity traits. The latter has already been explained previously and it is fundamentally related to the fact that if a given good or application of a good produces a positive or negative outcome in economical and societal terms. The former, appropriability, is a characteristic defined by the process through which a good is directly owned or not by an individual. Appropriability is a symbiotic characteristic. If, for example, an individual purchases a book, the use and property of the book are exclusive to the owner. He may enjoy the book without the need to purchase any other goods, for example by reading it during daylight (there is no other associated cost that enables the enjoyment of the book but light itself (which is costless during the day).

On the other hand, if a user purchases a computer, one may assert that it is partially appropriable. It effectively is partially appropriable because the user can´t enjoy the full capabilities of the computer without expending resources or monetary fluxes on internet and electricity.

Therefore, the computer is a partially appropriable good, since its complete use and ownership depend on the ownership of other goods and services. An example of a pure appropriable good is the air (oxygen) humans' breath or water from a natural public spring.

Later, in Romer´s paper, rivalry is mentioned to be a purely technological attribute. This argument can be disputed. Let's take the example of a natural free entrance park, a type of public good. If on a given day, too many people want to enjoy a natural free entrance park, at a certain point the last user that wishes to enjoy the park won´t be able to derive any use from it since the park is completely full. According to the definition of rivalry, the use of the park by the first (N) users limits the use of the park for the (N+1) user. This is a case where rivalry effectively occurs in a non-technological good. Conversely, Dr. Paul Romer mentions that, by definition, public goods are nonrival and nonexcludable. The point that one wants to make is that generalizing whether public, private, positive or appropriable, and other types of goods always have the same economic characteristics is a fallacy, as they must be analyzed case by case to fit them in the precise category where they should be. At some point Dr. Paul Romer also mentions that "rivalry and excludability" are closely linked because "there is no interesting sense in which a good can be rival but nonexcludable". This statement does not hold true today. Take the following example. Imagine there is Free-Wi-Fi at a tourist plaza. The Wi-Fi connection is free of charge, therefore nonexcludable, but if too many users (N) are connected to the Wi-Fi signal, the (N+1) user to connect is going to have a less prioritized connection, worse bandwidth and weaker signal strength that all the other (N) users. This is an example of a good, in an interesting sense, that is rivalrous but nonexcludable.

Later, there is also the mention that the ability to add is rival, since a given individual can´t be at two places at the same time teaching how to add. This was true in 1989, but it is not affirmatively concurrent today. With many online platforms, for example YouTube, a given person can teach multiple individuals how to add at the same time through the creation of a video that many viewers can enjoy at the same time.

At a certain point there is the mention that Arrow's (1962) concept in which an increase in Capital (K) necessarily translates to an equi-proportionate increase in knowledge through learning-by-doing.

This idea is circumstantially correct, but its veracity depends on two main factors occurring. The first one is that the user of the capital (K), that has been increased, must have the desire to increase the knowledge he now derives from the increment in K. The second one is that knowledge may equi-proportionately increase, but either in an extensive or intensive way. What this means is that an increase in K may allow for knowledge dispersion intensively about the concepts and notions that a given K increase allows to expand; or it may extensively increase the knowledge beyond the sectorial notions and concepts that are bounded circumstantially and structurally by K. Perhaps the notion of extensive and intensive increases in knowledge will be easier to assimilate through the following example.

On one hand, if a lawyer buys a Tax Code book to better understand a situation a client is in, the lawyer's investment in capital (the book) translates into an intensive increase in knowledge (increase about the fiscal and tax laws), that is, an increase in the knowledge he previously had but was insufficient about Tax laws. On the other hand, if Open AI increases its LLM capacity by 50% and it allows users to research more effectively, a given user may now increase his knowledge intensively about a certain topic or extensively about several other topics. Conversely, even if OpenAI increases their LLM capacity by 50%, an 50% increase in knowledge by-doing of users depends on the will of the users to actively derive, equi-proportionately, more information from the recently increased informational capacity. The argument being fundamentally conveyed is that an increase in capital (K) by X amount does not always translate into an increase of order X of the knowledge of the user and that knowledge may be increased extensively or intensively. This concludes the critical review of “Endogenous Technical Change” and the presentation of the derivative ideas this paper extrapolates from it.

(B) Social Media and the Internet

From now forward, this paper will critically analyze articles that assess both the impact of social media and of the internet on mental health, on business, on productivity, and on society, as whole as well as how algorithms structure social media platforms. This is highly relevant since the main crux of this paper is to determine whether social media and the internet have a positive or negative impact on Total Factor Productivity and how both negative and positive ideas that spring out from social media /internet applications impact productivity. It is noteworthy to mention that during the bibliographical investigation conducted, there seems to exist a relevant gap in the matter that this study aims to econometrically analyze, to which it can be assumed that this paper is pioneering, and perhaps paving the way for other econometrical studies regarding the underlying topic.

Social media and the internet have been found to greatly help businesses and companies thrive. Concretely, it allows to reinforce brand experience through inexpensive marketing, enhances communication channels between current and potential coworkers and aids in building a good reputation for a business organization. It helps to strengthen communication between current and potential customers, in both receiving feedback, product definition, product development and any forms of customer services and support (Edosomwan et al., 2011).

Regarding the impact of social media on employees´ wellbeing and productivity the picture can be quite contrasting. Evidence has been found that supports the fact that the overuse of social media can be portrayed as mood-wise addiction since it shares similarities with other types of addictions, such as withdrawal, conflict, relapse, tolerance, and mood alteration (Cao, et al., 2018). Concomitantly, some analyses have been conducted that conclude that social media and internet overuse affects users in a different number of ways. Lack of sleep, backache and eye strain, feelings of envy, lack of depth in relationships and a tendency to seek approval are some of the reported effects of the overuse of social media and of the internet as a whole, implicitly (Chetna et al., 2020). On the other hand, evidence has been found that supports the fact that social media provides opportunities to enhance mental health of users by easing social relationships and through peer support (Zsila et al., 2013; Naslund et al., 2020) whilst also reducing loneliness.

Regarding the negative impact of social media and internet addiction on work productivity, some of the associated effects reported are for example the capacity of not meeting deadlines, a compromise with the work quality and overall distraction from the work at hand (Chetna et al., 2020). It is well known that interacting with a smartphone is associated with reduced performance on the main task at hand, as attentional resources are shared between both tasks. Notifications play a big part in this distraction process, as they can trigger task-irrelevant thoughts, which have been associated with reduced task performance (Stolhart et al., 2015).

In a social experiment studying the interaction between 212 undergraduate students and the notifications and stimuli from smartphones, it became apparent that cellular notifications, even when not responded to or viewed, can negatively impact performance on attention-demanding tasks (Stolhart et al., 2015). The underlying study conducted does have some limitations, such as the reported fact that participants were aware of the distraction condition, which may have conditioned the validity of the results obtained (creating a sort of an inverted placebo effect)

On a second note, it is important to highlight the fact that when attentional processes are interrupted or disrupted, they impair memory and learning (Allport et al., 1972; Boila et al., 2020, Chen & Yan, 2016; Naveh-Benjamin & Brubaker, 2019; Lee et al., 2021). In the case where smartphones are present, its notifications attract attention to the incoming information alert and therefore disperse focus from the concurrent task at hand. This may be defined as multitasking, but it is in fact a process of task switching (Kaminske el al., 2022). In an experiment involving 105 undergraduate participants, response elasticity to certain tasks was studied, as cell notifications occurred. It was found that cell phone notifications do harm attention spans and overall focus on given tasks (Kaminske et al., 2022). These results are consistent with the evidence put forward by Stothart et al. (2015). Besides the attention scattering phenomena, there are other procedures that impact social media and internet users. The Fear of Missing Out (FoMO) is the process through which an individual experiences anxiety over missing out on rewarding experiences of that others display online. This phenomenon has been a strong predictor of internet, smartphone and social networks use disorders (Rozgonjuk et al., 2020).

In a survey involving a sample of 748 German-speaking individuals, participants were asked to answer several questions regarding their experience with internet, social media and smartphones. The Bivariate analysis conducted showed that the severity of social network disorders was positively correlated with FoMO and with social media´s negative impact on daily-life and productivity at work (Rozgonjuk et al., 2020). There are obvious limitations to this study, for example that the sample size of participants could be larger and the participant ethnicity could be more diverse, yet the results obtained are indicative of the negative impact of social media mis use. Internet and smartphones have an effective impact on users´ mental health, focus and productivity. A qualitative literature review of different experiments, conducted on several different clusters of participants, highlights the negative impact of social media/internet on mental health. It asserts that an exposure time of 10 to 20 minutes to it is enough to negatively or positively impact a user, whilst also stating that overall well-being and trait self-esteem of social media users can be negatively impacted with frequent and improper use (Sharma et al., 2020).

On the topic of social media, social comparison and mental health, there currently exists a vast amount of literature published. Social media and the internet, in its misuse, has been classified as more addictive than cigarettes and alcohol (Royal Society for Public Health, 2017). The use of social media platforms has also been linked to increased levels of depression and anxiety symptoms, which stem from procedures already mentioned such as social comparison and FoMO (Primka et al., 2017). A troublesome and worrisome use of smartphones, defined as an incapacity to regulate one´s use of a smartphone, eventually leads to consequences in a user's daily professional and personal life (Billieux, 2012). This has recently been described as an emerging public health problem (Van Velthoven et al., 2018).

Overall, social media and the internet, and the positive/negative derivative ideas that come from it, may have a symbiotic mental health effect on a user, as it has been highlighted by Warrender et al. (2020). The addictiveness of social media is a result of how social media companies commonly design their platforms. A relevant number of Governments have declared internet addiction a major public health concern, and the World Health Organization has characterized excessive internet and smartphone use as a growing challenge and deep-rooted societal problem (Bhargava et al., 2021).

To reinforce this idea, several studies have shown that the prolonged use of social media, social networks and internet is positively associated with mental health problems such as stress, anxiety, depression, induced isolation and a subtraction from social encounters, as it is negatively associated with overall well-being in the long-run (physically and mentally) (Hou et al., 2019; Eraslan-Capan, 2015; Hong & Huang,(2014); Malik & Khan, 2015; Marino et al., 2017; Pantic, 2014; Shakya & Christakis, 2017; Toker & Baturay, 2016).

In a survey conducted, the relationships between social media and of internet use were analyzed to determine the mental health and academic performance in college students, with their performance of an examination of the role of self-esteem as a potential mediator for these relationships. The sample size consisted of 250 students from Peking University in China. The empirical results obtained indicate that social media and internet addiction were negatively associated with college students´ mental health and academic performance (Hou et al., 2021; Pantic et al., 2012; Jelenchick et al., 2013), and that social media negatively affects self-esteem in its mis use. (Andreassen et al., 2017; Blachnio et al., 2016; Chou & Edge, 2012; Vogel et al., 2014) Social Media and the internet provoke, in a relevant number of cases, low levels of self-esteem that are consistent with mental disorders (Orth et al., 2008; Orth & Robins, 2013; Sowislo & Orth, 2013). Again, it is noteworthy to mention that the survey study has the clear limitation of having a reduced sample size.

The impact of social media on self-esteem can be greater than what it seems at face value. Major findings suggest that approximately 88% of users engage in making social comparisons on Facebook and out of these 88%, 98% of them are upward social comparisons (Jan et al., 2017). This and other studies at hand (Vogel et al., 2014) also suggest that, through empirical statistical resources, that there is a strong relationship between social media/internet use and self-esteem, with increases in social media/internet usage causing a decrease in the self-esteem of users. Concerns about potential negative effects of social media/internet on mental health have risen recently to the point where even the U.S. Senate held a committee hearing about the topic in late 2021 (Wells et al., 2021; Braghieri et al., 2022). Social Media's impact on mental health has been exhaustively studied, through different statistics, metrics, surveys and overall methods of assessments (Braghieri et al., 2022).

It has been found that the over and misuse of social media and of the internet have been partly responsible for the recent decrease in mental health quality among teenagers and young and middle-aged adults, and that social media platform owner´s and governmental regulators should act decisively on how these effects can be alleviated, mitigated or even reversed back to positive ones. The fundamental process is that social media platforms, and the internet, stimulate users through the release of dopamine (Gonzalez, 2023).

It has been asserted that it creates a loop that reinforces the desire for more content digestion. This chemical chain interaction withing the synaptic and neural receptors, occurring in the brain, leads to changes in the dopamine threshold, which results in overuse or addiction. It fundamentally perpetuates the dopamine loop in a fashion like the abuse of hard psychotropic substances. Social media and internet negative connotative addiction is a real and worrisome phenomenon, with it having an exponential-like demographic trend (Griffiths et al., 2014) The global impact of social media and the internet on society remains a difficult diagnostic to make. Besides the cited benefits of (Karim et al., 2020), and mental health issues that social media can cause in users (Karim et al., 2020), social media can also aid users in engaging in illicit activities, such as bullying, terrorism, fearmongering, dispersion of fake news and even black mailing (Amedie, 2015). It has been found that uncontrolled and compulsive use of internet resources (such as social media) increases loneliness as well as emotional loneliness (Bhat, 2016)

Overall, social media has become this mainstream phenomenon partially due to the machine and deep learning and neural networks it employs to enhance user experience. Social media platforms use neural networks to recursively suggest content that progressively matches user preferences based on engagement response (Taherdoost, 2023). Some argue that these algorithm-based models encourage addiction through dopamine release (Petrescu, 2020) but the opinion of this paper is that its addiction containment fundamentally depends on the control and discipline that the user has over himself whilst using social media and internet outlets.

To conclude, an analysis will be performed of the papers and articles that investigate the causality between social media and productivity.

In a survey conducted on 62 Indian participants, during the COVID era, several conclusions were made regarding the impact of social media on productivity (Ahmad et al., 2022). Firstly, that around 9.285% of the productivity of every employee is being lost daily because of the utilization of social media and internet platforms (unrelated to work) in the workplace, during working hours. Secondly, many of the respondents reported that social media use during working hours deviates them from their work, as it fundamentally wastes work time.

Meanwhile, 57% of respondents also felt that this phenomenon negatively impacts their productivity. To conclude, approximately 80% of the respondents feel that their organization should employ policies to regulate the use of social media and of the internet (unrelated to work) during working hours. There are some limitations to this study, with the most glaring ones being the fact that its sample constitution is exclusive to Indian participants and that its size is quite limited. Conversely, in a separate study where 322 questionnaires, from Taiwanese individuals, were collected, it was found that a socially oriented use of social media can lead to smoother social interactions and an increase in the awareness of social capital (ong et al., 2021). Again, there are limitations to this study, such as the fact that the conclusions obtained cannot be generalized to different countries, since the surveys were conducted in Taiwan.

Overall, and to conclude, there are clearcut positive and negative applications and outcomes of social media/internet use regarding mental health, productivity, socialization and business performance. What this paper fundamentally aims to determine is whether the use of social media and the internet by users in any given EU-27 population is a significant, positive or negative, predictor of Total Factor Productivity's recent evolution.

(C) AI Impact

The OECD (2019) details AI as a general-purpose technology (GPT), which means it fundamentally is a technology that has potential applications to a broad variety of industries, markets, and creative vocations (OECD 2021). It also possesses the ability to improve over time and to create complementary innovative processes. It can produce predictions (Agrawal et al., 2019) which can be inductive important inputs in decision-making across a plethora of different professional processes. Machine learning and neural networks, sub-layers of AI are, for example, able to self-improve (Brynjolfsson et al. 2017), enabling machines to perceive and learn the world as data points.

Several economists consider AI to be an automation technology, that is that it facilitates the automation of chores or tasks that would classically be performed by humans. This can result in a reduction of labor demand (employment levels) and consequently wages (Acemoglu and Restrepo 2018; Aghion et al., 2017). Until recently, automation affected mainly routine cyclical tasks (Autor, Levy and Murnane, 2003) and low-skilled tasks (Nedelkoska and Quintini, 2018). However, with recent developments in the field of AI, mainly in machine learning, deep learning and neural networks, AI has been found to also have the potential to substitute white-collar jobs that are associated to greater levels of education and would be orthodoxically considered secure, safe-locked jobs (OECDE 2019 Employment Outlook, 2019).

Some scientists believe in the phenomenon of the *singularity*. The *singularity* is a result of AI´s ability to self-improve. It mainly consists of a status quo where machine intelligence surpasses human intelligence (social, creatively and cognitively) and economic growth accelerates exponentially, while also diminishing the role of humans (especially logically) in the labor market (Boostrom 2006; Good, 1966). To support this, a survey was conducted on machine learning researchers about the potential of the *singularity* occurring, to which the researchers assigned a 50% probability chance of AI surpassing human general intelligence in 45 years in all tasks and leading to the automation of all human jobs in 122 years (Grace et al., 2017).

This 50% chance of course could fall in line with the famously known Schrodinger´s cat experiment, where a 50% chance of an outcome happening usually translates into that outcome progressively happening eventually over time.

Of course, all this is hypothetical and quite far in the future. One must focus on how AI will transform the world in the next coming years.

Several studies have been conducted to determine which occupations are most and least exposed to AI. An overview of the main studies found will now be performed. The case is made that high-skilled occupations, such as clinical lab technicians, optometrists and chemical engineers, and production jobs involving inspection and quality control, will have a high degree of exposure to AI (Webb, 2020). This fundamentally means that these jobs will be either complemented or substituted by it. It is also asserted that high-skilled occupations that require logical, deductive, and inductive reasoning, and interpersonal skills, such as researchers, teachers and managers, will be the least exposed (Webb, 2020). This paper fundamentally believes these statements may become incorrect due to the advent of LLM (large-language models) such as ChatGPT (OpenAI), Bard/Gemini (Google), GrokAI (xAI), Claude Sonnet and others.
Despite all considerations made so far, some researchers affirm that the Moravec´s Paradox might be in effect.

This paradox (identified in the literature of the economics of AI, firstly by Gries and Naudé (2018)) states that automation of high-level cognitive tasks demands fewer computational resources when compared to the high quantities of computational resources that sensor-motor skill automation requires. From here, it is possible to deduce that cognitive repetitive tasks will be automated at a higher pace than precision-demanding manual labor tasks.

But AI is not fundamentally going to replace all human labor in the coming years, as it will ultimately complement it. Many professions are composed of tasks that concomitantly have sub-tasks of which some are highly automated by machine/deep-learning, while others are not (Brynjolfsson et al., 2018). Complex, abstract reasoning is still a skill that commercial applications of AI have not demonstrated to possess (OECD 2021). A relevant amount of economics literature on AI stresses the fact that AI has the potential to complement and substitute human labor, increasing overall levels of productivity. It is argued that this increase in productivity, coupled with reduced costs and complementary innovations, will enable unprecedent levels of economic output.

However, conversely to this, and fundamentally key to this paper, there is a phenomenon recently observed denominated the modern productivity paradox (based on the Solow Paradox, in which investments in IT sectors do not yield equi-proportionate returns to productivity; or as Robert Solow put it “you can see the computer age everywhere but in the productivity statistics).

It was found that between 2006 and 2016 productivity growth was slower than in the preceding decade despite major advancements in both IT and AI (Gordon, 2018). The crux of the paradox at hand is one of the central questions this paper attempts to shine light on. What this paper will attempt to assert is that AI, applied to the internet and social media, and IT structures, are also applied to entertainment products, from which an abusive and unhealthy use of them may cause mental health decays and social capital loss, that translate into a loss of human productivity. Therefore, the healthy balancing effect can be counteracted by negative effects, which is one of the propositions this thesis aims to study. This will be more profoundly discussed in a section further below.

Substitution and complementation are not the only phenomena that AI will provoke in the labor market. It is already, and will continue, to develop new tasks for humans as it is being deployed. AI will create jobs due to the need for further development of it, its maintenance, its operation and its public and private regulation (PWC, 2018). This process of generation of new tasks will inevitably lead to the need for workers to re-skill or up-skill (OECD 2021). However, this process of adaptation, and the consequent effects on wages, will not be uniform across all workers.

Larger positive wage effects and adaptive capabilities to the adoption of AI occur in individuals with higher levels education and in higher wage occupations (Felten, Raj and Seamans, 2019; Fossen and Sorgner, 2019). This suggests that these individuals will be the ones most able to utilize AI in a complementary fashion and to overall derive more benefits from it.

This thesis, and its analysis on existing AI literature, considers that there is potential for inequality to increase drastically due to high probability of this outcome occurring, as it seems to already being partially in effect. The technical term for these new adaptive workers is AI technocrats.

On the other hand, individuals with professions that are less remunerated are found to be more likely to be substituted by AI (Acemoglu et al., 2020), which again may aggravate the concerns about potential drastic increases in inequality. This may increase the need for an drastic improvement in educational services, whether public or private.

SECTION 3 - Methodology

3.1 . Brief Introduction

In this section, a description of the statistical and modelling strategy is employed. An initial summary will be done about the initial regression model as well as the estimation techniques and tests that will be performed. The data set has the following countries: Belgium, Bulgaria, Czechia, Denmark, Germany, Estonia, Ireland, Greece, Spain, France, Croatia, Italy, Cyprus, Latvia, Lithuania, Luxembourg, Hungary, Malta, Netherlands, Austria, Poland, Portugal, Romania, Slovenia, Slovakia, Finland and Sweden. The data collected for these countries ranges from 2013 until 2021, which amounts to a total of around 243 observations.

3.2 Variable definition, source and choice

The table below identifies and describes the variables used in the regression process; the measure chosen for them as well as the data source from where they were collected.

Table1 - Variable definitions and sources

Variable	Measure	Source
TFP	Total Factor Productivity	Ameco Data Base
IDFIU	% of individuals of a given population that consecutively use the Internet on a daily basis	Eurostat
SMAM	Number of days (24hours) spent yearly by a given population on social media	Eurostat and Statista data combined, permutated and calculated
I4SMU	% of Individuals participating in social networks (Facebook, X, Instagram, YouTube, WhatsApp, Tik-Tok, etc.)	Eurostat
PIBpC	Gross Domestic Product at constant prices per Capita	Ameco Data Base
FDINFL	Foreign Direct Investment Inflows as a % of GDP	World Bank Development Indicators
DepRatio	Age dependency ratio is the ratio of dependents--people younger than 15 or older than 64--to the working-age population--those ages 15-64	World Bank Development Indicators
TradeOP	Import plus Exports as a % of GDP	World Bank Development Indicators
GNEPIB	Gross National Expense as a % of GDP	World Bank Development Indicators
sKL	Net Capital Stock at Constant Prices, per person employed	Ameco Data Base
Ladv	Labor force with advanced education (% of total working-age population with advanced education - short-cycle tertiary education, a bachelor's degree, a master's degree or doctoral degree)	World Bank Development Indicators
Rand	Research and development expense as a % of GDP	World Bank Development Indicators

The truth is never pure and rarely simple – Oscar Wilde

An exposition of the motives that constitute variable choice will now be performed.

Total Factor Productivity (TFP)

TFP is a measure that accounts for the application of how efficiently and effectively inputs, such as *capital and labor*, are utilized in production structures and what is their fundamental role in output(Robert Barro et al (2004)). With that being said, economic growth is not propelled by the number of inputs but also by their *quality of use* (Daron Acemoglu (2009)), more specifically the efficiency with which they are utilized. The TFP measure utilized in this paper (Ameco online database) captures both these traits (efficiency and effectiveness), as the formula below shows.

$$TFP = (E_L^{\alpha} E_K^{1-\alpha})(U_L^{\alpha} U_K^{1-\alpha}) \qquad (1.1)$$

In this formula, $E_L$and E_K represent the level of adjusted efficiency to which *capital (K) and labor(L)* are applied, and U_L and U_K their respective degree of excess capacity. The exponent α represents the weight given to each *labor (L)* metric and, concomitantly, 1- α represents the opposite symmetric weight given to each *capital (K)* metric. Economists such as Robert Solow have put emphasis on the idea that long-term economic growth can´t only depend on input accumulation, as input efficiency also plays a determinant role in economic development.

This assertion clearly positions TFP at the center of sustainable growth, making this metric differentiate between economies that innovate, improve and expand from those that solely increase their input amount. This dynamic is fundamental to advanced economies, where growth is progressively more driven by idea/knowledge-based industries and services.

Internet and Social Media Metrics

The influence of social media and of the internet on productivity is effectively a double-edged sword. On one hand, they divert attention and disrupt the flow of work, leading to decreased productivity in its misuse. On the other hand, it enables individuals and professionals to network, to share knowledge, allowing for quick information dispersion thus potentially increasing workplace productivity.

Social Media platforms allow users to collaborate and offer communication channels amongst employees, especially when distance is an imperative factor. This higher degree of connectivity improves productivity, enhancing problem-solving and idea generation. Ongoing debates exist regarding how the use of social media impacts employees´ mental health and, consequently, their productive performance.

Conversely, moderate use of social media may aid users in feeling more relaxed and in conserving their social relationships, which can be beneficial for the user´s mental health and productivity. Platforms such as LinkedIn and Twitter offer networking opportunities, which can result in higher levels of job satisfaction and productivity. It’s also noteworthy to mention that there are direct effects of social media and of the internet on businesses´ *modus operandi* (for example through branding and expanded advert)

Gross Domestic Product per Capita (GDP per capita)

GDP per capita is a measure that reflects the average economic output per individual in each region. Models developed by authors such as Robert Solow (growth models) and Paul Romer (endogenous growth theory) assert that TFP is a key metric for understanding how effectively economies apply inputs.

Increments in GDP per capita can be partially explained by a more efficient usage of inputs, a phenomenon that highlights the correlation between these two variables. This phenomenon exists because richer countries tend to invest more in technology, education and infrastructure, as they effectively increase productivity. A study conducted by Hall and Jones (Robert E. Hall et al (1999)) confirms that changes in TFP translate into differences in GDP per capita in multiple countries.

TFP factors encompass more than just quantitative inputs (labor and capital). It depicts efficiency, technological progress and the performance of institutions, all of which influence GDP per capita.

Overall, it is essential to acknowledge the bidirectional relationship between GDP per capita and TFP. On one hand GDP per capita reflects a given level of TFP. On the other hand, improvements in TFP lead to an increase in GDP per capita. This relationship fundamentally reflects a *symbiosis* between economic prosperity and productivity. Although much of the existing literature points towards a positive relationship between GDP and TFP, there are, as always, contradicting opinions that have identified inverse relationships in some regions and areas, with specific conditions.

Foreign Direct Investment (FDI) Inflows

The main mechanism by which FDI influences productivity is through the transfer of technology from one country to another. FDI often enables new machinery, technologies and productive techniques to inflow to target country, leading to increased productivity and economic growth in that country FDI also introduces superior management practices and skill development opportunities.

Foreign enterprises usually implement in the host country their international standards of management and training programs, which consequently fosters a more skilled workforce, leading to higher levels of productivity. The entry of foreign companies increases the competitiveness conditions on the domestic market, as local firms are often forced to improve efficiency and productivity in an attempt to maintain their competitive edge. This *spillover effect* usually occurs in certain local firms, driving them to improve their sectoral productivity.

By generating jobs and inflowing capital, FDI can contribute to economic growth, something that is associated with higher productivity. Increased employment usually translates into a better utilization of the labor force and, concomitantly, capital injections can lead to the modernization of equipment, tools and processes.

FDI may also boost domestic investment. The credence and financial stimulus provided by foreign investors will often incentivize local firms to invest in their operations, enhancing productivity through a competitive effect.

Age Dependency Ratio

The age dependency ratio depicts the ratio between the size of the non-working-age population (dependents) and the working-age population. A higher level of this ratio represents a larger scale of dependents, compared to those who maintain their working productive activities. This may constraint economic productivity since fewer individuals are participating in the economic circuit[30] while, conversely, more individuals rely on social support systems.

This overload on social support systems diverts financial and economic resources towards the maintenance of dependents, usually at the expense of productivity-enhancement investments. A greater level of the age dependency ratio can exert economic pressure that strains innovation and efficiency improvements in the labor force. Countries with high dependency ratios are often faced with increased public expenditure in health, pensions and other social benefits, which may translate into a higher fiscal burden (greater level of taxes) and reduced investment in areas directly related to productivity.

The dependency ratio indirectly represents labor market dynamics. This is since a lower ratio may lead to a more competitive labor market (since more individuals are effectively working and competing with each other). This can encourage firms to optimize their productivity levels to attract and retain the most skillful workers.

Trade Openness

Trade openness allows for greater market accessibility, enabling countries to specialize in producing goods and services where they have a comparative advantage, consequently enhancing efficiency and productivity in the industries where they specialize.

This higher degree of market accessibility may lead to economies of scale and more efficient resource allocation. When economies are more exposed to international markets, through trade, it often leads to the transfer of technology. Importing countries can gain access to advanced technologies, which is pivotal in enhancing their own productive circuit and productivity levels. Open trade enables foreign competition, forcing domestic companies to improve their efficiency and productivity in order to remain competitive.

This intrinsic forcing need for competition may drive innovation and optimization of resources within the domestic market. With trade openness, countries are not only limited and dependent to their domestic production capabilities, but they also gain access to different foreign products and services. This variety of products and services can increase the efficiency and productivity of domestic sectors, as they are the base inputs and technologies that will be applied to other production structures.

By maintaining commercial relationships with other countries, a given economy can learn new methods, technologies and practices, which can translate to enhanced productivity gains.

Gross National Expense (GNE) as a percentage of GDP

GNE as a percentage of GDP enables further insights into the *status quo* of economic activity and investment withing a given economy. High degree of consumption and investment usually implies a solid economic environment which can lead to higher productivity. This is because investment in infrastructure, technology and education can lead to more efficient production circuits and a more skillful workforce.

The components of GNE, such as household consumption and government expenditure, are indicators of domestic demand. A robust domestic demand can push businesses to improve their efficiency and productivity to meet this demand.

On a second note, government consumption and investment in public services and infrastructure can develop more conducive conditions for private sector productivity. Gross capital formation, which is a component of GNE, is directly related to investments in physical assets and in the latest technologies, which are fundamental drivers of productivity. Investments in machinery, technology, and infrastructure directly improve the capacity and efficiency of pure economic volume[41]. An equilibrium in the components of GNE is indicative of a healthy and sustainable economy. Overemphasis on an individual component (such as excessive consumption or investment) might lead to short-term increments in productivity but could risk long-term sustainability and growth.

Net Capital Stock per person employed

Net Capital Stock per person employed, a metric that encompasses the distribution of capital, is fundamental for understanding worker efficiency. More capital per work generally translates in access to better equipment, tools and technology, which intrinsically increases the amount of output each worker can produce.

The quality and modernity of the capital stock is highly relevant. Advanced machinery and technology enable workers to produce more sophisticated, high-value products, thereby incrementing the quality and quantity of output, which is directly linked with productivity.

Despite these previous assertions, it is imperative to state that an increase in capital per worker can necessitate higher skill levels (as workers need to re-skill or up-skill in order to be effective in using new technologies previously unknown to them), which demands that workers are more trained and educated. This symbiotic effect between the workforce´s compatibility with capital structures fuels labor productivity and impacts the labor market dynamics, leading to higher wages and improved working conditions.

On a final note, a larger net capital stock can provoke economies of scale, as the cost per unit of production decreases with an increase in scale. This may lead to more efficient production processes, decreasing costs and increasing productivity.

Labor with advanced education

Workers with advanced education possess higher-level skills, critical thinking abilities and specialized knowledge, allowing them to perform tasks more effectively, efficiently and creatively. These improvements contribute to increased productivity, as these workers can perform complex tasks, solve problems effectively and innovate.

Higher education equips individuals with the ability to adapt to new technologies, methodologies and productive processes. This adaptability is key in an ever-changing technological landscape, where the ability to learn and apply new technologies influence productivity.

Advanced education is linked with research and development (R&D) capabilities. Individuals with higher academic qualifications are usually at the forefront of R&D activities, leading to innovations that can increment processes, products and technologies, thereby causing productivity growth. Economies that have more well-educated workers are generally more diversified and robust to economic shocks.

A developed workforce can shift between sectors, assist in the growth of high-skilled industries and improve overall economic productivity.

Reseach and Developemnt (R&D) as a % of GDP

Investments in R&D fundamentally represent technological innovation. This innovation leads to the development of new products, processes and services, consequently enhancing the efficiency and quality of the productive circuit, thereby boosting overall productivity.

R&D activities also result in cultivating a highly skilled workforce adept at managing and developing these technologies. The knowledge and skill gained through R&D contributes to a more effective and productive workforce.

Constant investment in R&D provides a competitive advantage to a given economy in the global marketplace. Countries that lead in R&D investment typically have more advanced industries and a higher productivity rate since they can produce higher-value goods and services more efficiently.

R&D investments also have positive spillover effects, as its results usually and unintendedly benefit other sectors and industries, leading to a widespread increase in productivity.

3.3 Initial Regression Model – Pooled OLS

An initial estimation of the panel regression is done through the Pooled OLS method. The model takes the initial discrete form:

$$TFP_{it} = \beta_0 + \gamma_0 TFP_{i,t-1} + \beta_1 I4SMU_{it} + \beta_2 PIBpC_{it} + \beta_3 FDINFL_{it} + \beta_4 DepRatio_{it} \ \beta_5 TradeOp_{it} + \beta_6 GNEPIB_{it} + \beta_7 sKL_{it} + \beta_8 Ladv_{it} + \beta_9 Rand_{it} + du_t + \epsilon_{it} \quad (1.1)$$

Where:

- i=1,…,N (=27);
- t= 1,…,T(=9) ; factoring to a total number of observations of 243;
- TFP_{it} is the dependent variable, with its abbreviated form listed as per in Table 1;
- β_0 represents the constant term;
- γ_0 is the coefficient of the first lag of TFP for period $t-1$. Its value will be of interest in order to have the upper bound limit that sets the confidence interval for a correct estimation process of other models, as it will be explained further below.
- $\beta_1$through β_9 are the coefficients to be estimated for the explanatory variables;
- $TFP_{i,t-1}$ represents the first lag of TFP for period $t-1$ and country i and $I4SMU_{it}$ through $Rand_{it}$ represent the explanatory variables described in Table 1 for country i and time-period.
- γ_0 is the coefficient of interest of the first Lag of TFP.
- du_t are the time dummy variables, with du_{2013} having year = 2013, up through du_{2021} which has year = 2021.
- ϵ_{it} is the error term of the regression.

At this point it is important to note that given the macroeconomic data format at hand, where T (time periods/years) is smaller than N (groups/countries), a Generalized Method of Moments - GMM (dynamic panel model) estimation is a robust methodology recommended by several studies previously conducted (David Roodman, 2006; Stephen Bond, Anke Hoeffler & Jonathan Temple, 2001). This will be the approach chosen for the econometrical analysis employed.

The model can also take the following theoretical algebraic form:

$$y_{it} = \gamma_0 y_{i,t-1} + \boldsymbol{\beta} x_{it} + du_t + \epsilon_{i,t} \quad (1.2)$$

Where:

- $y_{it} = \begin{bmatrix} y_{11} & \cdots & y_{1N} \\ \vdots & \vdots & \vdots \\ y_{T1} & \cdots & y_{TN} \end{bmatrix}$ is the matrix with (T x N) observations of the dependent variable;

- γ_0 is the coefficient of interest of $y_{i,t-1}$ that will be estimated.

- $y_{i,t-1} = \begin{bmatrix} y_{2-1,1} & \cdots & y_{2-1,N} \\ \vdots & \vdots & \vdots \\ y_{T-1,1} & \cdots & y_{T-1,N} \end{bmatrix}$ is the matrix with (T-1xN) values of the lagged dependent variable inserted in the model as an explanatory variable.

- $\boldsymbol{\beta}$ are the parameter coefficients to be estimated.

- $x_{it} = \begin{bmatrix} 1 & x_{11} & \dots & x_{1N} \\ 1 & \vdots & \vdots & \vdots \\ 1 & x_{T1} & \dots & x_{TN} \end{bmatrix}$ is the matrix with T x (N + 1) observations of the explanatory variables;

- $du_t = \begin{bmatrix} du_1 \\ \vdots \\ du_T \end{bmatrix}$ is the vector of length (T) composed of the time dummy variables;

- $\epsilon_{it} = \begin{bmatrix} \epsilon_{11} & \cdots & \epsilon_{1N} \\ \vdots & \vdots & \vdots \\ \epsilon_{T1} & \cdots & \epsilon_{TN} \end{bmatrix}$ is the matrix with (T x N) random errors.

The pooled OLS method is computed through the minimization of the sum of squared residuals.

$$(1.3)\quad u_{it} = y_{it} - \hat{y}_{it}$$

Where:

- $u_{i,t}$ is vector of length T x N of residuals;
- y_{it} are the observed values of the dependent variable;
- $\hat{y}_{it}$ are the estimated values of the dependent variable.

The estimation of the Pooled OLS method amounts to minimizing the following

$$(1.4)\qquad [\sum_{t=1,i=1}^{T,I} u^2{}_{it}]$$

In this initial regression process the objective is to estimate γ_0. It will be utilized as the upper limit bound of the confidence interval that one should expect for the coefficient of $LogTFP_{i,t-1}$ when computing dynamic panel models (David Roodman, 2006; Stephen Bond, Anke Hoeffler & Jonathan Temple, 2001). In this sense:

- γ_0 – OLS (+-) > γ_0 – Difference and System Generalized Method of Moments (Bellow or close to the upper bound limit defined by OLS pooled)

3.4 Fixed-Effects Model

Let´s consider the following initial form for the Fixed-Effects model:

$$TFP_{it} = \boldsymbol{\alpha} + \beta_0 + \gamma_0 TFP_{i,t-1} + \beta_1 I4SMU_{it} + \beta_2 PIBpC_{it} + \beta_3 FDINFL_{it} + \beta_4 DepRatio_{it} \ \beta_5 TradeOp_{it} + \beta_6 GNEPIB_{it} + \beta_7 sKL_{it} + \beta_8 Ladv_{it} + \beta_9 Rand_{it} + du_t + \epsilon_{it} + v_i$$

(2.1)

Where:

- i=1,…,N (=27);
- t= 1,…,T(=9) ; factoring to a total number of observations of 243;
- TFP_{it} is the dependent variable, with its abbreviated form listed as per in Table 1;
- $\boldsymbol{\alpha}$ are the fixed individual effects.
- γ_0 is the coefficient of the first lag of TFP for period $t - 1$. Its value will be of interest in order to have the lower bound limit that sets the confidence interval for a correct estimation process of other models, as it will be explained further below.
- β_0 represents the constant term;
- $\beta_1$through β_9 are the coefficients to be estimated for the explanatory variables;
- $TFP_{i,t-1}$ represents the observations first lag of TFP for period $t-1$ and country i and $I4SMU_{it}$ through $Rand_{it}$ represent the observations explanatory variables described in Table 1 for country i and time-period t.

- du_t are the time dummy variables, with du_{2013} having year = 2013, up through du_{2021} which has year = 2021.
- ϵ_{it} is the error term of the regression.
- v_i is the unit specific error term of the regression.

The model can also take the following theoretical algebraic form:

(2.2) $$y_{it} = \boldsymbol{\alpha} + \gamma_0 y_{i,t-1} + \boldsymbol{\beta} x_{it} + du_t + \epsilon_{it} + v_i$$

Where:

- $y_{it} = [\begin{matrix} y_{11} & \cdots & y_{1N} \\ \vdots & \vdots & \vdots \\ y_{T1} & \cdots & y_{TN} \end{matrix}]$ is the vector with (T x N) observations of the dependent variable;
- $\boldsymbol{\alpha}$ are the fixed individual effects;
- $\boldsymbol{\beta}$ are the parameter coefficients to be estimated;
- γ_0 is the coefficient of interest of $y_{i,t-1}$ that will be estimated.
- $y_{i,t-1} = [\begin{matrix} y_{2-1,1} & \cdots & y_{2-1,N} \\ \vdots & \vdots & \vdots \\ y_{T-1,1} & \cdots & y_{T-1,N} \end{matrix}]$ is the matrix with (T-1xN) values of the lagged dependent variable inserted in the model as an explanatory variable.
- $x_{it} = [\begin{matrix} 1 & x_{11} & \dots & x_{1N} \\ 1 & \vdots & \vdots & \vdots \\ 1 & x_{T1} & \dots & x_{TN} \end{matrix}]$ is the matrix with T x (N + 1) observations of the explanatory variables;

- $du_t = \begin{bmatrix} du_1 \\ \vdots \\ du_T \end{bmatrix}$ is the vector of length (T) composed of the time dummy variables;

- $\epsilon_{it} = \begin{bmatrix} \epsilon_{11} & \cdots & \epsilon_{1N} \\ \vdots & \vdots & \vdots \\ \epsilon_{T1} & \cdots & \epsilon_{TN} \end{bmatrix}$ is the matrix with (T x N) random errors.

- $v_i = \begin{bmatrix} v_1 \\ \vdots \\ v_N \end{bmatrix}$ is the vector with (N) unit specific error terms.

Some algebra can be performed to obtain the equations that are necessary for the estimation process of both the Fixed Effects and Random Effects models. If the (2.2) is true, it must also be true that:

$$\bar{y}_i = \gamma_0 \bar{y}_{i,\frac{T-1}{T}} + \boldsymbol{\alpha} + \bar{x}_i \boldsymbol{\beta} + v_i + \bar{\epsilon}_i \tag{2.3}$$

where $\bar{y}_i = \sum_t y_{it} / T_i$, $\bar{y}_{i,\frac{T-1}{T}} = \sum_t y_{i,t-1} / T_i$ $\bar{x}_i = \sum_t x_{it} / T_i$, and $\bar{\epsilon}_i = \sum_t \epsilon_{it} / T_i$. When subtracting (2.3) from the (2.2) it is equally true that

$$(y_{it} - \bar{y}_i) = \gamma_0 (y_{i,t-1} - \bar{y}_{i,\frac{T-1}{T}})(x_{it} - \bar{x}_i)\boldsymbol{\beta} + (\epsilon_{it} - \bar{\epsilon}_i) + du_t \tag{2.4}$$

Equations (2.2), (2.3), and (2.4) provide the foundation for estimating $\boldsymbol{\beta}$. In the case of this paper, the Stata command *xtreg, fe* applied computes the Fixed-effects estimator (also known as the within estimator) and it essentially utilizes OLS to perform the estimation of (2.4).

It's important to note that to deal with the fixed effects the within estimation is employed, which assumes that the individual effects are correlated with the explanatory variables:

(2.5) $$Corr(\boldsymbol{\alpha}, x_{it}) \neq 0$$

In the Fixed-effects regression process the objective is to estimate γ_1. It will be utilized as the lower limit bound of the confidence interval that one should expect for the coefficient of $LogTFP_{i,t-1}$ when computing dynamic panel models (David Roodman, 2006; Stephen Bond, Anke Hoeffler & Jonathan Temple, 2001). In this sense:

- γ_0 – Fixed-Effects $<$ γ_0 – Difference and System Generalized Method of Moments.

3.5 Dynamic Panel Models - Generalized Method of Moments estimation (GMM)

3.5.1 Theoretical Framework

GMM style models are commonly used in situations where the estimation process has the following caveats:

1. The estimation process is dynamic, with current levels of the dependent variable influenced by past ones;
2. Some regressors are suspected to be endogenous.
3. The errors of the model that capture idiosyncratic disturbances may have individual-specific patterns of heteroskedasticity and serial correlation.
4. The utilization of internal instruments based on the lagged values of the dependent variables, whether in GMM-style or Instrument-Variable-style (IV) format.

These are the main details that compose the reason for choice of a dynamic panel model such as GMM. Regression equations of standard GMM models usually take the following data-generating process of estimation:

$$y_{it} = \gamma_0 y_{i,t-1} + \boldsymbol{\beta} x_{it} + du_t + \varepsilon_{it} \quad (3.1)$$

$$\varepsilon_{it} = \epsilon_{it} + n_i$$

$$E[\epsilon_{it}] = E[n_i] = E[\epsilon_{it} n_i] = 0$$

Difference-GMM utilizes the following equation to instrumentalize potential endogenous regressors (using its past realizations as instruments) and to also remove the fixed-effects (or time-invariant effects):

$$\Delta y_{it} = y_{it} - y_{i,t-1} \tag{3.2}$$

System-GMM applies the same equation first-differenced equation as Difference-GMM but also uses equations in levels to instrumentalize past levels of the regressors recursively:

$$\begin{aligned} \Delta y_{it} &= y_{i,t} - y_{i,t-1} \\ y_{i,t-1} &= y_{i,t-2} \\ x_{i,t-1} &= x_{i,t-2} \end{aligned} \tag{3.3}$$

It is highly relevant to mention that by adding time-dummy variables, as it has been done for OLS Pooled, Fixed-Effects and GMM models, the autocorrelation tests and the estimates of the coefficient standard errors assume no correlation across individuals in the idiosyncratic disturbances in the case of GMM estimations (Roodman, 2006). This justification is a robust reason as to why they have been included in the regression structure of all models.

Moreover, the coefficient γ_0 obtained in the GMM estimations must necessarily be between the following interval to have a correct model specification:

$$\gamma_0 - Fixed - Effects\ Model < \boldsymbol{\gamma_0 -} \\ \boldsymbol{Difference\ and\ System\ GMM} < (\pm)\gamma_0 - OLS\ Pooled$$

3.5.2 Difference GMM with forward orthogonal deviations

Suppose we have the following model in its concrete form:

$$TFP_{it} = \beta_0 + \gamma_0 TFP_{i,t-1} + \beta_1 I4SMU_{it} + \beta_2 PIBpC_{it} + \beta_3 FDINFL_{it} + \beta_4 DepRatio_{it} \ \beta_5 TradeOp_{it} + \beta_6 GNEPIB_{it} + \beta_7 sKL_{it} + \beta_8 Ladv_{it} + \beta_9 Rand_{it} + du_t + \epsilon_{it} + \tau n_i \quad (4.1)$$

Where:

- i=1,…,N (=27);
- t= 1,…,T(=9) ; factoring to a total number of observations of 243;
- TFP_{it} is the dependent variable, with its abbreviated form listed as per in Table 1;
- β_0 represents the constant term;
- γ_0 is the parameter coefficient of the first lag of TFP for period $t-1$.
- $\beta_1$through β_9 are the parameter coefficients to be estimated for the explanatory variables;
- $TFP_{i,t-1}$ represents the first lag of TFP for period $t-1$ and country i and $I4SMU_{it}$ through $Rand_{it}$ represent the observations explanatory variables described in Table 1 for country i and time-period.
- γ_0 is the coefficient of the past level of TFP (period t-1).
- du_t are the time dummy variables, with du_{2013} having year = 2013, up through du_{2021} which has year = 2021.
- ϵ_{it} is the error term of the regression that embody idiosyncratic shocks.

- τ is a vector of ones.
- n_i is the fixed effects or the time-invariant effect.

The model can also take the following algebraic form, which will be used to explain the estimation process of the Difference GMM method:

$$(4.2) \qquad y_{it} = \gamma_0 y_{i,t-1} + \boldsymbol{\beta} x_{it} + du_t + \epsilon_{it} + \tau n_i$$

Where:

- $y_{it} = \begin{bmatrix} y_{11} & \cdots & y_{1N} \\ \vdots & \vdots & \vdots \\ y_{T1} & \cdots & y_{TN} \end{bmatrix}$ is the vector with (T x N) observations of the dependent variable.
- $\boldsymbol{\beta}$ are the parameter coefficients to be estimated.
- γ_0 is the coefficient of interest of $y_{i,t-1}$ that will be estimated.
- $y_{i,t-1} = \begin{bmatrix} y_{2-1,1} & \cdots & y_{2-1,N} \\ \vdots & \vdots & \vdots \\ y_{T-1,1} & \cdots & y_{T-1,N} \end{bmatrix}$ is the matrix with (T-1xN) values of the lagged dependent variable inserted in the model as an explanatory variable.
- $x_{it} = \begin{bmatrix} 1 & x_{11} & \cdots & x_{1N} \\ 1 & \vdots & \vdots & \vdots \\ 1 & x_{T1} & \cdots & x_{TN} \end{bmatrix}$ is the matrix with T x (N + 1) observations of the explanatory variables;
- $du_t = \begin{bmatrix} du_1 \\ \vdots \\ du_T \end{bmatrix}$ is the vector of length (T) composed of the time dummy variables.
- $\epsilon_{it} = \begin{bmatrix} \epsilon_{11} & \cdots & \epsilon_{1N} \\ \vdots & \vdots & \vdots \\ \epsilon_{T1} & \cdots & \epsilon_{TN} \end{bmatrix}$ is the matrix with (T x N) random errors that embody idiosyncratic shocks

- $\tau = \begin{bmatrix} 1 \\ \vdots \\ 1 \end{bmatrix}$ is a vector of ones of length N.
- n_i is the unobserved time-invariant effect.

The time-invariant effect n_i is removed if one multiplies the aforementioned equation by a transformation matrix $\boldsymbol{K}$ that satisfies the condition $\boldsymbol{K}\tau = 0$. It is also important to note that if $\boldsymbol{KK}'$ is a positive definite matrix there must exist another transformation that produces the same estimator if, and only if, any instrument used in period s can be build upon the linear combination of instruments used for period t, for every $t \geq s$. The condition previously enunciated is satisfied in the case where the instruments consist of lagged predetermined variables and all available instruments are used (Arellano, 2003; Phillips, 2019a). Albeit other instrument conditions that are chosen also satisfy the instrument condition.

Theorem 1: Let z_{it} be a $k_t \times 1$ vector of instruments ($t = 1, \dots, R$). Also define the following:

$$\boldsymbol{Z}_{it} = \begin{bmatrix} z_{i1}' & 0 & \dots & 0 \\ 0 & z_{i2}' & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & z_{iR}' \end{bmatrix} \tag{4.3}$$

Let $\boldsymbol{K}$ be such that $\boldsymbol{K}\tau = 0$ and $\boldsymbol{KK}'$ is a positive definite. Consider β as the initial estimator of β and set $e_{it} = y_{it} - x_{it}\beta$. Set $\boldsymbol{F} = \boldsymbol{UK}$, where $\boldsymbol{U}$ is the upper triangular Cholesky factorization of $(\boldsymbol{KK}')^{-1}$. Next, let $\tilde{y}_{it} = \boldsymbol{K}y_{it}$, $\tilde{x}_{it} = \boldsymbol{K}x_{\boldsymbol{it}}$, and $\tilde{e}_{it} = \boldsymbol{K}e_{it}$. Also construct $\ddot{y}_{it} = \boldsymbol{F}y_{it}$, $\ddot{x}_{it} = \boldsymbol{F}x_{it}$, and $\ddot{e}_{it} = \boldsymbol{F}e_{it}$. With these equalities defined, the estimators of β can be set as:

$$\beta_K = [\textstyle\sum_{it} \tilde{x}_{it}' \boldsymbol{Z}_{it} (\sum_{it} \boldsymbol{Z}_{it}' \tilde{e}_{it}\tilde{e}_{it}' \boldsymbol{Z}_{it})^{-1} \sum_{it} \boldsymbol{Z}_{it}' \tilde{x}_{it}]^{-1} \times \sum_{it} \tilde{x}_{it}' \boldsymbol{Z}_{it} (\sum_{it} \boldsymbol{Z}_{it}' \tilde{e}_{it}\tilde{e}_{it}' \boldsymbol{Z}_{it})^{-1} \sum_{it} \boldsymbol{Z}_{it}' \tilde{y}_{it} \tag{4.4}$$

$$\beta_F = [\sum_{it} \ddot{x}'_{it} \boldsymbol{Z}_{it} (\sum_{it} \boldsymbol{Z}'_{it} \ddot{e}_{it} \ddot{e}_{it}' \boldsymbol{Z}_{it})^{-1} \sum_{it} \boldsymbol{Z}'_{it} \ddot{x}_{it}]^{-1} \times$$
$$\sum_{it} \ddot{x}'_{it} \boldsymbol{Z}_{it} (\sum_{it} \boldsymbol{Z}'_{it} \ddot{e}_{it} \ddot{e}_{it}' \boldsymbol{Z}_{it})^{-1} \sum_{it} \boldsymbol{Z}'_{it} \ddot{y}_{it} \quad (4.5)$$

$\beta_K = \beta_F$ if, and only if, every entry in z_{is} is a linear combination of entries in z_{it} .

A particular case of Theorem 1, which is of interest as it is being utilized in the estimation process of this paper, is a first-differenced GMM panel data model. In this case $\boldsymbol{K} = \boldsymbol{D}$ where:

$$(4.6) \qquad \boldsymbol{D} = \begin{bmatrix} -1 & 1 & 0 & \dots & 0 \\ 0 & -1 & 1 & \dots & 0 \\ \vdots & \vdots & \ddots & \ddots & \vdots \\ 0 & 0 & \dots & -1 & 1 \end{bmatrix}$$

Given $\boldsymbol{K} = \boldsymbol{D}$, the suitable $\boldsymbol{F}$ corresponds to the forward orthogonal deviations transformation matrix given by:

$$\boldsymbol{F} = diag\left(\left(\frac{T-1}{T}\right)^{\frac{1}{2}}, \left(\frac{T-2}{T-1}\right)^{\frac{1}{2}}, \dots, \left(\frac{1}{2}\right)^{\frac{1}{2}}\right) \times$$
$$\begin{bmatrix} 1 & -\frac{1}{T-1} & -\frac{1}{T-1} & \cdots & -\frac{1}{T-1} & -\frac{1}{T-1} & -\frac{1}{T-1} \\ 0 & 1 & -\frac{1}{T-2} & \cdots & -\frac{1}{T-2} & -\frac{1}{T-2} & -\frac{1}{T-2} \\ \vdots & \vdots & \vdots & \ddots & \vdots & \vdots & \vdots \\ 0 & 0 & 0 & \cdots & 1 & -\frac{1}{2} & -\frac{1}{2} \\ 0 & 0 & 0 & \cdots & 0 & 1 & -1 \end{bmatrix} \quad (4.7)$$

3.5.3 System GMM with forward orthogonal deviations

Suppose we have the following model in its concrete form:

$$TFP_{it} = \boldsymbol{\alpha}_0 + \gamma_0 TFP_{i,t-1} + \boldsymbol{\alpha}_1 I4SMU_{it} + \boldsymbol{\alpha}_2 PIBpC_{it} + \boldsymbol{\alpha}_3 FDINFL_{it} + \boldsymbol{\alpha}_4 DepRatio_{it} \ \boldsymbol{\alpha}_5 TradeOp_{it} + \boldsymbol{\alpha}_6 GNEPIB_{it} + \boldsymbol{\alpha}_7 sKL_{it} + \boldsymbol{\alpha}_8 Ladv_{it} + \boldsymbol{\alpha}_9 Rand_{it} + du_t + \epsilon_{it} + n_i$$

(5.1)

Where:

- i=1,…,N (=27);
- t= 1,…,T(=9) ; factoring to a total number of observations of 243;
- TFP_{it} is the dependent variable, with its abbreviated form listed as per in Table 1;
- $\boldsymbol{\alpha}_0$ represents the constant term;
- γ_0 is the parameter coefficient of the first lag of TFP for period $t-1$.
- $\boldsymbol{\alpha}_1$through $\boldsymbol{\alpha}_9$ are the parameter coefficients to be estimated for the explanatory variables;
- $TFP_{i,t-1}$ represents the first lag of TFP for period $t - 1$ and country i and $I4SMU_{it}$ through $Rand_{it}$ represent the observations explanatory variables described in Table 1 for country i and time-period.
- du_t are the time dummy variables, with du_{2013} having year = 2013, up through du_{2021} which has year = 2021.
- ϵ_{it} is the error term of the regression.
- n_i is the fixed effects, also defined as the time-invariant effect.

The model can also take the following algebraic form, which will be used to explain the estimation process of the System GMM method:

$$y_{it} = \boldsymbol{\gamma_0} y_{i,t-1} + \boldsymbol{\alpha} x_{it} + du_t + \epsilon_{it} + n_i \tag{5.2}$$

Where:

- $y_{it} = \begin{bmatrix} y_{11} & \cdots & y_{1N} \\ \vdots & \vdots & \vdots \\ y_{T1} & \cdots & y_{TN} \end{bmatrix}$ is the vector with (T x N) observations of the dependent variable;

- $\boldsymbol{\alpha}$ are the parameter coefficients to be estimated;

- $\boldsymbol{\gamma_0}$ is the coefficient of interest of $y_{i,t-1}$ that will be estimated;

- $y_{i,t-1} = \begin{bmatrix} y_{2-1,1} & \cdots & y_{2-1,N} \\ \vdots & \vdots & \vdots \\ y_{T-1,1} & \cdots & y_{T-1,N} \end{bmatrix}$ is the matrix with (T-1xN) values of the lagged dependent variable inserted in the model as an explanatory variable.

- $x_{it} = \begin{bmatrix} 1 & x_{11} & \ldots & x_{1N} \\ 1 & \vdots & \vdots & \vdots \\ 1 & x_{T1} & \ldots & x_{TN} \end{bmatrix}$ is the matrix with T x (N + 1) observations of the explanatory variables;

- $du_t = \begin{bmatrix} du_1 \\ \vdots \\ du_T \end{bmatrix}$ is the vector of length (T) composed of the time dummy variables;

- $\epsilon_{it} = \begin{bmatrix} \epsilon_{11} & \cdots & \epsilon_{1N} \\ \vdots & \vdots & \vdots \\ \epsilon_{T1} & \cdots & \epsilon_{TN} \end{bmatrix}$ is the matrix with (T x N) random errors;

- n_i is the unobserved time-invariant effect.

When suitable conditions are met, $\beta = (\boldsymbol{\gamma_0}, \boldsymbol{\alpha}')'$ can be computed with the system GMM estimator (Arellano and Bover, 1995; Blundell and Bond, 1998). In order to define the aforementioned estimator, assume $\boldsymbol{y_i} = (y_{i1}, \ldots, y_{iT})'$ and that $\boldsymbol{X_{it}}$ is a $(t \times K)$ matrix, with $(y_{i,t-1}, x'_{it})$ in its tth row $(t = 1, \ldots, T)$. Afterwards, define $\boldsymbol{y}^+_{it} = (y'_{it}\, y'_{it})'$ and $\boldsymbol{X}^+_{it} = (\boldsymbol{X}'_{it}\, \boldsymbol{X}'_{it})'$.

The system GMM estimator consists of differencing the observations of the first T rows in $\boldsymbol{y}_{it}^{+}$ and $\boldsymbol{X}_{it}^{+}$. Consequently, its utilizes the transformed data $\tilde{\boldsymbol{y}}_{it}^{+} = \boldsymbol{K}^{+}\boldsymbol{y}_{i}^{+}$ and $\tilde{\boldsymbol{X}}_{it}^{+} = \boldsymbol{K}^{+}\boldsymbol{X}_{it}^{+}$ $(i = 1, \dots, N)$, where:

$$\boldsymbol{K}^{+} = \begin{pmatrix} \boldsymbol{D} & 0 \\ 0 & \boldsymbol{I} \end{pmatrix} \tag{5.3}$$

To define the instrument matrix, let $\boldsymbol{Z}_{i1}$ and $\boldsymbol{Z}_{i2}$ be block-diagonal instrument matrices, where $\boldsymbol{Z}_{i1}$ has $1 \times k_t$ instrument vector z'_{it} in its tth diagonal block $(t = 1, \dots, T-1)$ and $\boldsymbol{Z}_{i2}$ has $x'_{i1} - x'_{i0}$ in its first diagonal block and $(y_{i,t-1} - y_{i,t-2}, x'_{it} - x'_{i,t-1})$ in diagonal blocks $t = 2, \dots, T$. Afterwards, define:

$$\boldsymbol{Z}_{i}^{+} = \begin{pmatrix} \boldsymbol{Z}_{i1} & 0 \\ 0 & \boldsymbol{Z}_{i2} \end{pmatrix} \tag{5.4}$$

By structuring and applying the transformation matrix and the preceding notation, the System GMM estimator can be expressed as:

$$\beta_{K+} = \left[\sum_{it} \boldsymbol{X}_{it}^{+\prime}\boldsymbol{Z}_{it}^{+} \left(\sum_{it} \boldsymbol{Z}_{it}^{+} \tilde{e}_{it}^{+}\tilde{e}_{it}^{+\prime}\boldsymbol{Z}_{it}\right)^{-1} \sum_{it} \boldsymbol{Z}_{it}^{+\prime} \boldsymbol{X}_{it}^{+}\right]^{-1} \times \sum_{it} \boldsymbol{X}_{it}^{+\prime}\boldsymbol{Z}_{it}^{+} \left(\sum_{it} \boldsymbol{Z}_{it}^{+\prime} \tilde{e}_{it}^{+}\tilde{e}_{it}^{+\prime}\boldsymbol{Z}_{it}^{+}\right)^{-1} \sum_{it} \boldsymbol{Z}_{it}^{+\prime} \tilde{\boldsymbol{y}}_{it}^{+} \tag{5.5}$$

Where $\tilde{e}_{it}^{+} = \tilde{\boldsymbol{y}}_{it}^{+} - \boldsymbol{X}_{it}^{+}\beta$ $(i = 1, \dots, N; t = 1, \dots, T)$ and β is the initial estimator of β. Conversely, if the system GMM estimator can be compiled using forward orthogonal deviations rather than first differences. In this case of interest, the transformation matrix is:

$$\boldsymbol{F}^{+} = \begin{pmatrix} \boldsymbol{F} & 0 \\ 0 & \boldsymbol{I} \end{pmatrix} \tag{5.6}$$

Where $\boldsymbol{F}$ is the forward orthogonal deviations transformation matrix given by equation (4.7). Now define $\ddot{\boldsymbol{y}}^{+}_{it} = \boldsymbol{F}^{+}\boldsymbol{y}^{+}_{it}$ and $\ddot{\boldsymbol{X}}^{+}_{it} = \boldsymbol{F}^{+}\boldsymbol{X}^{+}_{i}$, with $(i = 1, \dots N; t = 1, \dots, T)$. From here, set the forward orthogonal deviations estimator as:

$$(5.7)\beta_{F+} = [\sum_{it} \boldsymbol{X}^{+'}_{it}\boldsymbol{Z}^{+}_{it} (\sum_{it} \boldsymbol{Z}^{+'}_{it} \ddot{e}_{it}{}^{+}\ddot{e}_{it}{}^{+'}\boldsymbol{Z}^{+}_{it})^{-1} \sum_{it} \boldsymbol{Z}^{+'}_{it} \ddot{\boldsymbol{X}}^{+'}_{it}]^{-1} \times$$
$$\sum_{it} \boldsymbol{X}^{+'}_{it}\boldsymbol{Z}^{+}_{it} (\sum_{it} \boldsymbol{Z}^{+'}_{it} \ddot{e}_{it}{}^{+'}\ddot{e}_{it}{}^{+}\boldsymbol{Z}^{+}_{it})^{-1} \sum_{it} \boldsymbol{Z}^{+'}_{it} \ddot{\boldsymbol{y}}^{+}_{it}$$

Where $\ddot{e}_{it}{}^{+} = \ddot{\boldsymbol{y}}^{+}_{it} - \ddot{\boldsymbol{X}}^{+}_{it}\beta$.

With the conclusion of the mathematics now completed, it is fundamental to say that during the estimation and computation phases of these models, Difference GMM versions of the models were far from the acceptance criteria of tests and their metrics, hence System GMM is the model approach from where results, conclusions and their interpretations will be performed.

3.6 Statistical and Estimation Tests/Metrics

The following tests will be used to determine model validity:

<u>Variance Inflation Factor (VIF)</u>

- Hypothesis: The hypothesis is not explicitly tested in a VIF analysis but focuses on multicollinearity detection.
- Null Hypothesis (H0): There is no multicollinearity (VIF close to 1).
- Alternative Hypothesis (H1): There is multicollinearity (VIF significantly greater than 1).
- Equation: $VIF = 11 - Rj2VIF\ = \backslash frac\{1\}\{1\ -\ R\_j\hat{}2\}VIF = 1 - Rj21$
- High VIF values (typically > 10) indicate strong multicollinearity, suggesting potential issues with the regression coefficients.

<u>t-Test</u>

- Hypothesis: The test checks if the sample mean is significantly different from a known population mean.
- Null Hypothesis (H0): The sample mean is equal to the population mean.
- ($\mu = \mu 0 \backslash mu\ = \backslash mu\_0\mu = \mu 0$).
- Alternative Hypothesis (H1): The sample mean is not equal to the population mean.
- ($\mu \neq \mu 0 \backslash mu\ \backslash neq\ \backslash mu\_0\mu\ \ = \mu 0$).
- Equation: $t = X^{-} - \mu 0 snt\ = \backslash frac\{\backslash bar\{X\}\ - \backslash mu\_0\}\{\backslash frac\{s\}\{\backslash sqrt\{n\}\}\}t = nsX^{-} - \mu 0\ where\ X^{-}\backslash bar\{X\}X^{-}$ is the sample mean, $\mu 0 \backslash mu\_0\mu 0$ is the population mean, sss is the sample standard deviation, and nnn is the sample size.

Sargan Test

- Hypothesis: The test evaluates the validity of instruments used in instrumental variable estimation.
- Null Hypothesis (H0): The instruments are valid, meaning they are uncorrelated with the error terms.
- Alternative Hypothesis (H1): At least one of the instruments is invalid, meaning it is correlated with the error term.
- Equation: $J = n \cdot R2J = n \backslash cdot\ R\hat{}2J = n \cdot R2\ where\ R2R\hat{}2R2$ comes from the regression of the residuals on the instruments. A significant JJJ-value suggests some instruments are invalid.

Hansen Test

- Hypothesis: The test is similar to the Sargan test but is robust to heteroskedasticity.
- Null Hypothesis (H0): All instruments are valid.
- Alternative Hypothesis (H1): Some instruments are invalid.
- Equation: The test statistic is calculated similarly to the Sargan test and is compared to a chi-squared distribution. A high value indicates potential instrument problems.

Arellano-Bond Test

- Hypothesis: The test checks for autocorrelation in the residuals of dynamic panel models.
- Null Hypothesis (H0): There is no autocorrelation in the errors of the differenced model.
- Alternative Hypothesis (H1): There is autocorrelation in the errors of the differenced model.

- Equation: The test looks at the AR (1) and AR(2) statistics for first-order and second-order serial correlation in the residuals. The absence of second-order autocorrelation ($AR(2)AR(2)AR(2)$) is crucial for the consistency of the model.

“Our necessities are few, but our wants are endless.” – George Bernard Shaw

The difficulty lies not so much in developing new ideas as in escaping from old ones.” John Maynard Keynes

Section 4 – Results Interpretation and analysis

Table 1 – Initial Regression Table

*** p<.01, ** p<.05, * p<.1

1. Variable	Coefficients of Initial Model (with t-Test)
L.TFP	*1.002****
SMAM	*+-0*
I4SMU	*n/a*
IDIFU	*n/a*
FDInflow	*-0.003*
GNEPIB	*-0.024*
DepRatio	*-0.022*
sKL	*-0.001*
Ladv	*0.081**
TradeOP	*-0.004*
PIBpC	*0.003*
Rand	*-0.321*
D_2015	*0.722*
D_2016	*0.139*
D_2017	*1.317***
D_2018	*0.305*
D_2019	*0.32*
D_2020	*-0.1857***
Constant	*-3.218*

R-Squared	F-Test p-value	Number of observations
0.803	0.000	182

In this initial OLS pooled regression, the main objective is to determine and identify the values for certain coefficients, with the coefficient of the lag of TFP being of main interest.

For example, the lag of TFP (L.TFP) is individually statistically significant, with its coefficient being 1.002. That means that for an increase of one unit the TFP in (t-1) corresponds to an increase of 1.002 in TFP in (t).

Ladv is also statistically significant, albeit in a weaker state than L.TFP, in the t-Test metric. The interpretation of this is that for an increase of one unit in the % of the number of individuals with higher education over working population, corresponds to an increase of 0.081 in TFP. This is consistent with the expectations previously set.

On a final note, dummy variables 2017 and 2020 are statistically significant at an individual level, positively and negatively respectively. 2020's decrease in productivity may be due to the Covid-19 pandemic, that constrained productivity of individuals and enterprises alike, on the EU-27 level. The constant term is unsignificant. This initial version of the model, with only SMAM (there may be correlation issues between this variable and I4SMU and IDFIU, thus these were excluded) has a purpose of identifying important relationships and to view, through the VIF test, if there are issues of multicollinearity. As seen below, in Table 2, there are severe multicollinearity issues between PIBpC and sKL. This implies that the models that are going to be exposed afterwards have to be fractured into one with skL (excluding PIBpC), and another with PIBpC (excluding sKL). Its also important to note that in some cases the variable coefficient is so small that the Stata output presents it as zero, which happens in some variable states (presented as "**+-0"**).

Table 2- Variance inflation factor

	VIF	1/VIF
PIBpC	**177.87**	**.006**
sKL	**175.838**	**.006**
TradeOp	6.382	.157
GNEPIB	4.392	.228
dummy 2020	3.081	.325
dummy 2019	2.736	.366
dummy 2018	2.426	.412
L.TFP	2.247	.445
DepRatio	2.114	.473
dummy 2017	1.985	.504
dummy 2016	1.852	.54
Rand	1.795	.557
SMAM	1.771	.565
dummy 2015	1.736	.576
Ladv	1.387	.721
FDInflow	1.187	.842
Mean VIF	24.3	.

The model's index is as follows:

- Model 3 studies and analyzes SMAM with skL
- Model 4 studies and analyzes SMAM with PIBpC
- Model 5 studies and analyzes IDFIU with sKL
- Model 6 studies and analyzes IDFIU with PIBpC
- Model 7 studies and analyzes I4SMU with sKL
- Model 8 studies and analyzes I4SMU with PIBpC

The tables below will be aggregated by their type. That means that Table 3-A will have the results of OLS Pooled for Model versions 3,4,5,6,7 and 8. Table 4-C will have the results of the Fixed-Effects model versions 3,4,5,6,7 and 8. And, at last, Table 5-C will have the results of the GMM-FOD for versions 3,4,5,6,7 and 8.

Only dummy variables that are statistically significant will be included in the tables, with the irrelevant ones excluded.

It's noteworthy to mention that the regression process done in Stata excludes, from time to time, at least one dummy variable due to collinearity issues.

This limits the analysis, yet nothing could be done to prevent it, as it reinforces the model's structural validity. On a final note, in GMM-FOD estimations, there is usually one group that is excluded from the estimation and data generation process.

This happens because omitting a group and or using deviations from means aids in handling fixed effects. It also occurs because excluding one group avoids dummy variable traps and ensures proper model specifications.

Table 3 (A) – OLS Pooled Results

[* p<.01; ** p<.05; * p<.1] ----> (t-Test)**

Variable	**3 (A)Coeff.**	**4(A)Coeff.**	**5(A)Coeff.**	**6(A)Coeff.**	**7(A)Coeff.**	**8(A)Coeff.**
L.TFP	***1.01****	***1.01****	***1.023***	***1.022****	***1.02****	***1.019****
SMAM	***-0.00000000493**	***-0.00000000494**	*n/a*	*n/a*	*n/a*	*n/a*
I4SMU	n/a	*n/a*	*n/a*	*n/a*	***-0.038**	***-0.039**
IDIFU	n/a	*n/a*	***-0.046***	***-0.046***	*n/a*	*n/a*
FDInflow	*-0.003*	*-0.003*	*-0.001*	*-0.001*	*-0.002*	*0.002*
GNEPIB	-0.021	*-0.021*	*-0.016*	*-0.016*	*0.018*	*0.018*
DepRatio	*0.18*	*0.018*	0.042	*0.042*	*0.029*	*0.03*
sKL	*+-0*	*n/a*	+-0	*n/a*	*+-0*	*n/a*
Ladv	*0.069*	*0.71*	***0.093****	*0.094*	***0.107****	*0.11***
TradeOP	*-0.003*	*-0.003*	*0.003*	*0.003*	*0.004*	*0.004*
PIBpC	*n/a*	*+-0*	*n/a*	*+-0*	*n/a*	*+-0*
Rand	***-0,378**	***-0.377**	*0.027*	*0.029*	*-0.178*	*-0.17*
D_2017	***1.354****	***1.353****	***1.577*****	***1.576*****	***1.583****	***1.584****
D_2020	***-1.885****	***-1.884***	***-1.454**	***-1.452**	***-1.497**	***-1.486**

There are important details that will be dissected from the results of Table A. Again, it's noteworthy to mention that Rand (Research and development expense as a % of GDP) is individually, and statistically significant, related negatively to TFP in a couple of model versions. This may be due to R&D investments having a weaker impact on productivity when compared to other regions, something that explicitly shows negative effects due to inefficiencies and structural issues in innovation in the European Union and EU-27. The coefficient of the L.TFP is always positively, individually statistically significant, varying between [1.01:1.023]. This implies that TFP in (t-1) period is recursively and consecutively contributing to TFP in period (t). An increase of one unit in the L.TFP index corresponds to an increase of [1.01:1.023] units in TFP (period (t)). This interval will serve as the *upper bound limit criterion when selecting a GMM-FOD model*. An explanation as to why this recursive positive relationship exists will be performed later.

Secondly, all three social media and internet metrics are individually statistically significant (albeit at different p-value thresholds). An increase of one hour of social media consumed per year (SMAM)* corresponds to a decrease of [-0.00000000493: -0.00000000494**]** units in TFP. An increase of one unit, in percentage terms, in the number of people that utilize social media daily (I4SMU) ***** corresponds to a decrease of [-0.038: -0.039] units in TFP. Thirdly, an increase of one unit, in percentage terms, of the individuals that consume internet on a daily frequent basis (IDFIU)** translates into a decrease of -0.046 units in TFP. This occurs, as it was referred in the literature review section, due to decreased productivity levels mainly offspringing from interruptions and distractions, increased stress levels, information overload and mental health issues associated with its compulsive/impulsive use. Dummy variables of 2017 and 2020 are statistically relevant, individually, again. 2017 may be attributed to EU-27's economic recovery, its labor market improvements and its interconnection to the global economic environment. whilst 2020 is again, most probably, provoked by the Covid-19 pandemic.

Table 4 (B) – Fixed-Effects Results

***** p<.01; ** p<.05; * p<.1] ----> (t-Test)**

Variable	3 (B)Coeff.	4(B)Coeff.	5(B)Coeff.	6(B)Coeff.	7(B)Coeff.	8(B)Coeff.
L.TFP	***0.659******	**0.669*****	***0.65******	***0.658******	***0.666******	***0.675******
SMAM	*-0.00000000102*	*-0.000000000797*	*n/a*	*n/a*	*n/a*	*n/a*
I4SMU	*n/a*	*n/a*	*n/a*	*n/a*	***-0.015***	***-0.011***
IDIFU	*n/a*	*n/a*	***0.014***	***0.021***	*n/a*	*n/a*
FDInflow	*-0.001*	-0.001	-0.001	+-0	-0.001	-0.001
GNEPIB	***-0.285******	**-0.303*****	**-0.286*****	**-0.305*****	**0.288*****	-0.306
DepRatio	***0.843******	**0.82*****	**0.845*****	0.818***	**-0.848*****	0.823
sKL	*0.001*	*n/a*	0.001	*n/a*	0.001	n/a
Ladv	*0.082*	.083	0.123	.118	0.115	0.108
TradeOP	*0.016*	.021	0.018	.023	0.017	0.023
PIBpC	*n/a*	.003	*n/a*	*n/a*	n/a	0.003
Rand	*0.891*	0.846	*0.776*	0.725	.905	*0.853*
D_2014:D_2019	***(2.988; 3.412; 2.470; 3.573; 2.9; 2.611)******	***(3.034; 3.428; 2.245; 3.504; 2.802; 2.498)******	**(3.298; 3.651; 2.641; 3.669; 2.951;2.618)*****	**(3.395; 3.708; 2.644; 3.626; 2.877; 2.512) *****	***(2.985; 3.407; 2.462; 3.548; 2.85; 2.565)******	**(3.04; 3.43; 2.439; 3.485; 2.764; 2.461)*****

The Fixed-Effects models consistently display that both social media and the internet consumption variables are not statistically significant at any level. This may be indicative of their weak influence, in particular cases (due also to model specification), on TFP.

Apart from these variables of interest, Gross Nation Expense as a percentage of GDP appears to have a negative individual statistical significance, at the 0.01 p-value level ***(***)***, on TFP. This may be due to a big format government, associated to higher public expenditure, that usually leads to insufficiencies and inefficiencies in the allocation of resources (ECB Working Paper Series). DepRatio (Age-Dependency-Ratio) is found to have a statistically positive relationship with TFP, at the 0.01 p-value threshold ***(***)***. This may be due to the phenomenon through which an aging or younger workforce, beyond the limits of the 15-64 age interval, can provide experience and skills that are not present in the traditional, and common, age interval.

Now onto the results obtained of the dummy variables from 2014 to 2019. They are individually statistically significant ***(***)***, with a positive relationship with TFP. This is due to technological advancements, structural reforms implemented as well as investment in human capital Finally, the lag of TFP does, once again, recursively and consecutively impact positively, at a statistically significant level, TFP in the present. This phenomenon is mainly due to historical productivity trends impacting future productivity levels through reforms and digital revolutions as technology adoption and industry development.

60. ***"Public expenditure and growth: The role of government size and quality. ECB working paper No. 2084;*** this paper explores themes like crowding out effects that disperse private sector investment leading to smaller levels of capital being applied and used in private enterprises in their investments, lessening productivity-enhancing activities.
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Table 5(C) – System GMM-FOD **[*** p<.01; ** p<.05; * p<.1] ----> (t-Test)]**

Variable	**3 (C)Coef.**	**4(C)Coeff.**	**5(C)Coeff.**	**6(C)Coeff.**	**7(C)Coeff.**	**8(C)Coeff.**
L.TFP	***1.039****	**1.0365*****	***0.936****	***1.042****	***1.22****	***1.166****
SMAM	***-0.00000000493****	***-0.00000000494****	*n/a*	*n/a*	*n/a*	*n/a*
I4SMU	*n/a*	*n/a*	*n/a*	*n/a*	***-0.164****	***-0.199****
IDIFU	*n/a*	*n/a*	***-0.159***	***-0.214****	*n/a*	*n/a*
FDInflow	-.0003	0.017	-0.008	**-0.011***	0.21	0.013
GNEPIB	-0.248	0.268	*0.332*	-0.58	**0.224*****	***0.226****
DepRatio	-0.055	0.144	0.331	0.367	**-0.34*****	*-0.268*
sKL	+-0	*n/a*	+-0	*n/a*	*+-0*	n/a
Ladv	0.014	0.134	.213	*0.237*	*n/a*	**0.267*****
TradeOP	**-0.069***	.04	***0.051****	*0.031*	0.018	0.019
PIBpC	*n/a*	*+-0*	*n/a*	*+-0*	n/a	0.001
Rand	-1.045	-1.055	1.236	*1.308*	*1.596*	*1.858*
D_2015; D_2017; D_2018; D_2019	***(0.903**; 1.903***; 1.58*; n/a)***	***(0.9**; 1.891***; 1.578*; n/a)***	**(1.103*; 2.111*; n/a; n/a)**	**(1.193**; 2.079***; n/a; n/a)**	***(1.228**; 3.174***; n/a; n/a)***	**(1.404**; 3.371***; 2.445*; 2.423*)**
Sargan Test	***0.045*****	***0.039*****	**0.962**	**0.911**	***0.978***	**0.974**
Hansen Test	***0.781***	***0.768***	**0.781**	**0.880**	***0.901***	**0.877**
Hansen Difference Test	***0.781***	***0.768***	**n/a**	**0.880**	***0.901***	**0.877**
AR (2)	***0.537***	***0.535***	**0.690**	**0.659**	***0.534***	**0.568**
Nº of instruments	***22***	***22***	**19**	**22**	***19***	**20**
Nº of groups	***26***	***26***	**26**	**26**	***26***	**26**

Tests and model specification

Models 5-A and 6-A fail the Sargan test of overidentification of instruments, yet in the both the Hansen Test and Hansen Difference test (which are robust to Heteroskedasticity, to autocorrelation and to misspecification of the error distribution) all models pass the test, which ensures the correctness of model specification.

In the AR (2) test all models pass the test, which fundamentally means that there is no serial correlation of error terms of order 2, reinforcing model specification and validity. Continuing the specification analysis, in every model version in Table 5, the number of instruments is lower than the number of groups. This statistical phenomenon is fundamental as it ensures that there is no overfitting, no existence of weak instruments and no biased estimates of the models at hand[70].Finally, the coefficients of L.TFP are quite close to the upper bound limit set by the L.TFP coefficient of the OLS Pooled models, which, according to David Roodman's approach in *"How to Do xtabond2"* and *"GMM Estimation of Empirical Growth Models"* ,by Stephen Bond (et al. 2001) is a condition that by itself is enough for model approval (tests performed are also within reasonable and acceptable conditions).

Social media and Internet consumption variables

In all models versions ,3(C) to 8 (C), social media and Internet consumption variables are statistically significant at an individual level. The examination of their relevance, and its bibliographic support will now commence. Firstly, SMAM (the number of days-24 hours; consumed annually of social media by EU-27 countries) has a negative coefficient, between [-0.00000000493*; -0.00000000494*] (3(C) and 4(C)). This roughly translates to saying that for each increment of one day that a given population of a country of EU-27 consumes of social media, there is a decrease of [-0.00000000493; -0.00000000494] of TFP. As for I4SMU (% of a given EU-27 population that utilizes social media frequently) it has a negative coefficient, statistically significant.

This coefficient levels, and the relationship that it conveys, translates to saying that for each one more percentual unit of a given EU-27 population that consumes social media, there is a decrease of [-0.164*** ; -0.199***] in TFP.

Thirdly, IDFIU (% of a given EU-27 population that utilizes the internet frequently on a daily basis) has a statistically significant, negative coefficient. This analytical segment means that for each one more percentual unit of a given EU-27 population that utilizes the internet frequently, on a daily basis, there is a decrease of around 0.214** in TFP.

These results are consistent with a part of the literature review that supported the argument that social media and the internet's misuse outweighs the business and production advantages that it brings. This is mainly because of how social media and the internet divert attention and create constant interruptions, decreasing productivity due to forced multitasking and distractions.

Social media and the internet have a dual impact, some of which are positive and some negative. While it improves communication and knowledge sharing, it reduces productivity due to procrastination and increases stress levels.

Control and dummy variables

Regarding control and dummy variables, there are several cases of interest. Firstly, in the case of FDInflow (Foreign Direct Investment Inflows as a % of GDP), the variable has a negative coefficient, statistically significant* at the 0.01 p-value threshold. Its coefficient implies that for an increment of a unit in the Foreign Direct Investment Inflows as a % of GDP there is a decrease of 0.011* of TFP. As previously mentioned in the literature review, there is the expectation that FDInflow impacts positively TFP. The results point towards the opposite rational, for EU-27 countries, between 2013 and 2021. A study from the ECB (https://www.ecb.europa.eu/press/economicbulletin/articles/2018/html/ecb.ebart20180401.en.html))highlights these mixed effects, emphasizing the fact that FDInflows can lead to negative productivity outcomes due to the misallocation of capital, financial and human capital and also because of market saturation.

In the case of GNEPIB (Gross National Expense as a % of GDP), a positive, statistically significant coefficient, is obtained through the estimates obtained. An increase of one unit of GNEPIB roughly translates into an increment of 0.224/0.226*** in TFP. This estimation evidence found can be supported by a plethora of studies performed in the past. For example, in a paper formulated through and by the European Comission[75] ,it is argued that public spending that leads to human capital development and R&D, which increments productivity, in the short and long-run. Through infrastructure investment and crowding-In Effect (the stimulation of private investment through effective and cohesive public spending; improves business environment), higher levels of productivity are obtained.

As for Age-Dependency-Ratio (ratio of dependents--people younger than 15 or older than 64--to the working-age population--those ages 15-64) the estimates contrast with previous ones. It has a positive coefficient, that is statistically significant*****.** Taking into account the coefficient of DepRatio, it roughly translates into saying that an increase in the ratio of dependents over the workforce in one unit (whether by an increase of dependents or decrease of the workforce) corresponds to a decrease of around -0.34*** in TFP.

This occurs because of a panoply of reasons, that can be found and were already studied before. An increase in this ratio is linked to decreases in GDP, that are adjacent to decreases in labor force participation and productivity; mainly due to the fact that older workers tend to be less productive (Maestas, N., Mullen, K. J., & Powell, D. (2016).). A study was conducted with evidence from Panel Data and it shows age-dependency ratio is associated with relevant and significant declines in TFP growth (Aksoy, Y., Basso, H. S., Smith, R. P., & Grasl, T. (2019)). Reduced labor force, lower innovation and technological adoption and *instruction*, increased fiscal burden and capital dilution are also some reasonable circumstances that lead to the decrease of TFP, tied to DepRatio.

Next up, there is Ladv (% of total working-age population with advanced education - short-cycle tertiary education, a bachelor's degree, a master's degree or doctoral degree), which has a positive and statistically significant coefficient. An increase in a percentual unit in the working-age population with advanced education translates into an increase of 0.267*** units on the TFP index. A study performed in China (Liu, J., & Bi, C. (2019)) showed that higher levels of education lead to positive TFP spillover effects. Fundamentally speaking, higher levels of education improve human capital and enable technological adoption and innovation, which boost TFP growth.

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At last observations will be made regarding the dummy variable results. Dummies from 2015, 2017,2018 and 2019 were considered as statistically relevant and significant. During these years, the EU emphasized its investments in innovation and digitalization (in programs such as Horizon 2020); performed structural reforms that aimed at enhancing labor market efficiency and reducing bureaucracy, facilitating the allocation of resources and boosting TFP; and finally EU was in a period of economic recovery after the Eurozone crisis, from which a increment in demand led to economies of scale and improved productivity.

Section 5 – Conclusion

The final section is at hand. In part, the results obtained through a Generalized Method of Moments with Forward Orthogonal Deviations, applied to EU-27 countries, from 2013 to 2021, can be partially considered as a minute answer to the Modern Productivity Paradox (in the EU, at least).

From the hypothesis formulated in the literature review (and within the realms of its set expectations), it can be affirmed, without perfect exemption, that the harmful effects of the internet and of social media outweigh the positive professional, productive and personal ones. As collected in the literature review, the mental health effects of the overuse of internet and social media lead to a bigger productivity decrease than that of the positive productive benefits of them, at least for a relevant amount of EU-27's population.

This thesis aims to pave the way for other social and hard scientists to better understand and study the viral phenomenon that is the internet, social media and potentially AI. This paper fundamentally believes that AI can change the world for the better, if its instruction is properly done at all educational levels and throughout all ludic-educational institutions.

As presented in the literature review, the decision circle can be a form for a better understanding of how products, their derivatives and the industries that they constitute, impact the status quo; technological instruction is perhaps one of the most important issues to tackle in the 21st century.

Regarding the modern productivity paradox it can be stated, with partial confidence, that it is the **technological mis instructions** of **the internet and social media that lead to oddly proportional returns of internet, social media and AI input/output productivity use. This fundamentally occurs possibly because there are more negative derivative uses and ideas sprung from the internet and social media than good and positive ones.**

Albeit from all the evidence provided throughout this study, there are limitations. First, data is limited from 2013 until 2021, not capturing more contemporaneous trends in social media, internet and AI use. Secondly, it is only based on a small amount of 244 observations, with some variables even having non-existent values for some years (when GMM is applied to low samples, biased results may occur). Lastly, the estimation process (GMM) applied tends to be slightly biased given the small number of observations. Despite this, the authors of this thesis do believe that there are important conclusions that can be derived from the econometrical study performed.

To conclude, and to quote Chamath Palihapitiya (former executive and vice-president of user growth at Facebook/Meta) the internet and social media are a “a global problem. It is eroding the core foundations of how people behave by and between each other”. It is even stated, in this article, that “Social media companies have faced increased scrutiny over the past years as critics increasingly link growing political divisions across the globe to the handful of platforms that dominate online discourse.”

Fundamentally, this thesis hopes to be yet another spark in the pursuit of academical and scientific studies that analyze the nuclei phenomena that is the internet and its derivatives. There are studies that link productivity to happiness (and vice-versa) (Oswald, Andrew J.; Proto, Eugenio; Sgroi, Daniel (2009)), hence a puzzling question can be posed to humanity, at least of all Europeans: are all of us, collectively, and at least at the EU-27 level, more productive, and happier, in efficient and real terms, given the resources available now, than we were 10 years ago? These are the base expectations that this paper aims to pave the way for further discussion regarding human civilization and its condition in the 21st century.

This paper does not aim to shame, guilt or attribute direct responsibility either to social media and internet bureaucrats nor to its users, but it rather aims to stimulate a more open and trustworthy relationship between, and within, both. Essentially, this thesis aims to inspire more analysis of the topic and enhance true connections between people, no matter the receiving or giving end of the spectrum.

“It’s going to be interesting to see how society deals with artificial intelligence, but it will definitely be cool” – Colin Angle

A coisa mais dura é saber com algum detalhe a realidade da ignorância – Lewis Thomas

Section-6
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