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Mobile internet consumption: evolution and predictors of usage. The case of NOS *Comunicações SA*

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MOBILE INTERNET CONSUMPTION: EVOLUTION AND PREDICTORS OF USAGE. THE CASE OF NOS *COMUNICAÇÕES SA*

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RESUMO

Nos últimos anos a sociedade enfrentou mudanças verdadeiramente disruptivas. O progresso tecnológico veio influenciar os mercados e a sociedade como um todo, originando um novo paradigma marcado por elevados níveis de dinamismo. Com esta revolução tecnológica, foram surgindo novos produtos e serviços que, nos dias de hoje, são percecionados por muitos como uma verdadeira necessidade, contrariando o carácter de entretenimento e informação que esteve na origem da sua criação.

A indústria das telecomunicações, caracterizada pela sua saturação e elevados níveis de competitividade, surge como o principal facilitador do progresso tecnológico. Perante uma sociedade mais conectada do que nunca, a monetização dos consumos de internet assume um papel crítico no planeamento estratégico.

Este estudo foi desenvolvido com base numa experiência profissional da NOS Comunicações SA, uma das empresas líderes no mercado das telecomunicações em Portugal. O estudo foi motivado pela necessidade de uma melhor compreensão dos padrões de consumo para (1) definir a relação desta variável com possíveis preditores do consumo e (2) estudar o grau de complementaridade ou substituição que existe entre os serviços de internet móvel e outros serviços providenciados pelos operadores, como é o caso de SMS e serviços de voz. Os resultados mostram que utilizadores mais novos, com mais capacidades tecnológicas e com maior rendimento disponível são mais propensos a ter um consumo médio de internet superior. Adicionalmente, compararam-se os níveis de consumo de internet em 5G e em 4G de forma a estudar se esta inovação tecnológica se traduz num aumento do consumo de dados. Concluiu-se que não existe um efeito claro e significativo do 5G, contrariamente a algumas conclusões sugeridas por outros operadores e fabricantes. Relativamente à relação entre o consumo de internet móvel e os restantes serviços, foi observado um efeito de complementaridade, contudo a reduzida magnitude deixa dúvidas relativamente ao seu verdadeiro efeito.

Palavras-chaves: 5G, Quinta Geração, Telecomunicações, Conectividade, First-mover advantage, Network industry

ABSTRACT

In the past few years society has faced remarkable changes. Technological progress has influenced markets and society, giving rise to a new paradigm marked by high levels of dynamism. With this technological revolution, new products and services emerged which are now perceived by many as a true necessity, contradicting the entertainment and information character that was at the origin of their creation.

The telecommunications industry, characterized by its saturation and high levels of competitiveness, emerges as the main facilitator of technological progress. With a modern society that is more connected than ever, the monetization of internet consumption assumes a critical role in company's strategic planning.

This study was developed based on the professional experience at NOS *Comunicações SA*, one of the leading companies in the telecommunications market in Portugal. The study was motivated by the need for a better understanding of internet consumption patterns to (1) define the relationship of this variable with possible predictors of usage and (2) study the degree of complementarity or substitution that exists between internet services and other services provided by operators, such as SMS and voice services. The results show that younger users, with digital skills and with higher disposable income are expected to have a higher average level of data consumption. Also, the total consumption in 5G was compared to the one in 4G in order to understand if this new technology is translated into an increase in consumption. The conclusion was that there is no clear and significant 5G's effect, contrary to some conclusions suggested by other operators and manufacturers. Finally, regarding the relationship between mobile internet and the other services, a complementarity effect was observed even though its small magnitude leaves doubts about the true effect.

Keywords: 5G, Fifth Generation, Telecommunications, Connectivity, First-mover advantage, Network industry

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ABBREVIATION INDEX

1G = First Generation

2G = Second Generation

3G = Third Generation

4G = Fourth Generation

5G = Fifth Generation

ANACOM = National telecommunications' authority (Autoridade Nacional de Comunicações)

GB = Gigabyte

MB = Megabyte

GSM = Global System for Mobile Communications

GPT = General Purpose Technology

IoT = Internet of things

R&D = Research and development

SMS = Short message service

TSM = Telecommunications Single Market

1. INTRODUCTION

The need for a better and faster method of communication has been responsible for numerous innovations over time in the telecommunications industry, such as mobile phones (Gadzama et al., 2017) and smartphones: one of the most pervasive technological devices that society has ever seen (Emanuel et al., 2015). What started out as an innovative way to communicate - mobile phones - quickly became a source of entertainment, information, and networking, capable of restructuring human interactions (Williams, 2011). These constant flows of innovation have created a true technological revolution, with new gadgets and tools emerging on almost a daily basis. Hence, as the effects of technology ripple through society, technology, and its perceived relevance, began to assume an increasingly prominent role in recent times, being understood by many as a critical element.

These waves of innovation were, naturally, accompanied by dynamics and developments that impacted the society itself. Society, and its needs, have changed. Modern society is now more critical and demanding than ever: user-friendly and high-quality content, multi-purpose platforms, and speeds that allow real-time connectivity are the new normal (Nur-Al-Ahad & Nusrat, 2019). 5G technologies emerged as the newest and most powerful form of mobile connectivity capable of materialising the future digital revolution with horizons of possibilities broader than ever (Parcu et al., 2021).

As these new technologies spread throughout society, the dynamics reflected in the market become particularly important for companies whose core business depends on them. The Telco industry is an example of an area that thrives on technology and its development. The way people perceive the constant evolution of technology, the value attributed to new generation equipment, and even the profile of consumption and internet usage has a direct impact on the industry's profitability. Therefore, it becomes relevant to understand, and even predict, the evolution of society's needs. Only in this way will companies be able to define the best way to approach the market and to adapt their products in order to satisfy future needs which, consequently, ends up being an important advantage to stand out in a market where, by itself, there are few truly differentiating elements.

Therefore, as the internet is an essential element of our society, the more detail there is about its consumption, the greater the possibilities of monetization. The present study aims to ensure a better understanding of internet consumption, relating it to possible predictive variables. In fact, the possibility of forecasting and the consequent definition of different usage profiles can be an important tool for defining a more successful competitive strategy. The study also wants to understand the effect of 5G on internet consumption, realising if, effectively, better network quality will translate into higher levels of consumption. This study resulted from an internship held at NOS, one of the market leaders in the telecommunications sector in Portugal.

The present report is structured as follows. After the introduction, Section 2 presents the literature review focused on topics related to the telecommunications industry - starting with a brief contextualization, the evolution of the different generations, with special emphasis on the fifth generation, followed by the competitive landscape - and the role of new technologies in today's society. Section 3 details the academic internship carried out at NOS *Comunicações SA*. A brief overview of the context - Telco industry in Portugal in 2022 - as well as a contextualization of the NOS Group are also addressed in Section 3. Section 4 clarifies the study's objectives and the respective methodology. An approach to the econometric model used, as well as the respective results, are explored in Section 5. Lastly, in Section 6, the main conclusions are presented.

2. LITERATURE REVIEW

2.1 Telecommunication industry

2.1.1 Main industry's dynamics and characteristics

The last decades have been marked by strong social dynamics. Globalisation has changed the paradigm of competitiveness, creating a single market where society, and the economy itself, is more connected than ever (Alli et al., 2011). As a result, competitiveness was strengthened and the duality between innovation and/or design and price became even clearer. This means that a growing number of specialisations are needed in order to remain competitive, and at this point, telecommunications emerge as a fundamental element in technological development (Petralia et al., 2017). Recognized as capital intensive, this industry requires a high investment in infrastructure, and hence customer acquisition becomes highly related to the ability of telecommunication companies to be profitable. Additionally, the high fixed costs end up delimiting the competitive sphere, which is why the industry is made up of a small number of competitors (Asimakopoulos & Whalley, 2017; Cave, 2018).

Yet, even with a small number of players, the industry has a fiercely competitive environment and has faced an equilibrium where new technologies emerge in order to improve and add value to the existing offer (Cave, 2018). This industry is often associated with a high level of dynamism, with successive generations appearing to provide better quality services but, at the same time, creating opportunities for companies to develop new products and services, which inevitably impacts industry competition (Basole & Karla, 2011). In addition, changes in regulation and customer demand are also quite recurrent, shaping the competitive landscape of companies. Historically, telecommunication has been synonymous of transmission and communication between people. However, this industry has become much more comprehensive and is characterised by digital convergence, where consumers demand varied and integrated services and, therefore, the lines between voice, data, and video networks are increasingly blurred (Dutta, 2003).

2.1.2 Wireless communication

Considering wireless communication, characterised by the transfer of information without the use of electrical conductors (Bhalla & Bhalla, 2010), it is possible to highlight five major generations that emerged as catalysts for society's progress, marking different stages of its development. The evolution of large-scale wireless communication started in the 1980s with the appearance of the cellular concept, which used only analog radio signals, something that was later named as the First Generation, or simply 1G.

A decade later, in order to overcome the limitations of the First-Generation mobile communication systems, the Second Generation (2G) appears with significant improvements, primarily using the GSM (Global System for Mobile Communications) standard and using digital transmission instead of analogue transmission (Rao & Prasad, 2018). In addition to improvements of the communication quality, other services were also integrated, such as SMS. As a result, the emergence of 2G marked an exponential increase in the notoriety and use of mobile equipment but, as the concept spread and people began to use it in their daily lives, it became clear that the network was not stable enough and it was necessary to introduce new possibilities.

The Third Generation (3G) was hence introduced with major advancements in the network, especially related to transmission and speed, enabling a wider variety of innovative services as was the case of mobile internet.

As it would be expected considering the history of upgrades, a few years later, in 2010s, the Fourth Generation (4G) appears as an extension of the 3G network, showcasing higher bandwidth, wider services, and significant improvements in terms of speed, up to tenfold over 3G (Bhalla & Bhalla, 2010; Osseiran et al., 2016; Parcu et al., 2021; Rao & Prasad, 2018).

Finally, and the latest generation of wireless communications, 5G has emerged as a potential mechanism for a true society's revolution, bringing both incremental and radical changes with respect to previous technologies beyond the mobile telecommunication industry (Cave, 2018).

2.1.3 The Fifth Generation

5G materialises in much more than a state-of-the-art mobile network and its appearance unlocks a huge variety of technologies and products that were previously limited by the intrinsic characteristics of 4G. Consequently, 5G can be considered as the first mobile generation to be a potential General-Purpose Technology (GPT) (Parcu et al., 2021). Bresnahan and Trajtenberg (1995) suggest that GTP has the potential to be widely used in a variety of industries, stimulating generalised productivity gains, and thus one may consider it as a major driver for technical progress and economic growth. Hence, these technologies are not in themselves a final solution but, on the contrary, are opportunities for innovative complementarities that propagate throughout the economy, creating space for both product and process innovation (Carlaw & Lipsey, 2006; Williams, 2011).

Indeed, this new form of mobile connectivity has a very specific set of characteristics that make it a truly disruptive innovation, being a source of added value for the most varied economic sectors (Parcu et al., 2021). In addition to the characteristics of the network that alone make it more efficient than the previous ones, surpassing the limits of the legacy of mobile systems in all dimensions (Morgado et al., 2018), this new technology appears to meet the growing needs of society - a society that is more connected and technological than ever, requiring a flexible mobile network with high performance and capacity in real time. With more and more connected devices (Liu et al., 2020) arises the need for the wireless communication to support a high number of interactions, including not only the more traditional person-to-person communication (P2P), but also person-to-machine (P2M), or even machine-to-machine (M2M) (Zhang et al., 2014). Thus, challenges arise to make the network more capable, and 5G comes to solve the problem with its high bandwidth and huge speed. Additionally, network reliability and ultra-low latency appear as network enhancers, allowing new interactions that were not granted in previous networks (Kiesel et al., 2020). From these specificities, improvements to existing products and services arise, as well as opportunities for future innovations, making technology a fundamental element of today's society. Connected cars, control and surveillance systems, smart cities and smart homes (Hong et al., 2016), Internet of Things (IoT) (Bresciani et al., 2018; (Lv et al., 2020), telemedicine (Anwar & Prasad, 2018), virtual and augmented reality applications, cloud technology and industrial automation (Lv et al., 2020; Rao & Prasad, 2018) are just a few technologies that are in an embryonic stage and that benefiting from the widespread adoption of 5G will be launched and marketed at an exponential speed (Anwar & Prasad, 2018; Bresciani et al., 2018; Hong et al., 2016). As a consequence, these significant changes are expected to reach and impact the economy as a whole, and, for that reason, 5G is not merely seen as a matter of technological or economic competition between businesses (Brake, 2018; Parcu et al., 2021).

However, at a time when cybersecurity, privacy and net neutrality are recurring topics, the emergence of 5G raises some questions considering the current regulation. The Fifth

Generation aims to create a new revolutionary network, where it becomes possible to customise the network's capabilities according to the customer needs. That is, with the new characteristics of the network it will be possible to accommodate new products and services with different requirements in terms of network capacity that have not been supported until now and thus target different services with different requirements. In order to meet these emerging needs, the possibility arises of creating 'network slices' and charging them according to a 'pay-as-you-go' basis, segmenting users' demand (Frias & Pérez Martínez, 2018). However, this new business model of 'paid prioritisation' is not in full compliance with the Telecommunications Single Market (TSM) regulation, approved by the European Union in 2015. This regulation established some principles related to net neutrality with a view to guarantee transparency and traffic's non-discrimination. That is, in order to ensure fair competitiveness principles, TMS regulation requires that operators treat all internet traffic equally (European Union, 2015).

Moreover, with technology connecting numerous aspects of life throughout the network, it becomes necessary for this network to be highly reliable and secure and, consequently, with the arrival of 5G, issues related to security and privacy begin to gain new angles (Ahmad et al., 2019). In fact, with the emergence, and even trivialization, of IoT devices, the development of new services and the growing demand of user traffic, it is expected that the emergence of 5G will materialise in an exponential increase in the volume of data transacted (Bresciani et al., 2018). This massive data and transactions will create threats and security vulnerabilities which, in turn, give rise to challenges both for the network, and for the companies themselves in the most varied sectors that benefit from this mobile generation. Thus, the mechanisms used in previous generations will not be enough, highlighting the need for more robust security mechanisms (Ahmad et al., 2019).

2.1.4 Competitive landscape

In a competitive environment, achieving an advantage is a differentiating and fundamental element for the sustainability of any company. Thus, the ability to sustain a leadership position in terms of market share becomes one of the main organisational objectives in the management of a company and its strategic decisions (Ferrier et al., 1999). In network industries, such as the telecommunications, market leadership is highly related to the ability to make the best use of the companies' capabilities and resources (Finney et al., 2008), to the exploitation of network effects (McIntyre & Subramaniam, 2009) or even as a consequence of first-mover advantages (Lieberman & Montgomery, 1988).

Pioneer companies usually end up gaining a competitive advantage compared to their competitors and thus the first-mover advantage can appear as a consequence of the creation of switching costs, the pre-emption of scarce resources or, as is the case the case with the emergence of 5G, technological leadership (Lieberman & Montgomery, 1988). In this sense, pioneer companies can maintain their advantage as a result of the improvement of the learning curve or even because of R&D races and patents' success. While in the first scenario companies gain a cost advantage with cumulative output, creating a barrier to entry (Spence, 1981), the second one relates to the possibility to patent the used technology. Regarding the competitiveness in the specific case of the telecommunications industry, the launch of the Fifth Generation was associated with a radio-spectrum allocation and, therefore, the players that stood out in the auction ended up guaranteeing a competitive advantage in the long term. The spectrum licences acquired are fixed and unique for each company, thus creating a barrier to the entry of new competitors and, at the same time, delimiting the area of operation of each company.

At the time of the auction, the company that acquires a superior share of spectrum will, a priori, be the player with the greatest competitive advantage. Mobile operators that were able to acquire a more spectrum will have the capacity to deliver faster speeds, increasing the customers' perceived value, while, at the same time, facing less investment needs to meet mobile traffic (Bahia & Castells, 2022). Additionally, buyer switching costs also play an important role in this industry as it is highly associated with contracts between customers and operators (Lieberman & Montgomery, 1988). Hence, late entrants face an added difficulty in attracting new customers as many of those who value the service may have already joined the pioneering company. Reputation is also often associated with first-mover advantages (Kerin et al., 1992). As a result, the aforementioned advantages make it more difficult for competitors to compete with the leading firm, increasing their ability to generate better financial and operational performance.

This dynamic happens in any business area, but looking specifically at the telecommunications industry, which is marked by recurrent dynamics and changes (Cave, 2018), market leaders with significant advantages can fall behind and be overtaken by competitors if they are not able to sustain their positioning by actively adapting the existing market strategies to new conditions, as the resources and capabilities used in the previous conditions can become obsolete (Oughton et al., 2018).

However, there is evidence that in a fast-changing industry, competitive advantages might not hold as capabilities and knowledge may disappear in a short period of time because of technological progress (Christensen et al., 1998). Thus, the shift in environmental conditions may create an opportunity for competitors to gain an advantage over the market leader. Additionally, and following the same line of reasoning, Suárez and Lanzolla (2007) suggest that, since technological advances are later translated into products' quality, first-mover advantages are difficult to sustain when the quality of products is constantly increasing over time. As a consequence of this duality, Asimakopoulos and Whalley (2017) found that leading firms are associated with higher financial performance in comparison with competitors; however, technological discontinuities negatively impact the performance of leading firms as it creates an opportunity for further competition.

The telecommunications industry, as already indicated, has undergone strong dynamics over the last few years which requires constant redefinition of processes to cope with change (Cave, 2018). Hence, mobile operators must be empowered with dynamic capabilities in order to embrace change and, consequently, adapt the business to respond to the changing needs of society as well as the technological opportunities that arise. To sustain a strong competitive position in a dynamic environment, ownership of difficult-to-replicate assets is not enough. It is essential for companies to have unique dynamic capabilities that allow them to anticipate threats and opportunities, take advantage of business opportunities and maintain competitiveness (Teece, 2007).

In the presence of network effects, the initial customer base has a great impact on the companies' competitiveness. The adoption of the product or service by an additional user has effects on the network itself, increasing its value through the growth of communication options, but, at the same time, it also has a marginal impact on non-users in the form of incentive and motivation to adhere to the service (Doganoglu & Grzybowski, 2007). In fact, the value of the network is related to the number of users and is positively related to the companies' financial performance, that becomes more efficient than its competitors (Asimakopoulos & Whalley, 2017). Regarding this network value, it is possible to differentiate direct effects, which arise from the increase in consumption's utility as a consequence of a greater number of users, from indirect externalities that refer to the development of complementary products critical to the use of a given product (McIntyre & Subramaniam, 2009). Hence, the customer base can be a crucial element to increase relative performance which is later translated into profit maximisation (Asimakopoulos & Whalley, 2017).

2.2 The emergence of the internet and smartphones

2.2.1 The role on today's society

Since their emergence, the internet and mobile phones are perceived as decisive technologies of the Information Age (Castells, 2013), being true engines of development, with significant impacts on different economic and human activities (Phuc Nguyen et al., 2020). Naturally, these impacts vary depending on the level of development of the country in question (Phuc Nguyen et al., 2020) but, even so, emerging economies are also documenting significant levels of use of these tools, registering an exponential growth in recent years (Silver et al., 2019).

According to Phuc Nguyen et al. (2020), in 2017, 61% of the world's population used the internet. This figure is considerably up from the 5% observed in 1998. Regarding mobile usage, in 1998, there were only, on average, 9.6 mobile cellular subscriptions per 100 people, in contrast to 119 in 2017. Considering the limited use of these technologies among children and the older generation, Castells (2013) argues that it is possible to say that humankind is now almost entirely connected.

In fact, the rapid spread of these technologies is not incomprehensible. Mobile phones and the internet emerged as an important tool to improve interactive communication worldwide (Suvankulov et al., 2012), acting as a true facilitator of digitization and globalisation (Visser, 2019). The impact of these technologies is transversal, with records of social and economic effects in different areas, such as economic growth (Choi & Hoon Yi, 2009; Williams, 2011), production and consumption (Wang & Hao, 2018), politics (Stockemer, 2018), education (Badasyan & Silva, 2018), international trade (Visser, 2019), environmental sustainability (Wang & Hao, 2018; Williams, 2011), health (Wald et al., 2007) and market competitiveness (Brown & Goolsbee, 2002).

As a result of the profound way these new technologies have transformed society, Fuchs (2008) sees the internet as a "a dynamic techno-social system" which is incorporated and has a direct influence into the social context, as opposed to a simple technological aggregation of computer networks.

2.2.2 Mobile services substitution

Aforementioned, the diffusion of new technological features came with the emergence of technology. Social networks and new alternative communication and interaction platforms began to conquer a central role in society. Thus, one may argue that these alternative means of communication can impact the functioning of the more traditional methods of communication provided by mobile operators - SMS and voice services -, working as true substitutes. Mäkinen et al. (2014) describe service substitution as the consumption of a new service over another, providing similar functionalities and outcomes on consumers.

The existing theoretical literature predicts a degree of cannibalization between calling and text messages services by over-the-top (OTT) third party services (Mäkinen et al., 2014). Thus, since both can fulfil similar communication functionalities and needs, SMS usage intensity could be decreasing as more customers are shifting toward the online market (Verkasalo, 2008). Based on self-reporting, Mäkinen et al. (2014) conclude that a substitution effect exists to some extent and that, therefore, this could be a problem for mobile operators. However, Gerpott (2010) states that there is a degree of questionability to this type of evidence that supports conjectures in self reporting and self-assessment, not considering factual service use behaviour data.

In fact, quantitative evidence does not make a clear conclusion about how close substitutes for these services are, nor their effect. Mobile internet intensity use was found to positively affect SMS and mobile voice minutes services. However, despite the relationship being statistically significant, the absolute results were of small relevance (Gerpott et al., 2012). In a previous study, Gerpott (2010) found a negative relationship between the number of SMS and the use of mobile internet but, similarly, the effect was so small that it calls into question the association's relevance. Regarding the impact on mobile voice services, the author did not find any substitutability. With a different approach but a similar conclusion, Karikoski and Soikkeli (2011) found that people use different platforms and services depending on the context and, hence, these variables under analysis are direct substitutes. Thus, the relationship is indeed questionable with several studies pointing out the lack of clear evidence in favour of substitution (Karikoski & Luukkainen, 2011; Verkasalo, 2007).

2.2.3 Predictors of usage

The adoption of these new products and services is not generally observed in society. Section 2.2.1 mentioned the country's level of development influences the likelihood of using the internet. Furthermore, age, gender, disposable income, availability of technological devices, digital skills, educational level, and place of residence are stated as predictors of internet usage.

As the internet is a relatively recent technology, it is to be expected that its use will not be homogeneous for different age groups. Hargittai and Hinnant (2008) suggest that young people are the major users of the internet, and therefore an inverse relationship is expected between user age and levels of internet consumption.

Gender has also been pointed out in the literature as a possible explanatory factor. However, there is no consensus on the true effect of gender. While Gray et al. (2016) reveals that men are more likely to use the internet, there is also contradictory evidence (Martínez-Domínguez & Mora-Rivera, 2020). At the same time, there are also studies pointing out that the gap in internet use between men and women has been reducing as this technology is being spread throughout society (Hargittai & Hinnant, 2008).

The ability to keep up with technological developments has an associated cost, the purchase of internet plans and the equipment itself. Thus, disposable income is expected to influence internet consumption. However, although it seems like a paradox, there is no consensus among the literature regarding its effect. On the one hand, people with a higher disposable income are empowered with greater consumption opportunities and, therefore, in case of valuing this technology, they have more capacity to afford it (Fuchs, 2008; Manlove & Whitacre, 2019). On the other hand, low-income users are paying the most to go online on their smartphones. For many people with less economic possibility, mobile internet is the only method of accessing the internet. This may happen because they do not have the traditional broadband service at home, but also because they may be related to more precarious jobs, where Wi-Fi connections may not exist (Horrigan & Duggan, 2015; Brown et al., 2011). Goldfarb and Prince (2007) suggest that high-income people are more likely to adopt the internet but, when adopting, spend considerably less time online compared to people with less income.

As expected, and also related to the previous topic, the availability of technological equipment is highly related to the ability to go online. In addition to being a natural enabler, interest in technology is pointed out as an incentive to use the internet (Martínez-Domínguez & Mora-Rivera, 2020).

In terms of digital skills, evidence indicates that the likelihood of using the internet increases as users have more abilities. Scheerder et al. (2017) refer to the first-level digital divide as differences in infrastructural access that create, by themselves, inequalities in the ability to access and use the internet. Additionally, the authors mention the second level of digital divide as the differences in skills and usage patterns. Thus, assuming access to the internet, the skills possessed have a positive effect, being a determinant in the use and in the consequent repercussions that arise from it, even in an offline aspect (Martínez-Domínguez & Mora-Rivera, 2020; Van Deursen & Helsper, 2015).

Another determining factor, which is often positively associated with the digital skills possessed, is the educational level (Hargittai & Hinnant, 2008). To use the internet there are basic requirements, such as the ability to read and write. Also, a higher education level may be related to greater benefits when adopting the internet (Martínez-Domínguez & Mora-Rivera, 2020) and, simultaneously, people with more levels of education may be quicker to understand the advantages of using the internet, becoming earlier and more frequent adopters (Manlove & Whitacre, 2019).

Lastly, the place of residence ends up influencing the inhabitants in a decisive way, shaping their habits and behavioural patterns, which naturally impacts the use of the internet. As far as technology is concerned, the more rural areas end up evolving at a slower pace compared to the more urban areas. This can be explained by supply issues since technology's installation entails significant costs and thus there is a strategy associated with the investment planning. Areas with less population density and with greater distances can be perceived with a lower propensity for profit. As a result, these areas end up having less contact with technology, impacting the consumption habits of their inhabitants, who have a lower internet consumption compared to inhabitants of more urban locations (Hill et al., 2014).

2.2.4 The future of internet consumption

So far it is evident that these constant cycles of innovation have not left society unchanged. Society today, its behaviour and trends, are radically different from what was usual before this technological wave. The emergence of these new technologies, and their effects, influenced society, thus giving rise to new standards of acceptable and normality (Peslak et al., 2011).

As mentioned, the use of mobile phones, and in this case with greater emphasis on smartphones, has become something fundamental in everyone's daily life, being even perceived as a technological addiction - as is the case of the Internet (Billieux, Van der Linden & Rochat, 2008; Parasuraman et al., 2017). As a consequence, the number of mobile subscriptions has been steadily increasing every year (Parasuraman et al., 2017) but, as a matter of fact, most of the recent growth in smartphone usage time arises as a result of the increase in additional time spent per user, rather than additional active users (Dolan, 2022). Recent evidence suggests that people are increasingly attached to their cell phone, checking it an average of 70 times a day (Emanuel et al., 2015). Quantifying usage, among adult smartphone users, the average time spent on the smartphone in 2021 was 3 hours and 46 minutes, representing an increase of 8 minutes compared to the previous year (Dolan, 2022). When compared to other aspects of social life, Carlsson (2009) suggests that people spend more time online than with their friends. Deepening this technological addition, evidence points to the fact that society's addition is not to the equipment itself but instead to the entertainment, information, interactivity and to the connectivity that these technologies allow (Emanuel et al., 2015). Consequently, this social trend to be “always connected” (Carlsson, 2009; Nur-Al-Ahad & Nusrat, 2019) supports evidence that predicts that internet usage will continue to grow in coming years as well as its relevance in everyday life (Gadzama et al., 2017).

Additionally, the emergence of new products and more advanced features should support this mobile time’s evolution, preventing it from stabilising (Dolan, 2022). As mentioned in Section 2.1.3, with the arrival of 5G the market will undergo strong transformations, unlocking a real wave of disruption and innovation (Parcu et al., 2021). Thus, it is expected that this evolution will also boost the profile of internet consumption (Dolan, 2022). With the increasing digitization of products and services, it is natural that internet consumption, by itself, increases. Still, there is evidence that suggests that, even at the individual level, consumption in 5G is higher. Rizzato (2020), in a report published by Opensignal, a mobile analytics and insights on connectivity company, suggests that 5G customers consume up to 2.7x more mobile internet when compared to 4G users. Similarly, there are other studies by operators and manufacturers that conclude the same. For example, Ericsson suggests a growth of 2–3 times the amount of data when comparing 5G with 4G subscribers in North East Asia. However, for the mentioned cases there is a stated causality effect when, in fact, there is only evidence of correlation.

3. THE INTERNSHIP

This study is based on an academic internship held at NOS. The internship took place from January 2022 to June 2022, corresponding to approximately 952 hours, at the B2C Marketing department, more specifically in the Mobile Product team. The main objective of the internship was to monitor the consumption control initiative, the area responsible for managing SMS, calling and data plans. The first two areas are highly stable, and, for most customers, the subscribed plan meets their user needs. On the other hand, customers are often online, which means that, for many, subscribed data plans are not enough. As a result, there are constantly new offers, promotions and additional internet sales' push that end up dynamizing this component of the business. Thus, although the internship covered these three areas, most of the working time was dedicated to the management and analysis of the data consumed, both in terms of the subscribed plan and out-of-bundle.

Hence, to this end, the related functions were associated with two main aspects: the enhancement and improvement of the user experience from the customer's point of view and, in parallel, the optimization of revenue associated with this line of business.

The customer experience is a crucial element and, therefore, there is a continuous effort to deliver a service that exceeds the customer's expectations. In this way, and since most customers have contact with this internet component, it is important to communicate its functioning as clearly as possible and, at the same time, monitor the evolution of customer complaints in order to continually improve the service provided.

Considering the associated revenue, it is obviously one of the business objectives. Hence, there was a monitoring and follow-up of the results on a daily basis in order to understand if consumption was evolving as expected, which also ended up working as a detector of possible errors that may be occurring in the service. Especially with the introduction of the new generation mobile network – 5G – this internship component acquired an even more relevant role. One of the internship's goals, which is also subject of analysis in the recurrent report, was the quantification of the impact of 5G on the profile of mobile internet consumption. As 5G is the future, its influence on consumption will dictate new market trends and also help to define new marketing strategies.

The following sections present an overview of the telecommunications market in Portugal in 2022 and a brief contextualization of the NOS Group, with greater emphasis on NOS *Comunicações* SA.

3.1 Portuguese Telecommunications market in 2022

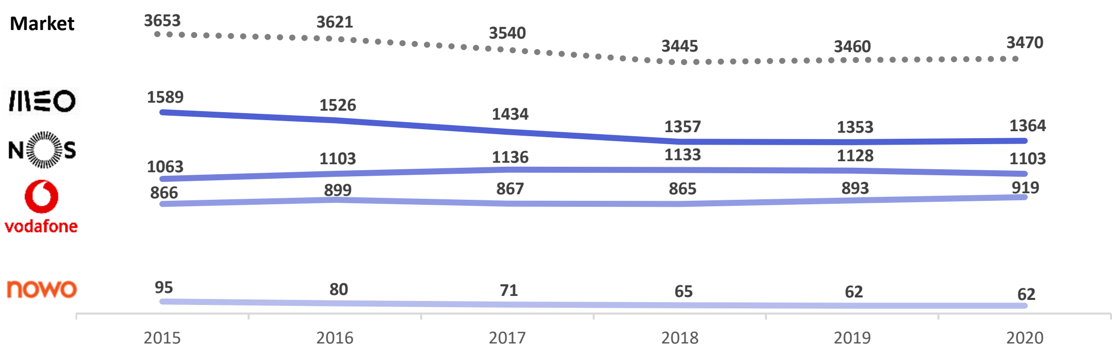
Portugal has a well-established telecommunications market with a growth trend that, in fact, is transversal to the vast majority of countries. As connectivity is one of the key elements of the 21st century, by association, the services provided by companies associated with telecommunications are, to a large extent, perceived as a commodity.

The sector's evolution ended up being accelerated in recent years as a consequence of the Covid-19 pandemic. What started as an isolated flu-like disease, quickly evolved into a global crisis where uncertainty took the lead. People were forced to stay at home due to mandatory restrictive measures and thus, for most of society, working and studying from home became a reality overnight. Hence, one may argue that the pandemic was a real driver of digitization, forcing everyone to adapt at a pace never seen before. According to ANACOM, comparing March 2020 (the month in which the Portuguese government declared the pandemic) with the period before the pandemic, there was an increase of 47% in voice traffic and 52% in the case of data. As the pandemic was brought under control and society returned to normality - as far as possible - electronic communications' traffic has been reducing, but never to the values prior to the pandemic. This suggests that the new consumption patterns and habits of use that have emerged as a result of Covid-19 will not simply disappear. In fact, this global crisis created new trends, patterns and behaviours that were truly disruptive to what was usual until then.

The pandemic also ended up impacting the launch of 5G. In 2016 the European Commission adopted a coordinated 5G action plan in order to guarantee that, at the latest, all member states had 5G services by the end of 2020. With Covid-19, and the ensuing global crisis, the European Commission's goal became impractical. In March 2020, ANACOM announced that, at the request of all operators, it would suspend the consultation on the 5G auction regulation indefinitely. The 5G auction started in December 2020 with an exclusive phase for the new entrants and in the following month, January 2021, the main phase of the auction began. A few months later, in October 2021, ANACOM announced the end of the auction, which totalled almost 567 million euros. NOS was the operator that invested the most in the auction, acquiring the maximum amount of spectrum that a single operator could for the exploration of the new technology. Comparing the main competitors, NOS acquired a total of 15 of the 58 lots available, totalling 165 million, while MEO paid 125.2 million to guarantee 12 lots and Vodafone spent 133.2 million for 11 lots.

Regarding the Portuguese market, it is made up of 4 relevant players and a few other operators of insignificant size mostly focused on B2B. Although these recent dynamics have contributed to the dynamism of the sector, the truth is that the Portuguese market, until 2020, was losing value (Graph 1) as competition from NOS and Vodafone contributed to the erosion of market share of MEO.

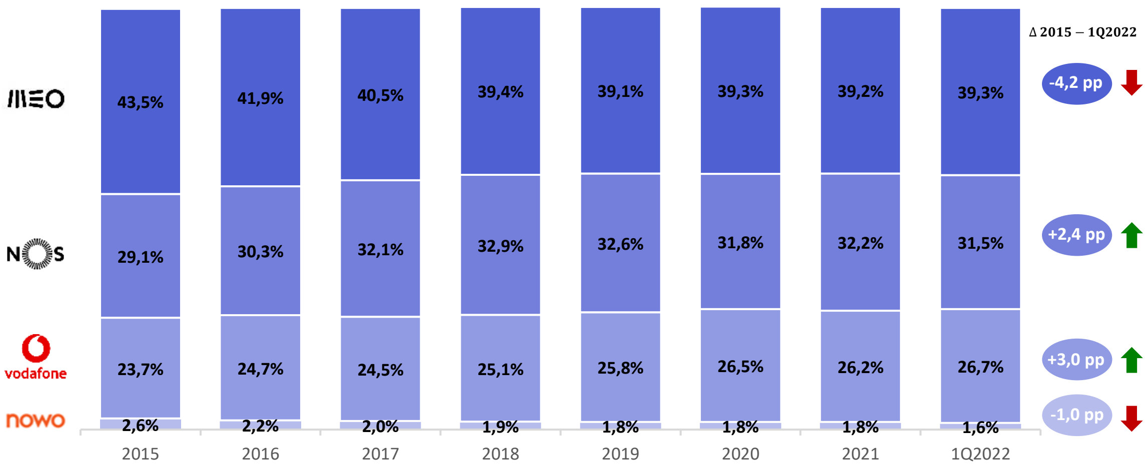
Graph 1: Sales per operator in the Portuguese Telco market (M€)



Source: ANACOM

Considering ANACOM's metrics, comparing the largest players, the market share in 2015 was distributed by MEO, NOS, Vodafone and NOWO according to the following percentages: 43.5%, 29.1%, 23.7% and 2.6%, respectively. Until the first quarter of 2022, even though the positions have not changed, MEO has lost market share, gaining only 39.3%, while NOS, Vodafone and NOWO add up to 31.5%, 26.7% and 0.7%, respectively (Graph 2).

Graph 2:Market shares (in value) of Portuguese telecommunications



Source: ANACOM

Deepening the metrics in Portugal in 2022, according to a report published by ANACOM for the first quarter of 2022, the number of subscriptions in the bundle segment increased by 3.3% compared to the same quarter of 2021, totalling 4.4 million subscriptions and 458 million euros in revenue. The majority (52.1%) of these services correspond to 4/5P subscriptions - which consist of bundles of 4/5 services - which is responsible for 64% of the total revenue. From the point of view of the competitive scenario, there are a total of 12 service providers in activity and the market leader is MEO (market share of 40.8%), followed by NOS (35.8%), Vodafone (2.1%) and NOWO (3.1%).

Considering the same report, with regard to mobile standalone services, there are a total of 13.2 million active cards, corresponding to 127 mobile services per 100 inhabitants (+8.6 p.p. compared to the same quarter of the previous year). Considering the type of offer, 65.2% corresponds to services that include both voice and data, with the average monthly traffic per access being 239 minutes and 6.2 GB (+25% compared to the same quarter of 2021). As in the bundle segment, the market leader is MEO (market share of 40.0%), followed by Vodafone (29.0%), NOS (27.6%) and NOWO (1.9%). Still in the competitive landscape, in the segment under analysis, NOS was the company with the most positive change in market share: +1.2 p.p. compared to the same period in 2021, while MEO, Vodafone and NOWO underwent a change of -0.6 p.p., -1.1 p.p. and +0.1p.p., respectively.

3.2 NOS SGPS

NOS SGPS, a public company quoted on the Portuguese stock exchange index (PSI-20), was created in 2014 as a result of the merger of two Portuguese companies: Optimus and ZON. Since then, it has operated in four business areas - Telco B2C, Telco B2B, Cinema, Content and Advertising - generating, in 2021, approximately 1.4 billion euros in revenue. The group became known for being one of the main players in the telecommunications industry in Portugal and, additionally, for being the owner of the largest networks of cinemas in the country. However, in addition to these areas of activity, NOS has stakes in other companies, such as SPORT TV and Dremia, among others (Appendix1).

NOS *Comunicações* SA presents itself to the market as an innovative and efficient company, capable of leading the new technological wave that is approaching. Nowadays, it is inevitable to talk about 5G when the topic is technology. And, in fact, the company's position regarding the launch of this new generation network is in line with the proposed strategy. With the ambition to lead, NOS was the company who invested the most in the 5G auction, thus enabling its network to offer the best service to customers and was also the first operator to launch 5G in Portugal. In addition to the aforementioned digital mindset, the company's proposals are based on centralising the customer journey as the company's main purpose and on empowering the organisation to respond in an increasingly differentiated way to the most pressing environmental and social challenges.

3.2.1 Business model under internet usage

The main goal is to study internet usage on smartphones but before that, it becomes relevant to clarify the business model behind it.

The Telco sector, for the wireless industry, has adopted a tiered pricing strategy where customers can choose the plan that best suits their needs. Mobile operators offer a set of different plans that differ in the volume of benefits included - SMS, minutes, and internet - corresponding, naturally, to different prices. To this extent, there is a fixed amount that is included in the subscription plan and that customers can use but, in case of exceeding the threshold, there is an additional charge. The included benefits on each subscription plan are renewed on a cyclical basis, normally monthly.

In the specific case of NOS, regarding data consumption, if customers use up the pre-defined limit subscribed, an extra is automatically activated (200MB/2.99€) up to a maximum of five. This limit can be managed autonomously, for example through the app, where customers can change the mentioned maximum value or even disable the automatic activation of data refills. Additionally, there is a set of additives that customers can subscribe to manually and, therefore, end up adding a certain number of GB to their monthly plafond for a given price. Thus, these two components, automatic and manual additives, are responsible for the out-of-bundle internet consumption.

Additionally, there are unlimited subscription plans where, as the name suggests, no data limit exists.

3.2.2 How customers can subscribe a 5G rate plan

As mentioned, one of the objectives of the study is to measure the effect of 5G on internet consumption. Thus, it is important to differentiate the accesses that customers had at their disposal to activate this 5G functionality.

At the time of the analysis, there were two possibilities of having an active 5G connection: a 5G addon and native 5G subscription plans. Rate plans with 10GB or more had the 5G option by default and, therefore, no action was required by the customer to activate it. On the other hand, in cases with a ceiling of less than 10GB, customers could activate a special 5G addon. The activation process was very simple, it was only necessary to access the NOS app and activate the addon, free of charge for a free trial period.

4. EMPIRICAL STUDY

4.1 Research objectives

Aligned with the goals of the internship, the aim of this study is to understand the profile of internet consumption on smartphones, its relation to other digital communication methods - text messaging (SMS) and voice services - as well as possible predictors of usage. In an era in which society is always connected (Carlsson, 2009), the monetization of connectivity assumes a fundamental role in the strategy of the telecommunications industry. Thus, this study aims to analyse internet consumption, both inside and outside the subscribed bundle, in order to outline possible patterns in consumption behaviour, something that can be an important enabler to improve current strategies and thus to define the best market approach.

4.1.1 Hypotheses

As mentioned, there are two major groups of hypotheses that will be studied and analysed in the course of the report.

Hypothesis 1: Analysis of predictors of data usage and their effect
Hypothesis 1a: Residence in urban areas positively influences data consumption;
Hypothesis 1b: Age negatively influences data consumption;
Hypothesis 1c: Digital skills positively influences data consumption;
Hypothesis 1d: Disposable income positively influences data consumption;
Hypothesis 1e: 5G traffic positively influences data consumption;
Hypothesis 1f: SMS usage intensity positively influences data consumption;
Hypothesis 1g: Voice services usage intensity positively influences data consumption.

Hypothesis 2: Data consumption and other services provided by operators
Hypothesis 2a: There is a complementary (or substitution) relationship between data consumption and the number of SMS sent;
Hypothesis 2b: There is a complementarity (or substitution) relationship between data consumption and the number of minutes spent on calls.

4.2 Research methodology

Considering the proposed objectives, and the accessible data typology, the present study follows a quantitative methodology. The quantitative methodology is characterised by the study of a given database using hypotheses and models. In this case, the conclusions turn out to be the result of processes that use numerical variables and, therefore, one of the advantages of this methodology is, precisely, the fact that it is highly objective and with exact interpretation. After the analysis is completed, interpreted, and evaluated, the results end up guiding the decision, representing an important tool in strategic planning (Waters, 1994; Welch, 2000).

This methodology was applied using the Stata program. After data collection, Stata was used for further data analysis and to test the presented hypotheses.

4.2.1 Data collection

The quantitative data presented were collected during a curricular internship at NOS. To carry out the study, several datasets from the company's data warehouse were analysed, which aggregates information collected by diverse individuals and departments. Considering the existing datasets and the reviewed literature, the most appropriate variables were selected for the analysis in question. Furthermore, archival records enable the analysis of a temporal dimension, being therefore a relevant source to explain the process of evolution and change (Welch, 2000).

After analysing and selecting the variables, 75 790 subscribers were randomly selected from the total company's customer base, only considering the ones that have an amount of GB of internet associated with the subscribed plan. Apart from this filter, no restriction was used. For this customer base, observations were collected from January 2021 to April 2022.

4.2.1.1 First hypothesis

The first hypothesis aims to predict internet consumption based on a set of variables and, therefore, the total data consumption (in GB) is considered as the dependent variable.

Considering the data available through the company's databases, six explanatory variables were selected: place of residence, traffic in 5G, disposable income, digital skills, age, SMS, and phone calls.

Since the place of residence is an important factor in determining consumption habits (Hill et al., 2014), a variable was added to account for this effect. More than relating consumption to the specific place where it was carried out, the effect to be studied is the location of the residence itself. In this sense, the most frequent district in a given month was collected - in this analysis February 2022 - and assumed as the customer's fixed place of residence. Then, the variable was related to the number of inhabitants and a scale of urbanisation was created (Appendix 2), which was later assigned to each customer.

A binary variable was created to ensure the identification of 5G traffic. For this purpose, customers were identified who had, at the same time, an equipment compatible with the 5G connection and who had subscribed to a plan that allowed 5G - either because they had associated a native 5G plan or because they activated the free 5G addon. It is important to note that these two conditions are necessary but not sufficient to guarantee that the traffic was carried out in 5G. This may happen for two different reasons: the customer, autonomously, deactivated the 5G connection on the smartphone’s settings and/or the customer is in an area without a 5G network. Due to the impossibility of signalling these two parameters, it will be assumed that the consumptions made by customers who ensure the two necessary conditions were made, at some point, in 5G. Even if customers have mixed consumption on 4G and 5G, the effect should be visible. In this way, native 5G customers started to be counted immediately after the introduction of the technology, while, in the case of customers who proactively activated the 5G addon, they were only counted from the moment of activation.

For the analysis of available income, a scale was also created (Appendix 3). Considering the available data, and the impossibility of creating an exact metric, a proxy was created to measure the impact of income. In this sense, data on the equipment used (brand and model) were collected - similarly to the previous case, also for February 2022 - and, based on this information, a scale was created considering the equipment market prices (in August 2022). Thus, although there may be exceptions, it was assumed that people with a higher disposable income own more expensive equipment. Another assumption that was created was the fact that income levels were assumed to be relatively stable for the majority of the sample and, thus, this association between equipment and income was carried out for only one month.

The next variable corresponds to digital skills, a variable that is difficult to quantify without direct observation of the sample. In this way, a binary variable was created to quantify this effect, which encompasses two aspects: first, customers whose subscribed data plan has more than 10GB are considered, as they correspond to customers with a higher need for internet usage; second, customers who activated the 5G addon were also accounted because they not only have the official NOS app but also because they show to be aware of the technological developments and were interested enough to proactively activate this functionality.

Considering the data sources, there is no specific and individual information to include the age variable in the model. Even so, and because it is expected to have a high predictive power (Hargittai & Hinnant, 2008), a binary variable was included to identify customers whose subscribed plan corresponds to a WTF. These plans are targeted at a younger segment, including a 25-year age limit for membership. Thus, although it is not possible to define an exact relationship between data consumption and age, it is possible to analyse the consumption of this younger segment and compare it with the other customers.

Lastly, following the previous analysis, the number of SMS sent and the total number of minutes on call were also considered.

Apart from the mentioned independent variables, some control variables were considered in the model. Two trend variables were included: T2 that considers the evolution of consumption in all periods under analysis to control for the overall market growth; and another, T, with greater emphasis on the period after the introduction of 5G to measure the impact of the new generation. Besides, monthly dummy variables were included to account for seasonality. Finally, regarding control variables, an individual-specific dummy was added to differentiate customers who have always been NOS customers from the ones who joined the service only halfway through the period under review.

4.2.1.2 Second hypothesis

For the hypotheses covering the relationship between mobile internet consumption and other services provided by operators a panel data regression was implemented.
The dataset covers the same clients over time, thus allowing the analysis of the evolution of a set of pre-selected variables over a time series measured at regular time intervals (in this case on a monthly basis). Regarding the unit of analysis, the same individuals are observed for each period, hence creating a fixed panel (as opposed to rotating panel data).

As the unit of analysis is on an individual-specific level, and also because of the sample's volume, a degree of heterogeneity is assumed. Thus, two estimation methods were used: fixed and random effects (Asteriou & Hall, 2021). From the initial subscriber base, 9 912 subscribers were not customers during the entire time horizon under analysis.

The number of SMS sent, the number of minutes in airtime, and the amount spent in GB were collected monthly between January 2021 and April 2022. The evolution and the relationship of these variables were analysed in order to understand if there is a substitutability relationship and, therefore, if the internet ends up being an alternative method of communication or if people who use cell phones more to communicate are also predisposed to use more mobile internet services.

5. THE MODEL

5.1 Data analysis

As shown in Table 1, which summarises the observed population's characteristics, the sample includes non-business subscribers, both from the residential segment (71%) and also from the standalone segment (30%). Of the total, 76% correspond to post-paid subscription plans and the remaining, approximately 24%, refer to pre-paid. From the sample, some variables were created to try to classify the type of customer, as this could influence their behaviour and consumption. Thus, customers with a WTF subscription plan (30%) were identified and, in parallel, users who were customers throughout the analysis process (87%) were identified from users who subscribed to the service only after January 2021 (13%). Additionally, 71% of the customers are more likely to have some digital skills.

Regarding 5G traffic, and considering the necessary versus sufficient conditions already mentioned, 71% of the selected base was considered eligible and counted as having 5G traffic in at least one month of analysis. As expected, of the selected sample, the districts with the highest population density end up having more expression in the study. This proportion is relevant since it makes the study more similar to reality and, consequently, highly comparable, conferring more reliability. Finally, regarding the income proxy calculated based on the equipment owned, the intermediary levels have more expression than the extremes.

Table 1: Characteristics of the study sample (n = 75 790)

	n	% Of total
1. Client's typology		
Residential (bundle)	53 160	71%
Standalone	21 390	29%
Post-paid	3538	17%
Pre-paid	17 852	83%
2. Segment		
WTF	22 653	30%
Not WTF	51 897	70%
3. 5G Traffic		
5G Native	47 169	63%
5G Addon	6 016	8%
Not 5G	21 365	29%

4. Status		
Old Client	64 638	87%
New client	9 912	13%
5. Location		
Level 1	37 492	50%
Level 2	28 680	38%
Level 3	2 829	4%
Level 4	2 607	3%
Level 5	2 846	4%
Level 6	96	0%
6. Income		
Level 1	2 072	3%
Level 2	33 995	46%
Level 3	20 377	27%
Level 4	7 651	10%
Level 5	11 695	16%
7. Digital skills		
Yes	53 185	71%
No	21 365	29%

Source: Own elaboration

Table 2 characterises the continuous variables. Regarding the dependent variable, the total GB spent, for the periods under analysis, the average monthly value is, approximately, 10.8 GB. Overall, the median was substantially lower than the mean of the variable, which indicates that the distribution of data consumption is positively skewed and, therefore, a reduced number of users under analysis generated a very high amount of internet consumption.

Table 2: Descriptive statistics for continuous variables

Variables	Mean	Std. Dev.	Min.	Max.
GB	10.73	15.30	0	732.13
SMS	311.73	761.75	0	323 107
Airtime	818.6	818.62	0	30 328.35

Source: Own elaboration

With a longitudinal analysis, it is possible to detect some seasonality in the dependent variable: there is a steady increase until the high season, reaching the peak of consumption in the month of August, and later mobile internet consumption returns to lower levels. Thus, summer ends up representing the peak of consumption, a trend that is explained by the high mobility of users at that time of the year. In addition to the annual variation, the values studied suggest an increase in consumption when comparing homologous months, thus supporting the trend of growth in internet consumption as suggested by Dolan (2022). In fact, when comparing the average consumption in the months of February, there was an increase of 64% from 2021 to 2022, approximately (Appendix 4).

5.2 Testing Hipotheses 1

Regarding the first analysis, the objective of the study was to analyse a possible relationship between mobile internet consumption and other variables that could work as usage predictors - traffic in 5G, location of residence, disposable income, digital skills, age, SMS, and phone calls. This information was collected for all pre-selected users at different time moments.

A multiple regression model was created in which data consumption was considered as the dependent variable. In this case, the dependent variable is continuous, while in the case of independent variables they are measured at both as continuous and a categorical level. For the categorical variables with more than two possible values - Location and Income - dummy variables were created to properly introduce the variables in the model. In case the variable has *m* categories, *(m-1)* dummy variables were then introduced to avoid multicollinearity (Gujarati & Porter, 2009).

Beyond determining the relationship between the stated variables, the model also allows determining the sensitivity of the predicted variable to the set of independent factors, i.e., how much the dependent variable is expected to change given different values of the explanatory variables (Kissell & Poserina, 2017).

Considering the selected database and the objective of predicting the relationship between the different variables selected, the regression parameters could be estimated following OLS techniques, which minimises the sum of squared residuals. However, in order to ensure that the conclusions are valid it is necessary to analyse the data distribution and validate some assumptions which may detect possible model misspecification.

The Stata program was used to carry out the tests in order to ensure the Gauss Markov theorem. In order to account for linearity, it is important to visualise the relationship between the variables. In fact, a nonlinear relationship between the variables was found, resembling a decreasing exponential distribution. To solve the nonlinear relationship, it was necessary to perform a log-transformation, thus fitting the model into a simpler linear model that can be easily evaluated. The variables under analysis assume zero values and, therefore, this possibility was considered at the time of transformation by adding a constant to all the values, as suggested by Bellégo et al. (2022). In the case of the internet, as the value is in GB, the impact of adding a constant could cause some noise and decrease the clarity and precision of the analysis. Thus, before this change, the internet variable was transformed from GB to MB, where the addition of a constant has a lower magnitude. Once normalized, the regression parameters can be estimated following the OLS techniques (Kissell & Poserina, 2017). Also, another factor that was analysed regarding the relationship between the variables is that they must be independent, thus not demonstrating any kind of multicollinearity, otherwise the outcomes can be influenced and biased to some extent (Kleinbaum et al., 2014).

Regarding the residuals term, the Breusch-Pagan and Cook-Weisberg test was used to check for possible linear heteroscedasticity (Hayes & Cai, 2007). In fact, there was evidence of heteroscedasticity which means that the variance of the error term is not constant, something that can be explained by the skewness of the distribution, especially when using a large sample as this one (Gujarati & Porter, 2009). Heteroscedasticity's problem was considered in Stata by looking for robust standard error results (Hayes & Cai, 2007).

The analysis in question has data from the same customer over time although, for this first hypothesis, the study is not carried out as a panel data analysis. Some variables under analysis are considered intrinsic to the user and, therefore, static over time. In fact, the stability assumed in the users' characteristics influences the estimation method since, in this case, there are records of variables over time – the amount of internet, SMS and voice services spent, for example – and, on the other hand, there are variables with a single record for the entire time horizon under analysis. As a result, if a panel data analysis was chosen, these static variables would be omitted from the model as they do not show any evolution. As the study's goal is to estimate and predict the effect of all variables, a non-panel data model was used. Furthermore, and also as a result of the variables' stability, possible situations of autocorrelation between the residual terms had to be controlled with the introduction of the cluster option by the identification number of each user.

The estimated model is defined as follows:

$$
\begin{aligned}
&\text{Ln MB}_i = \\
&\beta_0 \\
&+ \beta_1 \text{ ln\_SMS}_i \\
&+ \beta_2 \text{ ln\_Airtime}_i \\
&+ \beta_3 \text{ WTF\_Client}_i \\
&+ \beta_4 \text{ Old\_Client}_i \\
&+ \beta_5 \text{ Digital\_Skills}_i \\
&+ \beta_6 \text{ 5G\_Traffic}_i \\
&+ \beta_7 \text{ Loc2}_i + \beta_8 \text{ Loc3}_i + \beta_9 \text{ Loc4}_i + \beta_{10} \text{ Loc5}_i + \beta_{11} \text{ Loc6}_i \\
&+ \beta_{12} \text{ Inc2}_i + \beta_{13} \text{ Inc3}_i + \beta_{14} \text{ Inc4}_i + \beta_{15} \text{ Inc4}_i \\
&+ \beta_{16} \text{ Feb}_i + \beta_{17} \text{ Mar}_i + \beta_{18} \text{ Apr}_i + \beta_{19} \text{ May}_i + \beta_{20} \text{ Jun}_i + \beta_{21} \text{ Jul}_i + \beta_{22} \text{ Ago}_i + \\
&\beta_{23} \text{ Sep}_i + \beta_{24} \text{ Oct}_i + \beta_{25} \text{ Nov}_i + \beta_{26} \text{ Dec}_i \\
&+ \beta_{27} \text{ T}_i \\
&+ \beta_{28} \text{ T2}_i \\
&+ \varepsilon
\end{aligned}
$$

Where i is the user observed, $\beta 0$ is the constant of the model, $\beta 1$ until $\beta 28$ are the coefficients of the explanatory variables and ε is the error of the model that is not explained by the included variables.

5.2.1 Results

The R-Squared value for this econometric model was, approximately, 32%. Put differently, the selected variables help to explain about 32% of the variations in the dependent variable - mobile internet consumption. As a general principle, an econometric model is considered to have a high predictive power if the associated R-Square is high enough (Gujarati & Porter, 2009). However, it is important to emphasise that this maxim should not be applied and understood as an essential principle in any study. In fact, there are other factors that can level out what is acceptable, or not, in an R-squared. As an example, the area and context of the study take on a crucial role. It is not the same thing, and should not be compared, the adjustment of the model in the case of a study related to social research with a model designed for an exact science with a physical process (Asteriou & Hall, 2021; Ozili, 2022). Thus, and knowing that the objective of the analysis is to predict human behaviour regarding internet consumption, the obtained R-Squared is considered as acceptable, especially when most of the explanatory variables are statistically significant (Ozili, 2022).

Table 3 presents the coefficients and the standard errors of the model, as well as the associated p-value (Appendix 5). Before any conclusions, it is important to infer the significance of the variables to understand the extent to which the model is capable of producing a reliable relationship between the dependent and the explanatory variables.

Table 3: Regression's results (Stata)

Number of obs	Prob > F	R-Squared	
1 141 646	0.000	0.316	
Variables	Coef.	Std. Err.	P > |t|
lnAirtime	0.064	0.004	0.000
lnSMS	0.321	0.004	0.000
5G_Traffic	0.022	0.009	0.015
Digital_Skills	1.267	0.014	0.000
WTF_Client	1.172	0.009	0.000
Old_Client	0.897	0.023	0.000
Loc			
2	0.011	0.011	0.317
3	0.049	0.028	0.080
4	-0.065	0.028	0.022
5	0.001	0.028	0.978
6	-0.017	0.155	0.913
Eq			
2	0.895	0.043	0.000
3	1.200	0.044	0.000
4	1.449	0.045	0.000
5	1.426	0.044	0.000
5G Trend (T)	-0.092	0.003	0.000
Overall trend (T2)	0.066	0.001	0.000

Source: Own elaboration

In this analysis, for all variables, with the exception of location, the p-value is low enough ($P<0.000$) to reject the null hypothesis and, thus, there is statistical evidence that supports the significance of the variables.

Apart from the significance level, when analysing Table 3, it is possible to infer that the signs of the variables' coefficients are in accordance with what is expected by the literature presented on Section 2.2.3. Thus, the effect of the variables on the level of internet consumption correspond to what was expected, making the model in question consistent with the remaining studies and theories.

In addition to the explanatory variables, some control variables were included in the model. First, monthly dummies were added in order to control for some seasonality effects. As mentioned, there is a clear trend of increasing consumption until the summer season, reaching a peak in the so-called high season, and then the total of internet consumption returns to lower levels. Associated with this point, two trend variables were created – T (5G Trend) and T2 (Overall trend - to help determine the evolution of data consumption). While T signals the period after the introduction of 5G, the other variable allows to estimate the overall growth of internet consumption over time. Second, an individual-specific dummy was added which indicates if the user was a customer during the entire period under analysis or if, on the contrary, she/he joined the service in the middle of the analysed time horizon.

Considering the variables related to **SMS and voice services**, in both cases there is a positive, although of small magnitude, relationship. This association will be studied in more detail in the following analysis, which relies on panel data analysis.

The effect of **location** (Hip. 1a) on internet consumption is not clear in this model, as already mentioned. The lack of statistical significance can be justified with some assumptions that were made for the collection and treatment of this variable that may have affected the final result. First, as there was no individual-specific information about the users' address, a proxy with the most frequent location was assumed. Naturally, this comparison may not hold in cases of frequent mobility, for example. Second, for the interpretation of the variable, an index of urbanisation was created according to the number of inhabitants in the district. As a result, homogeneity within the district itself was assumed, which, in reality, does not exist. Thus, these assumptions may have weakened the model, not providing any predictive power to the variable in question.

Considering the different coefficients resulting from the regression and the respective average values of the variables, the average monthly consumption of mobile internet predicted by the model is 3.5GB, approximately.

Starting with the variable related to **age** (Hip. 1b), the variable under analysis identifies customers who belong to a subscription plan targeted at young people - WTF. Thus, although it is not possible to define a direct relationship between age and internet consumption, it provides a good comparison between the variables. Based on the coefficient shown in Table 3, and holding the other variables constant, it is possible to conclude that users who are included in this subscription plan, when compared to users that do not belong to this segment, consume, on average, 2.2 times the average amount of data, considering what is understood as the average consumption predicted by the model. Hence, there is a greater predisposition to use the internet among the younger group of users, as suggested by Hargittai and Hinnant (2008).

Similarly, the effect of **digital skills** (Hip. 1c) is also positive. In fact, one may argue that younger people are more open to technology and, therefore, considering the previous result, a positive relationship would also be expected in this variable (Martínez-Domínguez & Mora-Rivera, 2020). Considering a user who has digital skills, compared to a customer who does not, the associated consumption is 2.6 times the average internet consumption predicted by the model, holding other variables constant.

The **income** variable (Hip. 1d) was created based on the equipment owned and is measured considering five different levels - the higher the income (the more expensive the equipment), the higher the level assigned to the user. For the analysis, level one is considered as the reference variable, which corresponds to the lowest income level.

As seen on Table 3, the coefficients associated with the variables are all positive, which indicates that, compared to the reference level, all other users have, on average, a higher consumption. Furthermore, when comparing the coefficients, it is also possible to notice that there is a constant growth as the level under analysis increases, excluding level five which has a coefficient slightly lower than the previous one. For example, while a customer that belongs to level two consumes 1.5 times the average consumption predicted by the model for the reference level, a customer that is classified in the highest level consumes 3.2 times more. This means that, compared to the reference level, the higher the user's income, the greater the expected internet consumption. This positive relationship was already documented by Fuchs (2008) and Manlove and Whitacre (2019).

Finally, based on the coefficient of the binary variable identifying **5G traffic** (Hip. 1e), it is possible to infer that, holding the remaining conditions stable, 5G is related with an increase of 25% in total internet consumption, approximately. However, the interpretation of this variable must be particularly careful since there are other variables that may end up influencing this result.

4.2.2.1 The effect of 5G: a close up

In fact, regarding this specific analysis of 5G, there may be some cyclical effect that, due to the way the model was built, is not controlled, and can distort the results.

5G users are customers with the latest equipment and, in this specific case, with a higher data ceiling (higher or equal to 10GB) or who have activated the 5G trial addon. In any case, these characteristics end up being associated with more technologically advanced customers and, therefore, it is assumed that they have a different consumption pattern and needs. Thus, one may argue that when introducing this variable in the regression, and again considering the way in which the model is being analysed, there is a positive effect that can be compared to the introduction of a filter or a flag identifying the customers most likely to use data. Hence, considering this perspective, it would be expected that the consumption associated with these users would be higher.

To understand the true evolution of consumption, two trend variables were introduced which indicate different time horizons. By analysing T2, it is possible to infer that there is, in fact, a growth trend in consumption over time. Variable T was created to identify and measure, specifically, the consumptions made in the periods after the introduction of 5G. From the coefficients presented in Table 3, it can be argued that in the moments after the introduction of 5G there was indeed a decrease in the consumption's growth trend. Even so, customers in 5G showed higher consumption, it remains unclear whether for network reasons or another external factor

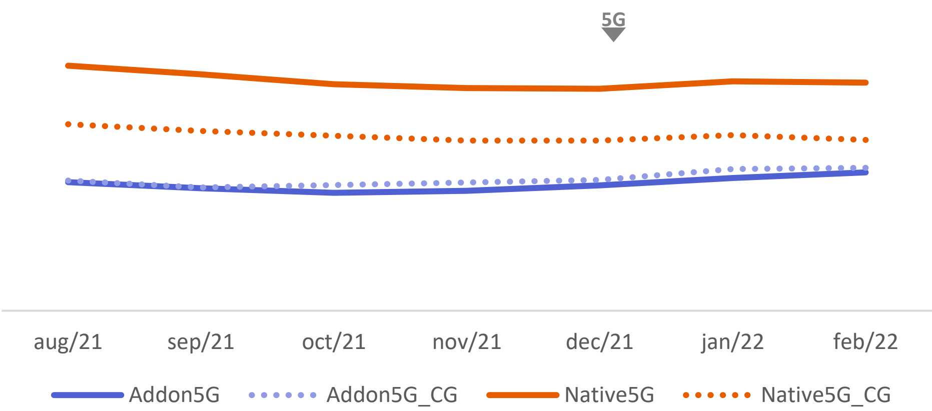
For a different perspective, a complementary analysis was carried out. Rather than comparing 4G and 5G customers in the same periods of time, it is important to analyse the evolution and compare the customer's own 4G and 5G consumption. To this end, data were collected on the amount of internet consumed, in GB, for moments immediately before - from August 2021 until November 2021 - and after the introduction of 5G - from December 2021 until February 2022.

For this analysis, all customers who were native to 5G (meaning with a subscription plan with 10GB or more) or who activated the addon in the app were selected. Then, the equipment compatibility with 5G ended up working as a flag to distinguish the target from the control group. That is, customers with a subscription plan and compatible equipment are customers who are assumed to be using 5G traffic (although, as mentioned, these two conditions are necessary but not sufficient to guarantee 5G traffic) and, on the other hand, customers with a subscription plan but without compatible equipment are considered as the control group that, inevitably, does not uses 5G.

From the total sample, 24% correspond to the target group and 76% correspond to the control group, approximately. In the target group, 31% of customers have activated the addon while 69% have a native 5G subscription plan. In the case of the control group, only 5% activated the 5G addon - and the action had no effect - while the rest, 95%, have native 5G tariffs. Additionally, in order to control variations in consumption for other reasons, only customers who, in the period under analysis, did not change their tariffs were selected. This filter excludes customers who actually had an increase in consumption not because they switched to 5G traffic, but because they changed their plan and, most likely, have an upper ceiling.

When plotting a simple graph with the evolution of consumption over time (Graph 3), it is possible to realise there was not a substantial change after the introduction of 5G.

Graph 3: Data consumption over time (aug/21 until feb/22)



Source: Own elaboration

There is, effectively, a small increase, but, in the addon group, this effect is also reflected in the control group. Thus, one may argue that the possible effect of 5G, at least in Portugal and for the selected sample, will not be as visible as suggested by Ericsson, for example. In the Ericsson mobile report, the company highlighted a growth of 2–3 times the amount of data when comparing 5G with 4G subscribers in North East Asia. If the relationship documented by Ericson hold for this analysis in question, from December onwards, the curve associated with the target group would have to distance itself considerably from the control group, reflecting a sharp increase.

Hence, and as a conclusion, there are other variables that were not controlled and could be influencing the result, thus making it impossible to suggest a sustained relationship between the type of connection and data consumption.

5.3 Testing Hipotheses 2

The following research question intends to explore the relationship between mobile internet usage, in MB, and other services provided by mobile operators, namely SMS and voice service.

A longitudinal analysis was carried out to understand the evolution of these variables over time, in this specific case from January 2021 until April 2022. Thus, the cross-section data set was used to study whether the increase in internet consumption creates any repercussions on the other two services. The methodological process used will be the one proposed by Park (2011).

The estimated model is defined as follows:

$$
\begin{aligned}
&\text{Ln } MB_i = \\
&\beta_0 \\
&+ \beta_1 \text{ ln\_SMS}_i \\
&+ \beta_2 \text{ ln\_Airtime}_i \\
&+ \beta_3 \text{ Feb}_i + \beta_4 \text{ Mar}_i + \beta_5 \text{ Apr}_i + \beta_6 \text{ May}_i + \beta_7 \text{ Jun}_i + \beta_8 \text{ Jul}_i + \beta_9 \text{ Ago}_i + \beta_{10} \\
&\text{Sep}_i + \beta_{11} \text{ Oct}_i + \beta_{12} \text{ Nov}_i + \beta_{13} \text{ Dec}_i \\
&+ \beta_{14} \text{ T}_i \\
&+ \beta_{15} \text{ T2}_i \\
&+ \varepsilon
\end{aligned}
$$

Where i is the user observed, β0 is the constant of the model, β1 until β15 are the coefficients of the explanatory variables and ε is the error of the model that is not explained by the included variables.

As mentioned in Section 4.2.1.2, as individuals are the unit of analysis, it is expected that there is a high level of heterogeneity among data. As a consequence, fixed (Table 4) and random (Table 5) effects estimation's methods were used (Appendix 6 and 7). These methods include a test to compare the model's result with OLS in order to verify if the goodness-of-fit is improved (Park, 2011). While a pooled (or homogeneous) panel data model assumes that there are no differences on the parameters across individuals, the heterogeneous model allows for any or all of the model parameters to vary across individuals (Asteriou & Hall, 2021).

Table 4: Regression with random effects (Stata)

Number of obs	Prob > Chi2
1 141 646	0.000

Variables	Coef.	Std. Err.	P > |t|
lnAirtime	0.240	0.002	0.000
lnSMS	0.297	0.002	0.000
5G Trend (T)	-0.078	0.002	0.000
Overall trend (T2)	0.058	0.001	0.000

Source: Own elaboration

Table 5: Regression with fixed effects (Stata)

Number of obs	Prob > Chi2
1 141 646	0.000

Variables	Coef.	Std. Err.	P > |t|
lnAirtime	0.207	0.002	0.000
lnSMS	0.327	0.002	0.000
5G Trend (T)	-0.076	0.002	0.000
Overall trend (T2)	0.057	0.001	0.000

Source: Own elaboration

After estimating the regression with both methods - fixed and random effects -, the Hausman specification test was performed to assist the choice between the two approaches which aims to test if individual effects are uncorrelated with any regressor in the model (Hausman, 1978). Hence, the test can be understood as a distance measure between the fixed effects and the random effects estimators, in which under the null hypothesis the random effects estimators are consistent and efficient (Asteriou & Hall, 2021).

5.3.1 Results

Considering the Hausman Test, the p-value is small enough to reject the null hypothesis of no correlation, so it is possible to conclude that individual effects are significantly correlated with at least one regressors in the model. Therefore, the fixed effects estimator is more appropriate (Park, 2011).

At the 0.05 significance level, all the independent variables under analysis are statistically significant. Similar to the previous analysis, control variables related to seasonality effects and consumption growth trend were added to the model and produced similar effects to those already discussed in the previous section.

Regarding the variables associated with text messaging, also known as SMS, and voice services, the object of study of this second hypothesis, both are positively related to the independent variable. Holding other variables constant, a 1% increase in the number of **SMS** sent is associated with an average increase of 0.21% in data consumption, considering the average value predicted by the model. Regarding the effect of **voice services**, a 1% increase in the total number of minutes spent monthly causes, on average, a 0.33% increase in data consumption.

However, although there is an unquestionable positive effect, its magnitude calls into question the true relevance of relationships and whether there is actually a complementarity effect between these services. These results are consistent with the existing empirical evidence that also question the association's small relevance (Gerpott et al., 2012 ; Karikoski & Luukkainen, 2011)

6. CONCLUSION

6.1 Final remarks and managerial implications

The present study aimed to study in greater depth the trends and consumption patterns associated with the mobile internet. In fact, at a time when society is more connected than ever, the internet is perceived by many as a necessity, being much more than a form of entertainment and information (Williams, 2011).

This technological wave is impacting society as a whole, with no industry being indifferent to it. The telco sector thus assumes a fundamental role in this evolution, being responsible for the constant innovations that impact the market and society itself. Hence, the greater the understanding of users' behavior in relation to the connectivity services offered, the greater the monetization capacity.

As would be expected considering the context of the analysis, when the object of study is reality and the human being, there is always an associated complexity and uncertainty. Thus, it is difficult to individualize the different effects since the explanatory factors are not totally independent. Even so, the analyses developed during the study are in line with what is considered by the existing literature.

Internet consumption is not homogeneous, and it is possible to highlight some traits and personal characteristics that can dictate the greater probability of consumption. It is expected that younger users, who have digital skills and with higher disposable income, will be responsible for a higher average consumption. Additionally, a complementarity effect was observed between data consumption and the more traditional communication services provided by mobile operators – SMS and voice services – although, as discussed, their small magnitude leaves some doubts about the true effect. Lastly, the data suggest a positive effect on consumption when traffic is carried on 5G. However, this last relationship should be discussed with greater caution, not being understood as a general rule. It is not evident that this additional consumption in 5G customers is merely a result of the type of connection. Additionally, there is a clear growth trend in data consumption, something that would be expected given the technological evolution that has been impacting society.

Considering the results, and in a more strategic perspective, segmenting consumers based on some characteristics and approaching these same segments with a different offer and value proposition can be an enabler for monetization. In fact, NOS is already adopting this marketing strategy and has created new products and services with a very specific target. The WTF subscription plan, already mentioned in the study, is an example of a product that is highly targeted to the young audience that ends up being more demanding regarding the internet needed. In addition to these subscription plans having more GB available, and even a specific amount only for apps, this plan is characterized by a more colorful and appealing image and an informal communication. Additionally, another example is WOO's subscription plans. This sub-company distinguishes itself from the rest of the competitors for being totally digital, with a highly simplified joining and canceling process, and also a substantially lower price compared to the average on the market.

Additionally, another suggestion would be to better monitor the evolution of 5G to see if, in fact, this network consumes more internet. With the emergence of 5G, many services and products are unlocked that were not possible until then with previous networks and, therefore, consumption in general is expected to increase. However, more than this effect, it would be relevant to understand whether in the same day-to-day activities 5G consumption is higher than 4G consumption. The time horizon studied may not be sufficient given that it is only considered a very early introductory phase, which could lead to slightly premature conclusion. Even so, the fact is that, according to the conclusions of the study, it is not evident that there is a clear and prominent effect of 5G, contrary to reports from other operators and manufacturers. This result turned out to be relevant for NOS as it was an important finding for the strategic planning. If there were indeed an effect of 5G, one of the possible strategies to adopt would be to reduce the prices of equipment compatible with 5G, leveling them to older equipment only compatible with 4G. In this sense, given the two options with similar prices, a large part of customers would choose to purchase the latest equipment, which would be reflected in a higher data consumption in the long term.

6.2 Limitation and further research

This study was based on archival records provided by NOS and, therefore, no survey or interaction existed with the selected customer base. As a consequence, the database for the analysis was conditioned, by itself, by the variables available to be used. Having this limitation, some assumptions had to be considered, which may, naturally, have biased the results and consequent conclusions. Namely, the income variable was introduced in the model with a proxy which relied on the price of the equipment owned, thus assuming that the most expensive mobile phones are owned by high-income customers. As one may argue, this condition does not mirror the diversity of reality. In fact, perceived importance plays a crucial role in individual household consumption choices and, therefore, it is expected that there are people who value technology the most and even having a lower income compared to their peers, end up investing more and owning a more expensive equipment, and vice versa. Similarly, the location variable was also introduced in the model as a proxy. In this case, this variable proved to be non-significant. This failure of predictive power may arise as a result of some assumptions made. As mentioned in Section 5.2.1., the fact that the most frequent location is considered to be the place of residence can lead to some inaccuracies. Furthermore, there was also an assumption that the supposed residents of the same district have the same level of urbanization, which does not hold in reality. Thus, it would be relevant to include a survey in order to incorporate more concrete conclusions about the studied customer base.

As already mentioned in a previous section, the variable responsible for determining whether the traffic was carried out in 5G or not was obtained from the combination of two criteria: subscription plan and the equipment owned by the user. In fact, for traffic to be carried out on this state-of-the-art network it is necessary that the customer has an eligible plan and, at the same time, that the equipment itself allows 5G connectivity. However, the connection is influenced by other factors, making these conditions necessary but not sufficient to guarantee 5G. Connectivity is dependent on infrastructures that are not available in all locations, especially in this initial and introductory phase of the network, and, in addition, it would be necessary to ensure that the user has not disabled this feature from the smartphone's settings. Hence, to truly quantify the effect of 5G, it would be important to collect and cross more data in order to guarantee the best traffic classification.

Another limitation, also related to the variables to consider, is that there are other variables that are indicated in the literature as possible predictors of use and, once again, by carrying out a survey it would be possible to collect information that is not available in the database (Hargittai & Hinnant, 2008). The level of education, for example, is considered as a variable with explanatory power that was not analysed in the current model due to the lack of detailed and individual-specific information. In fact, the combination of different research strategies and sources of evidence is pointed out as a potential cause to increase reliability as well as provide new insights into the development (Welch, 2000).

Finally, and regarding the relationship between mobile internet and the services provided by operators - voice and text messaging - the degree of substitutability between these variables was analysed and tested. However, the internet is much broader and encompasses more services than just communication applications. Thus, a correction to the study would be to consider only the GBs that were spent on specific communication services, and, in that case, there would be more comparability with voice and SMS services (Gerpott, 2015).

7. BIBLIOGRAPHIC REFERENCES

Ahmad, I., Shahabuddin, S., Kumar, T., Okwuibe, J., Gurtov, A., & Ylianttila, M. (2019). Security for 5G and Beyond. *IEEE Communications Surveys & Tutorials*, *21*(4), 3682–3722. https://doi.org/10.1109/comst.2019.2916180

Alli, A. M., Winter, G. S., & May, D. L. (2011). Globalization: Its Effects. *International Business & Economics Research Journal (IBER), 6*(1). https://doi.org/10.19030/iber.v6i1.3339

ANACOM. (2022). Pandemia Covid-19: Impacto na utilização dos serviços de comunicações.

ANACOM. (2022). Facts & Figures 2022 (first quarter).

Anwar, S., & Prasad, R. (2018). Framework for Future Telemedicine Planning and Infrastructure using 5G Technology. *Wireless Personal Communications, 100*(1), 193–208. https://doi.org/10.1007/s11277-018-5622-8

Asimakopoulos, G., & Whalley, J. (2017). Market leadership, technological progress and relative performance in the mobile telecommunications industry. *Technological Forecasting and Social Change, 123*, 57–67. https://doi.org/10.1016/j.techfore.2017.06.021

Asteriou, D., & Hall, S. (2021). *Applied Econometrics* (4th ed.). Macmillan Education UK.

Badasyan, N., & Silva, S. (2018). The impact of internet access at home and/or school on students' academic performance in urban areas in Brazil. *International Journal Of Education Economics And Development*, *9*(2), 149-171. https://doi.org/10.1504/ijeed.2018.092198

Bahia, K., & Castells, P. (2022). The impact of spectrum assignment policies on consumer welfare. *Telecommunications Policy, 46*(1), 102228. https://doi.org/10.1016/j.telpol.2021.102228

Basole, R. C., & Karla, J. (2011). On the Evolution of Mobile Platform Ecosystem Structure and Strategy. *Business & Information Systems Engineering, 3*(5), 313–322. https://doi.org/10.1007/s12599-011-0174-4

Bellégo, C., Benatia, D., & Pape, L. (2022). Dealing with Logs and Zeros in Regression Models. *Arxiv*. https://doi.org/https://doi.org/10.48550/arXiv.2203.11820

Bhalla, M. R., & Bhalla, A. V. (2010). Generations of Mobile Wireless Technology: A Survey. *International Journal of Computer Applications, 5*(4), 26–32. https://doi.org/10.5120/905-1282

Billieux, J., Van der Linden, M., & Rochat, L. (2008). The role of impulsivity in actual and problematic use of the mobile phone. *Applied Cognitive Psychology*, *22*(9), 1195-1210. https://doi.org/10.1002/acp.1429

Brake, D. (2018). Economic Competitiveness and National Security Dynamics in the Race for 5G between the United States and China. *TPRC 46: The 46th Research Conference on Communication, Information and Internet Policy 2018*. https://doi.org/10.2139/ssrn.3142229

Bresciani, S., Ferraris, A., & del Giudice, M. (2018). The management of organizational ambidexterity through alliances in a new context of analysis: Internet of Things (IoT) smart city projects. *Technological Forecasting and Social Change*, *136*, 331–338. https://doi.org/10.1016/j.techfore.2017.03.002

Bresnahan, T. F., & Trajtenberg, M. (1995). General purpose technologies 'Engines of growth'? *Journal of Econometrics, 65*(1), 83–108. https://doi.org/10.1016/0304-4076(94)01598-t

Brown, J., & Goolsbee, A. (2002). Does the Internet Make Markets More Competitive? Evidence from the Life Insurance Industry. *Journal Of Political Economy*, *110*(3), 481-507. https://doi.org/10.1086/339714

Brown, K., Campbell, S., & Ling, R. (2011). Mobile Phones Bridging the Digital Divide for Teens in the US?. *Future Internet*, *3*(2), 144-158. https://doi.org/10.3390/fi3020144

Carlaw, K. I., & Lipsey, R. G. (2006). GPT-Driven, Endogenous Growth. *The Economic Journal, 116*(508), 155–174. https://doi.org/10.1111/j.1468-0297.2006.01051.x

Cave, M. (2018). How disruptive is 5G? *Telecommunications Policy, 42*(8), 653–658. https://doi.org/10.1016/j.telpol.2018.05.005

Castells, M. (2022). *The Impact of the Internet on Society: A Global Perspective*. OpenMind. Retrieved 13 September 2022, from https://www.bbvaopenmind.com/en/articles/the-impact-of-the-internet-on-society-a-global-perspective/.

Creanza, N., Kolodny, O., & Feldman, M. (2017). Cultural evolutionary theory: How culture evolves and why it matters. *Proceedings Of The National Academy Of Sciences*, *114*(30), 7782-7789. https://doi.org/10.1073/pnas.1620732114

Choi, C., & Hoon Yi, M. (2009). The effect of the Internet on economic growth: Evidence from cross-country panel data. *Economics Letters*, *105*(1), 39-41. https://doi.org/10.1016/j.econlet.2009.03.028

Christensen, C. M., Suárez, F. F., & Christensen, C. M., Suárez, F. F., & Utterback, J. M. (1998). Strategies for Survival in Fast-Changing Industries. *Management Science, 44*(12), 207–220. https://doi.org/10.1287/mnsc.44.12.s207

Doganoglu, T., & Grzybowski, L. (2007). Estimating network effects in mobile telephony in Germany. *Information Economics and Policy, 19*(1), 65–79. https://doi.org/10.1016/j.infoecopol.2006.11.001

Dolan, S. (2022). *How mobile users spend their time on their smartphones in 2022*. Insider Intelligence. Retrieved 22 August 2022, from https://www.insiderintelligence.com/insights/mobile-users-smartphone-usage/.

Dutta, A. (2003). Telecommunications Industry. *Encyclopedia Of Information Systems*, 403-417. https://doi.org/10.1016/b0-12-227240-4/00182-9

European Union (2015). Regulation (EU) 2015/2120 of the European Parliament and of the Council of 25 November 2015 laying down measures concerning open internet access and amending Directive 2002/22/EC on universal service and users' rights relating to electronic communications networks and services and Regulation (EU) No 531/2012 on roaming on public mobile communications networks within the Union.

Emanuel, R., Bell, R., Cotton, C., Craig, J., Drummond, D., & Gibson, S. et al. (2015). The truth about smartphone addiction. *College Student Journal, 49*(2), 291-299.

Ferrier, W. J., Smith, K. G., & Grimm, C. M. (1999). The role of competitive action in market share erosion and industry dethronement: A study of industry leaders and challengers. *The Academy of Management Journal, 42*(4), 372–388. https://doi.org/10.2307/257009

Finney, R. Z., Lueg, J. E., & Campbell, N. D. (2008). Market pioneers, late movers, and the resource-based view (RBV): A conceptual model. *Journal of Business Research, 61*(9), 925–932. https://doi.org/10.1016/j.jbusres.2007.09.023

Frias, Z., & Pérez Martínez, J. (2018). 5G networks: Will technology and policy collide? *Telecommunications Policy, 42*(8), 612–621. https://doi.org/10.1016/j.telpol.2017.06.003

Fuchs, C. (2008). *Internet and society: Social Theory in the Information Age*. Routledge.

Gadzama, W., Joseph, B., & Aduwamai, N. (2017). Global Smartphone Ownership, Internet Usage And Their Impacts On Humans. *Researchjournali'S Journal Of Communications Networks*, *1*(1).

Gerpott, T. (2010). Impacts of mobile Internet use intensity on the demand for SMS and voice services of mobile network operators: An empirical multi-method study of German mobile Internet customers. *Telecommunications Policy, 34*(8), 430-443. https://doi.org/10.1016/j.telpol.2010.06.003

Gerpott, T., Thomas, S., & Weichert, M. (2012). Usage of established and novel mobile communication services: Substitutional, independent or complementary?. *Information Systems Frontiers, 16*(3), 491-507. https://doi.org/10.1007/s10796-012-9356-y

Gerpott, T. (2015). SMS use intensity changes in the age of ubiquitous mobile Internet access – A two-level investigation of residential mobile communications customers in Germany. *Telematics And Informatics, 32*(4), 809-822. https://doi.org/10.1016/j.tele.2015.03.005

Goldfarb, A., & Prince, J. (2008). Internet adoption and usage patterns are different: Implications for the digital divide. *Information Economics And Policy*, *20*(1), 2-15. https://doi.org/10.1016/j.infoecopol.2007.05.001

Gray, T., Gainous, J., & Wagner, K. (2016). Gender and the Digital Divide in Latin America. *Social Science Quarterly, 98*(1), 326-340. https://doi.org/10.1111/ssqu.12270

Gujarati, D., & Porter, D. (2009). *Basic econometrics* (5th ed.). McGraw-Hill/Irwin.

Hargittai, E., & Hinnant, A. (2008). Digital Inequality. *Communication Research*, *35*(5), 602-621. https://doi.org/10.1177/0093650208321782

Hausman, J. (1978). Specification Tests in Econometrics. *Econometrica, 46*(6), 1251-1271. https://doi.org/10.2307/1913827

Hayes, A., & Cai, L. (2007). Using heteroskedasticity-consistent standard error estimators in OLS regression: An introduction and software implementation. *Behavior Research Methods, 39*(4), 709-722. https://doi.org/10.3758/bf03192961

Hong, J., Shin, J., & Lee, D. (2016). Strategic management of next-generation connected life: Focusing on smart key and car–home connectivity. *Technological Forecasting and Social Change, 103*, 11–20. https://doi.org/10.1016/j.techfore.2015.10.006

Horrigan, J., & Duggan, M. (2015). *Home Broadband 2015*. Pew Research Center: Internet, Science & Tech. Retrieved 14 September 2022, from https://www.pewresearch.org/internet/2015/12/21/home-broadband-2015/.

Karikoski, J., & Luukkainen, S. (2011). Substitution in smartphone communication services. *2011 15Th International Conference On Intelligence In Next Generation Networks*. https://doi.org/10.1109/icin.2011.6081096

Karikoski, J., & Soikkeli, T. (2011). Contextual usage patterns in smartphone communication services. *Personal And Ubiquitous Computing, 17*(3), 491-502. https://doi.org/10.1007/s00779-011-0503-0

Kerin, R. A., Varadarajan, P. R., & Peterson, R. A. (1992). First-Mover Advantage: A Synthesis, Conceptual Framework, and Research Propositions. *Journal of Marketing, 56*(4), 33–52. https://doi.org/10.2307/1251985

Kiesel, R., Roessel, J. V., & Schmitt, R. H. (2020). Quantification of economic potential of 5G for latency critical applications in production. *Procedia Manufacturing, 52*, 113–120. https://doi.org/10.1016/j.promfg.2020.11.021

Kleinbaum, D., Kupper, L., Nizam, A., & Rosenberg, E. (2014). *Applied Regression Analysis and Other Multivariable Methods* (5th ed., p. 363). Cengage Learning.

Kissell, R., & Poserina, J. (2017). *Optimal sports math, statistics, and fantasy* (1st ed., pp. 39-69). Academic Press.

Lapointe, L., Boudreau-Pinsonneault, C., & Vaghefi, I. (2013). Is Smartphone Usage Truly Smart? A Qualitative Investigation of IT Addictive Behaviors. *2013 46Th Hawaii International Conference On System Sciences*. https://doi.org/10.1109/hicss.2013.367

Lieberman, M. B., & Montgomery, D. B. (1988). First-mover advantages. *Strategic Management Journal, 9*(S1), 41–58. https://doi.org/10.1002/smj.4250090706

Liu, Y., Peng, M., Shou, G., Chen, Y., & Chen, S. (2020). Toward Edge Intelligence: Multiaccess Edge Computing for 5G and Internet of Things. *IEEE Internet of Things Journal, 7*(8), 6722–6747. https://doi.org/10.1109/jiot.2020.3004500

Lv, Z., Lloret, J., & Song, H. (2020). Internet of Things and augmented reality in the age of 5G. *Computer Communications*, *164*(1), 158-161. https://doi.org/10.1016/j.comcom.2020.08.019

Mäkinen, O., Luukkainen, S., & Karikoski, J. (2014). Mobile Service Substitution on Modern Smartphones: Case Facebook. *2014 International Conference On Mobile Business, 12*.

Manlove, J., & Whitacre, B. (2019). Understanding the trend to mobile-only internet connections:A decomposition analysis. *Telecommunications Policy*, *43*(1), 76-87. https://doi.org/10.1016/j.telpol.2018.03.012

Martínez-Domínguez, M., & Mora-Rivera, J. (2020). Internet adoption and usage patterns in rural Mexico. *Technology In Society*, *60*, 101226. https://doi.org/10.1016/j.techsoc.2019.101226

McIntyre, D. P., & Subramaniam, M. (2009). Strategy in Network Industries: A Review and Research Agenda. *Journal of Management, 35*(6), 1494–1517. https://doi.org/10.1177/0149206309346734

Morgado, A., Huq, K. M. S., Mumtaz, S., & Rodriguez, J. (2018). A survey of 5G technologies: regulatory, standardization and industrial perspectives. *Digital Communications and Networks, 4*(2), 87–97. https://doi.org/10.1016/j.dcan.2017.09.010

Number of smartphone subscriptions worldwide from 2016 to 2021, with forecasts from 2022 to 2027. Statista. (2022). Retrieved 4 September 2022, from https://www.statista.com/statistics/330695/number-of-smartphone-users-worldwide/.

Nur-Al-Ahad, M., & Nusrat, S. (2019). New Trends in Behavioral Economics: A Content Analysis of Social Communications of Youth. *Business Ethics And Leadership*, *3*(3), 107-115. https://doi.org/10.21272/bel.3(3).107-115.2019

Osseiran, A., Monserrat, J. F., & Marsch, P. (2016). 5G Mobile and Wireless Communications Technology (1st ed.). *Cambridge University Press*. https://doi.org/10.1017/CBO9781316417744

Oughton, E., Frias, Z., Russell, T., Sicker, D., & Cleevely, D. D. (2018). Towards 5G: Scenario-based assessment of the future supply and demand for mobile telecommunications infrastructure. *Technological Forecasting and Social Change, 133*, 141–155. https://doi.org/10.1016/j.techfore.2018.03.016

Ozili, P. (2022). The Acceptable R-Square in Empirical Modelling for Social Science Research. Retrieved 7 September 2022, from http://dx.doi.org/10.2139/ssrn.4128165

Parasuraman, S., Sam, A., Yee, S., Chuon, B., & Ren, L. (2017). Smartphone usage and increased risk of mobile phone addiction: A concurrent study. *International Journal Of Pharmaceutical Investigation*, *7*(3), 125. https://doi.org/10.4103/jphi.jphi_56_17

Parcu, P. L., Innocenti, N., & Carrozza, C. (2021). Ubiquitous technologies and 5G development. Who is leading the race? *Telecommunications Policy*. https://doi.org/10.1016/j.telpol.2021.102277

Park, Hun Myoung. 2011. Practical Guides To Panel Data Modeling: A Step-by-step Analysis Using Stata. Tutorial Working Paper. Graduate School of International Relations, International University of Japan

Peighambari, K., Sattari, S., Kordestani, A., & Oghazi, P. (2016). Consumer Behavior Research. *SAGE Open*, *6*(2). https://doi.org/10.1177/2158244016645638

Peslak, A., Shannon, L., & Ceccucci, W. (2011). An empirical study of cell phone and smartphone usage. *Issues In Information Systems*, *12*(1), 407-417. https://doi.org/10.48009/1_iis_2011_407-417

Petralia, S., Balland, P. A., & Morrison, A. (2017). Climbing the ladder of technological development. *Research Policy, 46*(5), 956–969. https://doi.org/10.1016/j.respol.2017.03.012

Phuc Nguyen, C., Dinh Su, T., & Doytch, N. (2020). The drivers of financial development: Global evidence from internet and mobile usage. *Information Economics And Policy*, *53*, 100892. https://doi.org/10.1016/j.infoecopol.2020.100892

Rao, S. K., & Prasad, R. (2018). Impact of 5G Technologies on Industry 4.0. *Wireless Personal Communications, 100*(1), 145–159. https://doi.org/10.1007/s11277-018-5615-7

Rappoport, P., Taylor, L., & Alleman, J. (2004). WTP Analysis of Mobile Internet Demand. *Frontiers Of Broadband, Electronic And Mobile Commerce*, 165-179. https://doi.org/10.1007/978-3-7908-2676-0_11

Rizzato, F. (2020). 5G users on average consume up to 2.7x more mobile data compared to 4G users. Opensignal. Retrieved 4 September 2022, from https://www.opensignal.com/2020/10/21/5g-users-on-average-consume-up-to-27x-more-mobile-data-compared-to-4g-users.

Scheerder, A., van Deursen, A., & van Dijk, J. (2017). Determinants of Internet skills, uses and outcomes. A systematic review of the second- and third-level digital divide. *Telematics And Informatics*, *34*(8), 1607-1624. https://doi.org/10.1016/j.tele.2017.07.007

Silver, L., Smith, A., Johnson, C., Jiang, J., Anderson, M., & Rainie, L. (2022). *Use of smartphones and social media is common across most emerging economies*. Pew Research Center: Internet, Science & Tech. Retrieved 4 September 2022, from https://www.pewresearch.org/internet/2019/03/07/use-of-smartphones-and-social-media-is-common-across-most-emerging-economies/.

Spence, A. M. (1981). The Learning Curve and Competition. *The Bell Journal of Economics, 12*(1), 49–70. https://doi.org/10.2307/3003508

Stockemer, D. (2018). The internet: An important tool to strengthening electoral integrity. *Government Information Quarterly*, *35*(1), 43–49. https://doi.org/10.1016/j.giq.2017.11.009

Suarez, F. F., & Lanzolla, G. (2007). The Role of Environmental Dynamics in Building a First Mover Advantage Theory. *Academy of Management Review, 32*(2), 377–392. https://doi.org/10.5465/amr.2007.24349587

Suvankulov, F., Chi Keung Lau, M., & Ho Chi Chau, F. (2012). Job search on the internet and its outcome. *Internet Research*, *22*(3), 298-317. https://doi.org/10.1108/10662241211235662

Teece, D. J. (2007). Explicating dynamic capabilities: the nature and microfoundations of (sustainable) enterprise performance. *Strategic Management Journal, 28*(13), 1319–1350. https://doi.org/10.1002/smj.640

Van Deursen, A., & Helsper, E. (2015). The Third-Level Digital Divide: Who Benefits Most from Being Online?. *Communication And Information Technologies Annual*, 29-52. https://doi.org/10.1108/s2050-206020150000010002

Verkasalo, H. (2007). Handset-based measurement of smartphone service evolution in Finland. *Journal Of Targeting, Measurement And Analysis For Marketing, 16*(1), 7-25. https://doi.org/10.1057/palgrave.jt.5750060

Verkasalo, H. (2008). Handset-based measurement of mobile service demand and value. *Info, 10*(3), 51-69. https://doi.org/10.1108/14636690810874395

Visser, R. (2019). The effect of the internet on the margins of trade. *Information Economics And Policy*, *46*, 41-54. https://doi.org/10.1016/j.infoecopol.2018.12.001

Zhang, S., Xu, X., Wu, Y., & Lu, L. (2014). 5G: Towards energy-efficient, low-latency and high-reliable communications networks. *2014 IEEE International Conference on Communication Systems*, 197–201. https://doi.org/10.1109/iccs.2014.7024793

Wald, H., Dube, C., & Anthony, D. (2007). Untangling the Web—The impact of Internet use on health care and the physician–patient relationship. *Patient Education And Counseling*, *68*(3), 218-224. https://doi.org/10.1016/j.pec.2007.05.016

Wang, Y., & Hao, F. (2018). Does Internet penetration encourage sustainable consumption? A cross-national analysis. *Sustainable Production And Consumption*, *16*, 237-248. https://doi.org/10.1016/j.spc.2018.08.011

Welch, C. (2000). The archaeology of business networks: the use of archival records in case study research. *Journal Of Strategic Marketing, 8*(2), 197-208. https://doi.org/10.1080/0965254x.2000.10815560

Williams, E. (2011). Environmental effects of information and communications technologies. *Nature*, *479*(7373), 354-358. https://doi.org/10.1038/nature10682

8. APPENDIX

8.1 Appendix 1: NOS Group

Company	Ownership
NOS Comunicações, S.A.	100%
NOS Lusomundo Audiovisuais, S.A.	100%
NOS Lusomundo Cinemas, S.A.	100%
NOS Technology, S.A.	100%
NOS Sistemas, S.A.	100%
NOS Inovação, S.A.	100%
NOS Corporate Center, S.A.	100%
NOS Audio Sales & Distribution, S.A.	100%
NOS Wholesale, S.A.	100%
NOS Açores Comunicações, S.A.	84%
NOS Madeira Comunicações, S.A.	78%
DREAMIA, S.A.	50%
ZAP	30%
SPORT TV, S.A.	25%

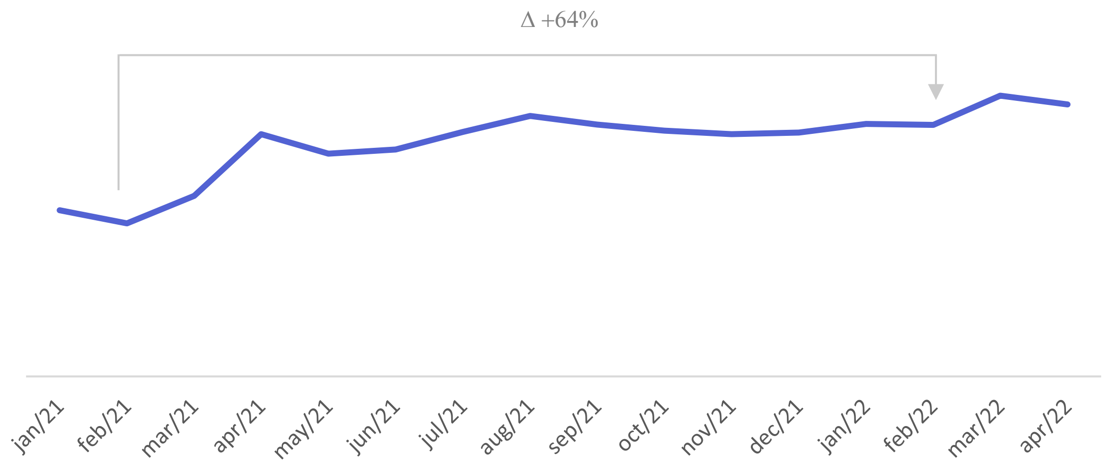
8.2 Appendix 2: Scale used for the location variable

1	2	3	4	5	6	
0 - 15 000	15 000 - 150 000	150 000 - 200 000	200 000 - 350 000	350 000 - 1 000 000	+ 1 000 000	inhabitants
Ilha da Graciosa	Beja	Castelo Branco	Ilha da Madeira	Aveiro	Lisboa	
Ilha das Flores	Bragança	Évora	Viana do Castelo	Braga	Porto	
Ilha de Porto Santo	Guarda	Vila real		Coimbra		
Ilha do Corvo	Ilha de São Miguel			Faro		
Ilha do Faial	Ilha Terceira			Leiria		
Ilha da Graciosa	Portalegre			Santarém		
				Setúbal		
				Viseu		

8.3 Appendix 3: Scale used for the income variable

	euros
1	0 - 100
2	101 - 300
3	301 - 500
4	501 - 700
5	+ 701

8.3 Appendix 4: Data consumption over time



8.4 Appendix 5: Regression's results from Stata

Linear regression

Number of obs	=	1,141,646
F(28, 74548)	=	2511.56
Prob > F	=	0.0000
R-squared	=	0.3160
Root MSE	=	1.7463

(Std. Err. adjusted for **74,549** clusters in MSISDN)

lnMB	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
lnAirtime	.0637431	.0043596	14.62	0.000	.0551984	.0722879
lnSMS	.3213139	.0040578	79.18	0.000	.3133605	.3292672
G	.0222595	.0091405	2.44	0.015	.0043442	.0401747
DS	1.266605	.0135225	93.67	0.000	1.240101	1.29311
seWTF	1.171706	.0099428	117.84	0.000	1.152218	1.191194
sejáexistia	.8971831	.0234311	38.29	0.000	.8512583	.9431078
Loc						
2	.0111941	.011188	1.00	0.317	-.0107344	.0331226
3	.0486595	.0277582	1.75	0.080	-.0057466	.1030655
4	-.0649882	.0284516	-2.28	0.022	-.1207532	-.0092233
5	.0007514	.0277597	0.03	0.978	-.0536574	.0551602
6	-.0168962	.1554268	-0.11	0.913	-.3215322	.2877397
Eq						
2	.8954005	.0432543	20.70	0.000	.8106223	.9801788
3	1.199899	.0435402	27.56	0.000	1.11456	1.285237
4	1.44915	.0445529	32.53	0.000	1.361827	1.536474
5	1.42571	.0439226	32.46	0.000	1.339622	1.511799
T	-.0919442	.0025412	-36.18	0.000	-.096925	-.0869633
T2	.0657552	.0009976	65.91	0.000	.0637999	.0677106
fev	-.0540324	.0033571	-16.10	0.000	-.0606122	-.0474525
mar	.0457536	.004072	11.24	0.000	.0377725	.0537347
abr	.1573611	.0047399	33.20	0.000	.148071	.1666512
mai	.1261161	.0053006	23.79	0.000	.1157269	.1365053
jun	.1179617	.0057998	20.34	0.000	.1065941	.1293294
jul	.1540894	.0063428	24.29	0.000	.1416576	.1665211
ago	.1907537	.0070627	27.01	0.000	.1769109	.2045965
set	.0707984	.0074027	9.56	0.000	.0562892	.0853076
out	-.0283689	.0079694	-3.56	0.000	-.0439889	-.0127489
nov	-.1054418	.0084847	-12.43	0.000	-.1220719	-.0888118
dec	-.0717513	.0048966	-14.65	0.000	-.0813486	-.062154
_cons	2.56441	.0533831	48.04	0.000	2.45978	2.669041

8.5 Appendix 6: Regression's results from Stata (Random-effects)

```
Random-effects GLS regression                   Number of obs     =  1,141,646
Group variable: MSISDN                          Number of groups  =     74,549

R-sq:                                           Obs per group:
     within  = 0.1165                                         min =          1
     between = 0.0663                                         avg =       15.3
     overall = 0.0754                                         max =         16

                                                Wald chi2(15)     =  145209.39
corr(u_i, X)   = 0 (assumed)                    Prob > chi2       =     0.0000
```

lnMB	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
lnSMS	.2399696	.0016459	145.80	0.000	.2367437	.2431955
lnAirtime	.2974229	.0015106	196.89	0.000	.2944622	.3003836
T	-.0782417	.0024633	-31.76	0.000	-.0830696	-.0734138
T2	.0577439	.0007593	76.05	0.000	.0562557	.059232
fev	-.0380764	.0039602	-9.61	0.000	-.0458382	-.0303145
mar	.0532099	.0040893	13.01	0.000	.045195	.0612247
abr	.1751477	.0043041	40.69	0.000	.1667119	.1835836
mai	.173373	.0049154	35.27	0.000	.163739	.1830069
jun	.1503334	.0050515	29.76	0.000	.1404327	.1602341
jul	.1980214	.0053022	37.35	0.000	.1876292	.2084135
ago	.2667708	.0056583	47.15	0.000	.2556808	.2778608
set	.1245596	.0060674	20.53	0.000	.1126677	.1364515
out	.0399582	.0065605	6.09	0.000	.0270998	.0528166
nov	-.0317627	.007093	-4.48	0.000	-.0456648	-.0178607
dec	.0003484	.0059517	0.06	0.953	-.0113167	.0120135
_cons	4.790203	.0119793	399.87	0.000	4.766724	4.813682
sigma_u	1.6768418					
sigma_e	1.0250406					
rho	.72797244	(fraction of variance due to u_i)				

8.6 Appendix 7: Regression's results from Stata (Fixed-effects)

```
Fixed-effects (within) regression               Number of obs     =  1,141,646
Group variable: MSISDN                          Number of groups  =     74,549

R-sq:                                           Obs per group:
     within  = 0.1170                                         min =          1
     between = 0.0559                                         avg =       15.3
     overall = 0.0673                                         max =         16

                                                F(15,1067082)     =    9424.04
corr(u_i, Xb)  = -0.0633                        Prob > F          =     0.0000
```

lnMB	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
lnSMS	.2071347	.0017132	120.90	0.000	.2037768	.2104925
lnAirtime	.3272724	.0015614	209.61	0.000	.3242121	.3303326
T	-.0760859	.0024509	-31.04	0.000	-.0808895	-.0712823
T2	.0574939	.0007557	76.08	0.000	.0560128	.058975
fev	-.0400728	.0039407	-10.17	0.000	-.0477964	-.0323492
mar	.0522328	.0040683	12.84	0.000	.044259	.0602066
abr	.1766468	.004282	41.25	0.000	.1682542	.1850393
mai	.182189	.004891	37.25	0.000	.1726027	.1917753
jun	.157056	.0050261	31.25	0.000	.1472051	.1669069
jul	.2065155	.0052759	39.14	0.000	.1961749	.216856
ago	.2788142	.0056316	49.51	0.000	.2677765	.2898518
set	.1341925	.0060375	22.23	0.000	.1223592	.1460259
out	.0528314	.0065287	8.09	0.000	.0400353	.0656275
nov	-.019494	.0070585	-2.76	0.006	-.0333284	-.0056596
dec	.010921	.0059225	1.84	0.065	-.0006869	.0225288
_cons	4.814176	.0106877	450.44	0.000	4.793229	4.835124
sigma_u	1.8388017					
sigma_e	1.0250406					
rho	.76292149	(fraction of variance due to u_i)				

F test that all u_i=0: F(74548, 1067082) = 43.03   Prob > F = 0.0000

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