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HEDONIC PRICING APPROACH TO BUNDLE REVENUE MANAGEMENT IN TELECOMMUNICATIONS

Master's Thesis by the 2nd year student

Concentration – Master in Corporate Finance

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ЗАЯВЛЕНИЕ О САМОСТОЯТЕЛЬНОМ ХАРАКТЕРЕ ВЫПОЛНЕНИЯ ВЫПУСКНОЙ КВАЛИФИКАЦИОННОЙ РАБОТЫ

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30/05/2021 (Date)

АННОТАЦИЯ

Автор	Чечкова Анастасия Игоревна
Название магистерской диссертации	Гедонистический анализ доходов от пакетов телекоммуникационных услуг
Образовательная программа	38.04.02 Менеджмент
Направление подготовки	ВМ.5603.2019 Корпоративные финансы
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Научный руководитель	Макарова Ольга Всеволодовна, кандидат экономических наук
Описание цели, задач и основных результатов	Цель данной работы заключается в определении влияния телекоммуникационных услуг, включенных в пакеты (bundles), на выручку телекоммуникационных компаний. Для достижения поставленной цели мы построили две эконометрические модели. Первая модель определяет факторы, влияющие на среднюю выручку на одного пользователя (ARPU). Вторая модель рассматривает услуги на более детальном уровне (например, как количество минут влияет на цену пакета услуг). Для тестирования моделей были составлены две выборки с перекрестными данными. Первая выборка включает 70 показателей ARPU 22 компаний из 49 стран (за 2020 год). Вторая выборка включает 100 цен на пакеты услуг 12 операторов из 5 стран (на февраль 2021 года). Результаты исследования выявили, что главными драйверами выручки телекома являются проводной интернет и мобильная связь. Дополнительные услуги (например, подписка на Netflix) оказывают негативное влияние на ARPU в странах с низким уровнем доходов населения. Рост ВВП связан с ростом ARPU. Услуги проводной телефонной связи не влияют на показатель ARPU. Включение в пакет услуг безлимитной мобильной связи (интернет или количество минут) повышает стоимость пакета на 39-51%.
Ключевые слова	Телекоммуникации, телеком, доходы, доходность, пакет услуг, ARPU, средняя выручка на одного пользователя, ценообразование

ABSTRACT

Master Student's Name	Anastasiia Chechkova
Master Thesis Title	Hedonic Pricing Approach to Bundle Revenue Management in Telecommunications
Educational Program	38.04.02 Management
Main field of study	BM.5603.2019 Master in Corporate Finance - MCF
Year	2021
Academic Advisor’s Name	Olga V. Makarova, Senior Lecturer
Description of the goal, task and main results	The research goal of this master thesis is to determine how services offered in a bundle affect telecom’s revenues. To achieve this goal, we use a sequential methodology. First, we build an econometric model to identify the average revenue per user (ARPU) determinants on a high level (what offerings, in general, drive the revenues). Then we build a hedonic pricing model to look at the impact of particular service characteristics on the bundle price (for example, the data allowance or a family-friendly feature). For these purposes, two cross-sectional datasets were constructed. The first dataset included 70 average revenue per user (ARPU) indicators from 22 telecom companies operating in 49 countries as of 2020. The second dataset included 100 bundle prices from 12 operators across 5 countries as of February 2021. According to the findings, broadband internet followed by mobile services is the main driver of bundle prices and telecom’s revenues. Non-core services have a negative impact on revenues in low-income countries. There is a positive relationship between GDP per capita and ARPU. Landline services are no longer driving telecom’s revenues and are mostly included in the bundle free of charge. The bundles with an unlimited data allowance for mobile services can significantly increase the price of the bundle (up to 39-52%).
Keywords	Bundling, pricing, bundle, telecommunications, telecom, hedonic pricing model, hedonic approach, revenue management, average revenue per user (ARPU)

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INTRODUCTION

Background information

The telecommunication industry (also referred to as telecom) touches almost every business and individual around the world. Numerous studies agree that it is woven into the lives of billions of people (Serentschy 2012; Laitsou, et al. 2017; Nokia and Oliver Wyman 2019; Siddiqui and Siddiqui 2020):

- there is a link between the **economic growth** of a country (Mehmood and Siddiqui 2013) and the development of the telecommunications infrastructure (Laitsou, et al. 2017). Its development is also associated with poverty alleviation (Decoster, et al. 2019).
- the telecommunication sector is one of the main government sources for tax collection (Gruber and Koutroumpis 2011). In many developing countries, telecom revenues account for a **significant portion of the country's gross domestic product (GDP)**.
- the COVID-19 crisis demonstrated the extent to which our society depends on telecommunication technologies (Nattermann and Sauer-Sidor 2020). The crisis also put **the importance of connectivity** into the spotlight (Diop 2020). Forced to switch to technological solutions, businesses and individuals have begun relying on the telecom infrastructure as much as never before (Veligura, et al. 2020; World Bank 2020).

Overall, researchers and industry experts agree that digitalization is not only a buzzword but a new reality that is being enabled by the telecom infrastructure (Decoster, et al. 2019; Forbes 2020). Thus, it is not surprising that there exists a large body of research exploring the characteristics, trends and performance of the companies in this industry.

Research problem and relevance

Telecom is a capital-intensive industry that requires high-volume investments into infrastructure and new services. It is challenging to measure the impact of these services on the telecom's financial performance partly because companies have shifted towards bundling practices where a customer purchases not a single product but a combination of several features. Therefore, telecom revenue drivers are not always clear.

Besides, the telecommunication sector is facing increased pressure from regulators who introduce upper tariffs on telecommunication services. To successfully address regulators' concerns, telecom needs to be able to justify price increases and better understand what drives the price of the bundle.

According to the Economist Industry report (2019), the average revenue per user (ARPU) indicator has stagnated or has been decreasing in many telecommunication markets for several years. Consultancy agencies are recommending telecom to go beyond their core competencies and include additional services in the bundle (Bamberger et al. 2018). Nevertheless, there is not enough research about how these bundled services impact telecom's financial performance.

Research questions, aim and objectives

The research aim of this master thesis is to analyze how services offered in a bundle affect telecom's revenues. Thus, there are two research questions:

1) How do external (market environment) and internal factors (service features) impact the average revenue per user (ARPU) across different countries?
2) What are the bundle price drivers? Since most of the telecom services are offered in bundles, we will use this term interchangeably with bundle revenue drivers.

To answer these questions, we first look at the high-level relationship between bundled services and ARPU and then have a closer look at what service features, in particular, drive the bundle prices. Following the example of Bughin and Mendonça (2007), we use a sequential methodology and construct two models to define revenue and then bundle price drivers.

There are three main objectives:

- to divide the bundle into several components (revenue streams)
- to determine which of these services have a higher impact on telecom's revenues
- to identify to which extent each driver impacts ARPU and/or the bundle price

The research paper structure

This research paper consists of three chapters (excluding Introduction and Conclusion). In the "Literature overview" chapter, we introduce the main definitions and theoretical background of the bundling phenomenon and its relation to telecom's revenue management. In this chapter, we also provide a brief overview of the hedonic approach and its use cases.

In the “Practical implementation” chapter, we apply the theory and explain our methodology and two models. We also discuss the data collection process and describe the datasets that were used for the construction of both models.

In the “Econometric analysis” chapter, we construct the models that were described in the second chapter and provide a detailed econometric analysis of 14 model specifications. The managerial and academic implications of the empirical research are discussed in “Conclusion” which also summarizes the whole paper. To make sure that all the relevant details are included in the paper, we also added “Appendix” with additional information on the econometric analysis and the data.

CHAPTER 1. LITERATURE OVERVIEW

The telecommunication sector is commonly defined as a sector that includes organizations that provide communications services such as telephone (wired or wireless), satellite, cable and internet connection (Beers 2019). Due to the ongoing and accelerating business model transformation, it has become challenging to clearly define the telecommunication industry. Companies operating in the tech, media and telecom (TMT) sector are continuing to converge, and this process blurs the lines between them (Messerschmitt 1996; Ramachandran 2018). To our knowledge, there is no universally accepted definition of modern telecom.

In this master thesis, we will define telecommunication companies as organizations whose primary activity relates to enabling any transmission, emission or reception of data (Brooks Johnston 2003).

The word *primary* is important. Like media companies (for example, Netflix), telecom can produce, acquire and distribute content but it also owns the infrastructure that enables this data exchange (Wang and Ma 2020). One of the prominent examples is Comcast, the biggest communication provider in the U.S. and also the owner of the media conglomerate NBC. By emphasizing the word *primary*, we avoid the inclusion of media and technology companies into the current research.

1.1. Three main reasons for declining telecom's revenues

Over the last decade, the telecommunication industry has been changing rapidly and radically across four dimensions:

- competition,
- technology,
- regulations,
- customer behavior.

The service providers have reviewed their product portfolios, adjusted pricing models and upgraded infrastructure (EY 2015). According to the Economist Industry report (2019), the average revenue per user (ARPU) indicator has stagnated or has been decreasing in many telecommunication markets for several years. Fig 1 below summarizes the main challenges in the industry and actions taken by telecom.

Fig 1. Industry challenges vs response

Source: based on the summary of the literature review

Overall, there are three main reasons for declining telecom's revenues:

- the emergence of new competitors,
- strict government regulations,
- changing customer expectations.

Telecom companies operate in two-way competition markets: service-based and infrastructure-based (Leal 2014). The convergence of the TMT sector has led to the emergence of new competitors (generally known as over-the-top (OTT) service providers) who have access to the telecom infrastructure without sharing the burden of capital expenditures (Kim, Nam and Ryu 2020). This issue is generally known as a **"dumb pipeline" problem** (Kim, Nam and Ryu 2020) i.e., a situation when OTT services are becoming increasingly popular among customers who prefer to use the telecom infrastructure only as a "pipeline" to get access to the OTT products.

Nevertheless, governments limit telecom's ability to charge competitors for network congestion (Leal 2014; Wang and Ma 2020). For example, many countries across the globe adapted a form of **a rate of return regulation** (a price cap) and have set an upper limit on prices in the telecommunication sector (Janssen and Mendys-Kamphorst 2008; Sappington and Weisman 2010). In February 2021, the Federal Antimonopoly Service of Russia initiated a case against Tele2 for mobile services price increase although the operator tried to justify the increase by the rising infrastructure investments (FAS 2021). Besides, recent regulatory developments in Europe and in Russia caused a drastic decrease in the roaming revenues making telecom even more vulnerable to new competitors (Mohr and Meffert 2017).

To illustrate the drastically **changing customer demands**, one of the researchers suggested treating the rising volumes of data consumption as an addiction (Bailey 2016). According to Munnukka (2006), customers who have high-level usage experience look for different features offered in one product compared to customers with lesser experience. This partly explains the rising popularity of bundled services in the last decade which are often considered a telecom's revenue driver. Oliver Wyman also notes that now customers take connectivity for granted (Palencia and Asensio 2019). For example, they are expecting telecom to provide a countrywide coverage.

New services and a wide coverage require modern technology, and it does not come at a cheap price. Therefore, telecom is looking for new revenue streams (Arthur D. Little 2020). Companies need to grow and invest in their infrastructure but declining revenues and increasing capital expenditures limit their growth potential. The marginal cost of information goods (e.g., the cost of serving an additional customer) is almost negligible (Krämer 2009; Yang and Ng 2010). While they have been decreasing, fixed costs remained high (Papandrea, Stoeckl and Daly 2004). Without having adequate research and development (R&D) investments, telecommunication companies risk losing their competitiveness (Serentschy 2012). Telecom is now facing an increased pressure to **ensure periodical investments** to the infrastructure development and, consequently, providing a high quality of services (Rahmoun 2020; Veligura, et al. 2020).

1.2. Revenue management in telecom

Although the telecommunication industry shares some similarities with other service-related industries, a large body of the revenue management (RM) literature has focused exclusively on the airlines, tourism and transportation markets (McGill and van Ryzin 1999).

There are two revenue measures that are commonly used in telecom for peer comparisons and revenue, cash flow and demand forecasts (Monk 2003):

- the average revenue per user (ARPU)
- the average revenue per line (ARPL)

While being one of the most scrutinized indicators in the telecommunication industry, ARPU has been neglected in the academic literature (McCloughan and Lyons 2006). At the company level, this indicator is usually calculated as follows:

$$ARPU = \frac{Total\ revenues\ per\ month}{Number\ of\ active\ users}$$

Despite its popularity, the International Telecommunication Union (Monk 2003) notes that this indicator can be misleading because there are no strict definitions for determining

- the number of active users. Some companies may include wireless and fixed-line subscriptions whereas others prefer to differentiate between these sources of revenues. Sometimes companies also calculate the number of accounts using an average revenue per account (ARPA) indicator.
- total revenues. As mentioned above, it can include either mobile revenues or mobile and fixed-line revenues.

ARPL is also a closely monitored indicator although it is not commonly reported by telecommunication companies. According to Monk (2003), while ARPU is mostly focused on individual subscribers, ARPL indicates the company's dependence on business customers.

Historically, the telecommunication business has concentrated on growing its revenues by attracting new clients (Yang and Ng 2010). The COVID-19 crisis and the digitalization process forced telecom to re-think and shift their focus in revenue management from customer acquisition to customer retention practices (Deloitte 2020). This shift required telecommunication companies to reconsider the way they

(a) address new customer expectations
(b) differentiate customers

Addressing new customer expectations. To introduce new services that meet customers' requirements and generate new revenue streams, telecom is engaging in excessive M&A activity and trying to take charge of the content delivery value chain and compete with OTT services (Suharevskay and Kantyshev 2018; Bamberger, et al. 2020). At the same time, new partnerships have helped telecom meet some of the customer's needs and also share some of the costs, for example, by sharing infrastructure (EY and TAIPA 2020).

Originally, telecom delivered fixed telephone services also known as voice transmission services (Nora and Minc 1980) but data communications have evolved into other channels with the majority of revenues being generated by data traffic (Calzada and Martínez-Santos 2016). Telecom customers have become interested in getting access to a variety of services and expect them to be not only integrated into a single system but also offered at a reasonable price and as quickly as possible (Dutta 2003). This integrated transformation process is commonly referred to as "digital convergence" (OECD 2007). It is the ability of different network platforms to provide similar communication services (Krämer 2009).

Differentiating customers. Instead of looking at customers as members of a specific group (e.g., students, businesspeople, retirees) depending on their age or social status, telecom decided to differentiate them on the consumption-based patterns (Papandrea, Stoeckl and Daly 2004). For example, telecom providers store and manage a wealth of customer personal data (Hitachi Vantara and LiquidHub 2019). This information can be analyzed and used for finding patterns and hidden relationships and providing custom-tailored offerings (Joo, Jun and Kim 2002; Podobnik and Lovrek 2015).

By introducing new services, acquiring new businesses and forming new partnerships, telecom built a diverse ecosystem and created packages with different services (Pandey, Dutta and Joshi 2017). The shift to customer consumption patterns and the digital convergence also required telecom to explore new ways of serving its customers (Krämer 2009). All of this led to the growing popularity of bundling strategies (Kim, Choi and Lee 2016) as one of the methods to combine telecom offerings in one package (Calzada and Martínez-Santos 2016) and overcome the existing challenges (Díaz-Pinés and Fanfalone 2017) that were described in section 1.1.

Moreover, telecom is gradually becoming a utility (GlobalData Technology 2019) with recurring revenues being one of its main characteristics. Recurring revenue streams are revenues generated by a subscription product or service that customers reorder on a regular basis (Harvard Business Review 2020). Revenue models built for the telecom sector usually include macroeconomic factors such as GDP per capita or income level. Since telecommunication services are classified as recurring customer expenses, clients might not be willing to pay the premium for new services if their income is not growing (McCloughan and Lyons 2006). This explains the need for macroeconomic control variables in telecom's revenue models.

1.3. Bundling as a revenue driver

1.3.1. Definition of bundling and bundles

There exist several definitions of bundling and no consensus on which one is the most accurate (Lipowski 2015). Although it is becoming increasingly popular among telecom providers (OECD 2015), bundling is not a new phenomenon. It has been used in other industries (Díaz-Pinés and Vareda 2016) and researched for several centuries already (Cournot 1838).

As noted by Nalebuff (2004), in a broad sense, almost everything can be considered as a bundle. For example, a computer is a bundle of different hardware components and a software system.

Product or service bundling is a marketing strategy of combining several features and benefits of different offerings in one product (Smith 2012, 215).

The term *different offerings* requires special attention. We follow the example of Stremersch and Tellis (2002), and by *different offerings*, we understand products for which separate markets exist. This clarification narrows down the definition of bundling used by some researchers (Salinger 1995) who classified a pair of shoes as a bundle, thus, blurring the distinction between a product and a bundle.

There is another confusion between the terms *bundling* and *bundle*. Whereas bundling is a strategy, a bundle is a type of product:

Bundle is a package of various telecommunication services (OECD 2002).

In the academic literature, there is a third confusion regarding the concept of bundling. For example, some scientific papers refer to bundling as a product bundling marketing strategy (Reinders, Frambach and Schoormans 2010) whereas others consider it to be one of the pricing strategies (Rafiei, et al. 2013). The reason for this confusion is the existence of two terms, namely:

- product bundling
- price bundling

In academic literature, these terms are often used interchangeably. According to Stremersch and Tellis (2002), product bundling and price bundling are two different strategies that should not be confused and can complement each other if the company fully understands the distinction between them. The researchers define price bundling as the sale of several products at discount without any integration. For example, a season ticket for the theater or a combo meal. This bundle does not create any additional value for the buyer.

Table 1. Product vs price bundling. Source: Stremersch and Tellis (2002)

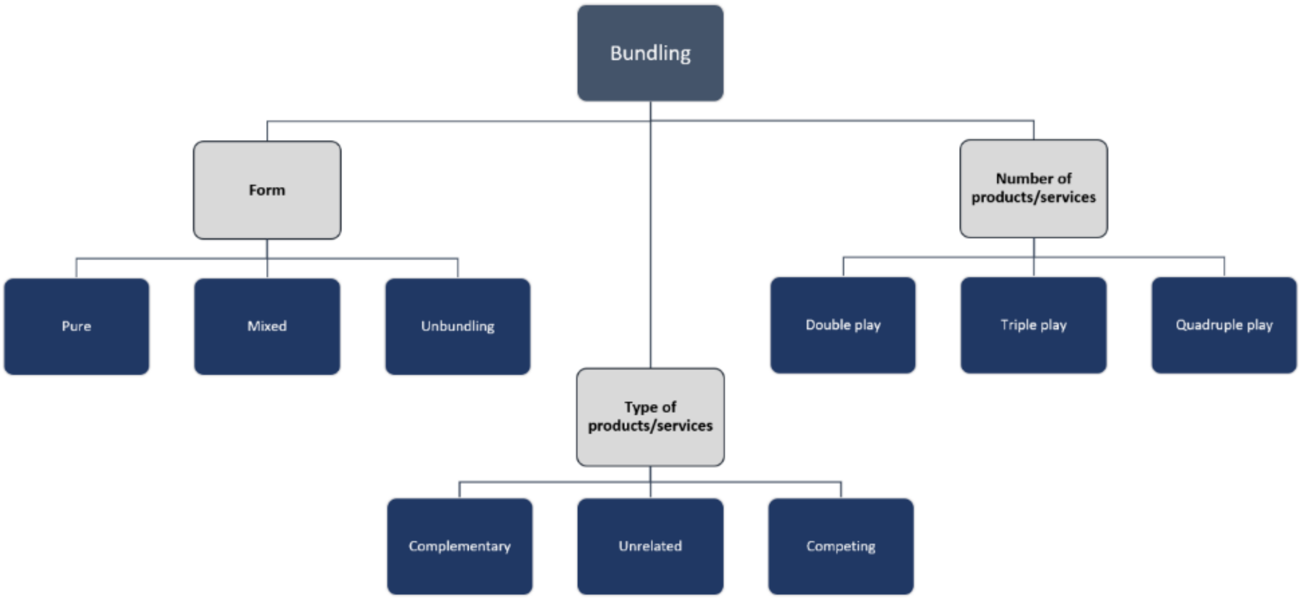
Product Bundling	Price Bundling
Strategic tool	Promotional tool
Long-term effect	Short-term effect
Requires much planning and preparation	Requires little planning and preparation
Offered at discount with integrated services	Offered at discount without integration

On the contrary, by subscribing to a bundled telecom plan, the client can enjoy the benefits of integrated billing and does not need to pay for each service separately. Thus, telecom companies pursue a product bundling strategy and create an added value for the customer by providing bundles with integrated services.

1.3.2. Types of bundling and bundles

The decision to bundle is influenced by the firm's strategy, consumer preferences and competitors' offerings (Venkatesh and Mahajan 2009). There exist different bundling practices (Lipowski 2015) that can be divided into three groups depending on (a) the form of bundling, (b) the types of bundles and (c) the number of services/products in the bundle.

Fig 2. Different classifications of bundling and bundles



Source: Adams and Yellen (1976), Bouwman, Haaker and de Vos (2007), Bughin and Mendonça (2007)

(a) Bundling can exist in three forms (Adams and Yellen 1976):

- pure
- mixed
- unbundling

Unbundling is a situation when a firm offers the products only separately. Pure bundling is a strategy when the items can be purchased only together and are not offered separately. Mixed bundling is a strategy when the products can be bought both separately and in a bundle.

Mixed bundling is widespread in highly competitive markets. According to Prince and Greenstein (2014) and Bughin and Mendonça (2007), mixed bundling is commonly used in telecom. Many telecom products are substitutes and due to the intense competition firms have to provide flexibility to customers. This has led to the explosive growth of mixed bundling in the telecommunication industry (Stremersch and Tellis 2002).

(b) Services and products within one bundle can have interdependencies. Based on the role that they are playing within a bundle, Bouwman, Haaker and de Vos (2007) divided them into

- complementary (e.g., a mobile phone and mobile Internet),

- unrelated (e.g., mobile phone and a magazine subscription),
- competing (e.g., mobile internet and cable internet).

The researchers also introduced a category *mutually reinforcing* and provided two examples for illustration, namely, communication and presence information. Nevertheless, there is no definition of what is meant by mutually reinforcing services and how they differ from complementary ones.

(c) Bundles can also consist of different numbers of products and services. In the academic literature devoted to the telecom industry, researchers use the term *multi-play*. Although there is no strict definition of this concept (Pápai, Lorincz and Édes 2011), it is convenient to use because the term *n-play* can be applied to several situations (Bughin and Mendonça 2007):

1) **double-play** includes fixed telephone (fixed voice) and high-speed internet (broadband services),
2) **triple-play** includes double-play services plus television (pay television services) offered over a single local loop,
3) **quadruple-play** includes triple-play services plus wireless (mobile) services.

Telecom bundles are not limited by these examples. According to the OECD report (2015), operators have started to include other services in their bundles either as a complimentary or subscription-based option. The new services are offered in partnership with other companies and comprise products such as OTT applications (e.g., Netflix and Spotify), security services (antivirus software), cloud storage services, e-baking, etc. (OECD 2015). BCG notes that effective bundles are often a combination of a core product and a product from an adjacent business (Izaret and Pineda 2013).

1.3.3. Recurring revenues and bundling

The academic literature considers bundles a marketing tool that telecom can use to attract more clients. In this study, we would like to argue that bundling is also a revenue, in particular, a recurring revenue tool. For example, some studies note that bundles can help businesses capture additional revenues by reducing customers' heterogeneity (Nalebuff 2004). For companies, it is easier and cheaper to forecast customers' valuation of a bundle than their valuation of separate products because the difference in preferences complicates the revenue maximization process (Bakos and Brynjolfsson 1999).

Recently, there has been a lot of attention to the *rundle*, a newly coined term by New York University professor Scott Galloway, that stands for *recurring revenue bundle* (Gartner 2019). According to Galloway, today customers would like to have less choice and prefer to opt for simplicity. By combining a recurring revenue model with bundling businesses, companies can increase their revenues (Gherini 2019).

By introducing bundles, companies are able to attract new customers who would not have bought the bundled products separately (OECD 2015, 13). For example, telecom has started exploring partnership opportunities with companies such as Netflix and including these offers into their bundles to make them more attractive (OECD 2015). Since retention rate is important for the success of the recurring revenue model, bundling helps not only acquire new customers but also retain them.

Bundling is one of the ways to price up the market by introducing new services to existing bundles and justifying price increases (Palencia and Asensio 2019). This “more-for-more” strategy helps telecom to capture a great market share through connecting the whole household. This practice usually leads to several waves of the price increase which consequently lead to increased revenues.

Although telecom’s bundling is tightly connected with the recurring revenue model, there are also other reasons why companies use it. For example, Nalebuff (2003) classified all reasons into two categories: efficiency and strategic ones. Efficiency reasons include cost reduction, price discrimination and the elimination of double marginalization. Strategic reasons include (but are not limited to) creating entry barriers, mitigating competition and gaining competitive advantage.

Fig 3. Reasons to bundle

Source: Nalebuff (2003)

Efficiency reasons

One of the main reasons to bundle two or more products together is the **cost synergy and cost reduction** benefit (Díaz-Pinés and Fanfalone 2015). For example, pay TV services popularity has been marked by a significant decline whereas the costs of providing these services have drastically increased (Rizzo and FitzGerald 2020). As the result, telecom adds pay TV services to some bundles to motivate customers to use these services (OECD 2015). Moreover, to serve bundle customers, companies require only one billing system and one call center which leads to administration cost reduction as well as to decreasing consumer churn rate (Howell and Potgieter 2019) and increased customer loyalty (Bughin and Mendonça 2007).

Since bundling reduces customers' heterogeneity, the academic literature often considers it an effective **price discrimination tool** (Nalebuff 2003; Gans and King 2005; Díaz-Pinés and Vareda 2016; Díaz-Pinés and Fanfalone 2017).

Bundling is also beneficial for complementary products (services or goods that are usually purchased together) and can be used to avoid **double marginalization** (Nalebuff 2003). If there are two monopolists on the market that provide complementary products, they would try to maximize their profits and may set inefficient prices leading to double marginalization. Such firms would benefit from merging and bundling their products together (Krämer 2009).

Strategic reasons

According to Nalebuff (2004), bundling can often be used as an **entry-deterrent strategy** in an oligopolistic market. If a firm has a competitive advantage in two products, by bundling them, this firm can make it harder for potential competitors to enter the market (Díaz-Pinés and Vareda 2016).

Contrary to Nalebuff (2004), who examined bundling as an intentional entry-deterrent strategy, Rey and Tirole (2007) mentioned that bundling can indirectly lead to **higher barriers to entry**. For example, by providing discounts, companies are raising customer's switching costs.

Creating entry barriers is one of the ways to **mitigate competition** (Díaz-Pinés and Vareda 2017). For example, bundling can be used to divide the market and build a differentiated product (Nalebuff 2003). In this case, one company offers only product A whereas another company is offering a bundle and gets the customers who are interested in both products A and B.

Companies can also choose to bundle because they would like to **gain a competitive advantage** (Nalebuff 2003). Usually, telecom companies bundle substitute goods such as cable and satellite television. By bundling substitute services or goods, the company can lower customer's willingness to pay for rival's unbundled offerings. In one of the papers, Choi (2003) also mentions that bundling new products with the old ones can signal quality and have a positive impact on the company's reputation.

1.4. Models for evaluating revenue drivers

By better understanding revenue streams and drivers, telecom companies can see how their value is changing. There are different ways to determine the value of a business including a time-revenue method (Senobari and Chitband 2019). According to this method, a stream of revenues that has been generated over a certain time period is multiplied by a specific number that depends on the industry (Tiran 2020).

To our knowledge, there are only three studies that tried to investigate the relationship between telecom's revenues and internal (services characteristics) and external (the market environment) factors. For example, **Boylaud and Nicoletti (2000)** used data across 23 OECD countries over the period between 1991 and 1997. The scholars focused on the deregulation's impact on the telecom's financial performance. Previously, telecommunication markets were considered highly regulated, but they have started moving towards deregulation (Oredegbe and Zhang 2020). Boylaud and Nicoletti constructed the following model:

$$y_{ist} = c + \alpha_{is} f_i + Z_s{}' \beta_s + M_s{}' \gamma_s + R_s{}' \delta_s + \varepsilon_{ist}$$

where

y_{ist} – a performance measure (from a set of 10 different measures)

i – country,

s – sector,

t – period,

f_i – country-specific effects

Z_s – exogenous economic characteristics

M_s – market structure indicators

R_s – regulatory indicators

The scholars used several performance indicators (dependant variables) for the empirical analysis including a variable *mobile*. In the appendix, they elaborated on this variable and defined it as “mobile revenues divided by the number of cellular subscribers”. This is one of the ARPU’s definitions. For more details, please refer to section 1.2.

There is a study that shares many similarities with the research conducted by Boylaud and Nicoletti (2000). **McCloughan and Lyons (2006)** also constructed a model to examine several groups of ARPU determinants. Contrary to Boylaud and Nicoletti, they focused not only on the external environment but also included independent variables that describe service quality and quantity of service:

$LogARPU = f(S, M, R, Q)$, where

S – service quality (reputation, network congestion, network coverage)

M – market environment (population density, personal income, market maturity)

R – regulation (requirements for MNP, national roaming services)

Q – service quantity (characteristics of the bundles such as data allowance)

For this model, McCloughan and Lyons (2006) used a modified pricing model developed by Shew (1994) who investigated the determinants of mobile telephone prices using a wide set of variables. Similar to Boylaud and Nicoletti, McCloughan and Lyons' paper primarily addresses regulators and to some extent industry observers. McCloughan and Lyons' findings discuss the extent of concentration in the national mobile markets and the implication of the national income on ARPU. This narrow focus partly explains why the researchers did not include any bundle characteristics in their model. According to their results, higher GDP per capita increases ARPU.

McCloughan and Lyons were not the first scholars who took into account the GDP indicator when analyzing the telecommunication market. For example, Hausman and Ros (2013) developed econometric demand models to compare mobile and fixed-line prices in Mexico with other countries by using the purchasing power party (PPP) conversion rate and selecting a sample of countries similar to Mexico in terms of GDP per capita. Other researchers noted that when it comes to telecommunication services, customer behaviour varies with consumers' socioeconomic and demographic characteristics (Urama and Ogbu 2018).

Genakos et al. (2018) also examined the influence of market structure and operator's characteristics on the ARPU indicator. Contrary to McCloughan and Lyons' results, their analysis suggested that the market structure and the operator-specific variables do not have any significant influence on ARPU.

1.5. Hedonic pricing approach to bundle prices

Since most of the telecommunication services are offered in bundles, we consider them bundle revenue drivers. Bundling is often viewed as a revenue strategy (Wittmer and Oberlin 2014). Some researchers also argued that ARPU can be used as a proxy for a bundle price (McCloughan and Lyons 2006) emphasizing the link between telecom's revenue and bundle pricing.

According to the academic literature, it is a common practice to view pricing as a part of the revenue management process (McGill and van Ryzin 1999) since prices have a significant influence on customers' evaluation of the telecom services (Munnukka 2006) and, as the result, on the demand and profitability (Rajagopal 2019). Moreover, communication services are intangible products which means that the price is the only tangible aspect of this offering that can be thoroughly analyzed (Finch, Becherer and Casavant 1998). Therefore, in the context of revenue management, it is also relevant to examine the determinants of the bundle price.

A bundle is a product that combines heterogenous qualities (Mohammed 2018). It is a complex task to compare prices across different plans, companies, countries and periods. The variety of offerings in bundles impact the price which makes it difficult to perform direct comparison (Corrado and Ukhaneva 2016). Therefore, researchers often use a hedonic approach to analyse the price of products whose value proposition changes on a regular basis (Ofcom 2018). Previously, hedonic models were mostly used for the computer and automobile industries and the housing market where the final products are examples of a bundle that consists of several independent components (Griliches 1961; Taylor 2003).

According to the hedonic pricing approach, each component is considered to have some weight in the overall price of the product. Following this reasoning, Rosen (1974) formulated the property of price as the weighted sum of different characteristics that constitute the product.

> A **hedonic function** expresses the price of a certain product (both goods and services) as a function of its qualities (Díaz-Pinés and Fanfalone 2015).

The hedonic model can have some econometric problems (Taylor 2003). For example, endogeneity is a situation when the independent variable is correlated with the error term. Such problems occur when modelling customer’s preferences and utility functions but as noted by Bishop and Timmins (2011), the hedonic model structure assumes no fundamental endogeneity problem in general and is widely applied in many cases.

Although Rosen (1974) described the hedonic approach as a method to be applied to price analysis, it has been also used to determine what drives the value of an asset or a company (Gerrard, Parent and Slack 2007). For example, Yankaya and Celik (2000) and Henneberry (1998) applied the hedonic model to the residential property value to determine the impact of a public transportation investment on the house value. Following these studies, Shakina and Barajas (2013) built a hedonic model to examine how intellectual capital components influence the company value across different countries and industries.

Following the increasing popularity of bundling plans, the telecommunication market was required to restructure towards a so-called “platform-converged market” (Calzada and Martínez-Santos 2016). Companies operating in this newly emerged market provide all core communications services. By providing more services and incurring higher investment needs, telecom has been forced to increase prices in low ARPU countries (Bloomberg 2020). As mentioned in the previous section, price increases are usually supervised by regulation authorities. Telecom needs to be able to justify the price increase. By dividing bundles into different components i.e., revenue streams, telecom can optimize their revenue management practices (Song 2018).

Nevertheless, only a limited number of researchers have applied the hedonic approach to communications-related settings (Varoutas, et al. 2008). For example, **Lyons and Savage (2012)** applied the hedonic regression analysis to the Irish telecommunication market by comparing operators’ tariffs and subscriber base. The researchers tried to investigate how much Ireland-based customers are willing to pay for a faster broadband service using the dataset of 743 plans from 19 operators. Their results suggest that the marginal cost of providing high-speed broadband will fall to a very low level because of technological advances.

Crocioni and Correa (2012) used the hedonic approach to construct five regressions – two for the Irish market and three for the Dutch one. By dividing the broadband package prices into different components such as upload speed, download speed, technologies used, the authors tried to understand which operator has pricing power. According to their findings, bundles with satellite technology are usually priced much higher than DSL and cable technology packages. One of the explanations might be that satellite connections can be accessed from thinly populated areas. Therefore, to recover initial investments, operators need to consider both the cost of provision and the satellite’s inability to compete with other more advanced technologies in densely populated areas.

Calzada and Martínez-Santos (2016) also focused on broadband plan prices. Their sample consisted of data from 37 countries between 2011 and 2014. They did not include only bundle characteristics (for example, the number of gigabytes included in the plan, the number of call minutes contracted, the technology used) but also an access fee and a possible penalty fee for exceeding the gigabytes allowance. According to their results, plans with unlimited data allowance are priced higher than limited ones. They also observed that when pricing call allowances, some operators do not distinguish between mobile-to-mobile and mobile-to-fixed calls anymore.

Wallsten and Riso (2010) conducted comprehensive research with a large dataset spanning over 25,000 plans from 2007-2009 in 30 different countries. They used the hedonic methodology to examine the relationship between plan components and pricing. The researchers mostly focused on data caps and their implications on broadband prices. Their results revealed that data caps do not always increase consumer prices and can be more beneficial than unlimited plans.

Díaz-Pinés and Fanfalone (2015) analyzed triple- and quadruple-play bundles price determinants for telecommunication operators in France, the United Kingdom and the United States. The researchers also considered the type of technology used by operators as one of the characteristics. One of the advantages of the hedonic approach is the possibility to use non-numeric attributes that are coded by dummy variables (OECD 2011). For example, their results suggest that although internet consumption is steadily increasing, customers still value mobile calls and their inclusion into the bundle increases the price of the bundle by 16-32% depending on the number of calls.

The below table summarizes the hedonic approach used in the above-described papers. Most of the researchers applied this approach to the analysis of the broadband plans.

Table 2. Summary of the hedonic pricing models in the academic literature

Year	**Authors**	**Model**	**Dataset**
2010	Wallsten and Riso	$Price_{it}$ = f (download $speet_{it}$, $bitcap_{it}$, tax $included_{it}$, $contract_{it}$, technology $type_{it}$, video $bundle_{it}$, φ_{it}, γ_{it})	25,279 broadband plans 169 operators 12 quarters (2007Q1–2009Q4)
2012	Lyons and Savage	$Price_{it}$ = f (downaload $speed_{it}$, upload $speed_{it}$, contention $ratio_{it}$, email, $unlimited_{it}$, access $type_{it}$, $contract_{it}$, minimum contract $period_{it}$, online $billing_{it}$, limited data $transfer_{it}$, transfer $limit_{it}$, $bundled_{it}$, φ_{it}, γ_{it})	743 plans 19 operators

2012	Crocioni and Correa	Regression 1: Price = f (DSL, Satellite, ADSL2+, Cable, Company 1, Company 2, Company 3, download speed, upload speed) Regression 2: Price = f (ADSL, Cable, Company 1, Company 2, Company 3, Websize, FixedIP, DynamicIP, NoTelephony, download speed)	96 broadband-only packages 11 providers
2015	Díaz-Pinés and Fanfalone	12 regressions Log Price in (USD PPP) Types of independent variables: • Technology (log download speed, bitcap, unlimited bitcap, cable, fibre, satellite) • Contract (term) • Dummy variables (operator, country) • Bundle indicators (fixed phone, fixed broadband, TV, mobile, 2-play, 3-play, 4-play) • Fixed telephony indicators (unlimited national calls, unlimited international calls, ulimited local calls, unlimited calls weekend, unlimited call to mobile, some local calls, some international calls) • TV variables (log of number of TV channels, log of sports quality index, log of movies quality index, log of other premium TV index, log of TV quality, DVR) • Mobile indicators (basic mobile, advanced mobile)	300 offers incl. standalone and bundle prices (April 2014) 15 operators 3 countries (France, UK, US)
2016	Calzada and Martínez-Santos	$Price_{moit}$ = f (limited $data_{moit}$, $penalty_{moit}$, $volume_{moit}$, $volume^2_{moit}$, $speed_{moit}$, $technology_{moit}$, limited $voice_{moite}$, $minvoice_{moit}$, $smartphone_{moit}$, $historical_{moit}$, $NPlans_{moit}$, country, year)	2909 plans 37 countries 2011–2014

1.6. Summary

As seen from this section, bundling has become an essential part of telecom's strategy. Nevertheless, a large body of research is focused on the customer-side of this topic and investigates the reasons why customers prefer to bundle or what types of customers are likely to bundle (Üner, Güven and Cavusgil 2015; Lee 2017; Media Samosa 2020; Google 2020).

There are only a couple of papers that look at bundling from the company perspective and are based on the publicly available operational and financial data. Among those is the article written by Díaz-Pinés and Fanfalone (2017) about the relationship between telecom's financial indicators and their bundling strategies.

Therefore, our literature review suggests that there exist at least four research gaps:

Table 3. The summary of four research gaps identified during the literature review

From the academic perspective	From the managerial perspective
Limited industry-specific academic research. Bundling practices have been extensively researched. Nevertheless, the academic literature on bundling in telecommunication services is limited. As mentioned by Lee (2017), this is partly due to the scarce public data availability.	**Emphasis on regulators instead of managers**. There are only a few research papers that provide managerial implications. Most of the papers focus on recommendations to the regulatory authorities or investors.
Limited research of the Russian market. In their studies, researchers focus either on the US and EU markets or on some specific developing regions (e.g., Africa or India). The research for the Russian telecommunication market has not been conducted to the same extent as for other markets.	**Emphasis on the marketing implications instead of the financial implications**. A large body of research focuses on the bundling practices from the marketing perspective by analyzing the social welfare benefits or ways to increase customer acquisition/retention rates. Only a few papers attempted to measure the impact of bundling on the financial performance of the telecom provider.

Moreover, previous empirical studies focus on analyzing the relationship between bundle characteristics and the bundle price and consider mostly the significance of this relationship while ignoring the contribution value that those characteristics (features) provide.

Therefore, this study will close several gaps by

(a) including Russian telecom in the data analysis,

(b) contributing to the finance-related studies on bundling services,

(c) providing managerial implications.

CHAPTER 2. METHODOLOGY

2.1. Methodology and models

To determine how bundle services affect telecom's revenue, we use a sequential methodology that was applied by Bughin and Mendonça (2007) in their study. First, we build an econometric model to identify the ARPU determinants on a high level: for example, what offerings, in general, drive the revenues (core vs non-core telecommunication services). Then we build a hedonic pricing model to look at the impact of particular service characteristics on the bundle price (for example, the data allowance or a family-friendly feature).

For these purposes, two cross-sectional datasets were constructed which are described in more details in the subsequent section. We followed the approach by Díaz-Pinés and Fanfalone (2015) who also used cross-sectional data and analyzed only prices as of April 2014. The time component was deliberately omitted from the analysis due to two factors:

- First, the ARPU indicators are not published by all companies on a regular basis. Therefore, it was decided to use the most recent data from the 2020 annual reports. Otherwise, the constructed dataset would have been imbalanced panel data. This would have made it difficult to detect any meaningful trends across periods.
- Secondly, only a few operators publish historic information about their plans that are no longer available for purchase. Therefore, it was decided to focus only on the current information available on the operator's websites. Moreover, contrary to the studies reviewed in the previous chapter, all the data for this research was collected manually and was not provided by a large research institute. Therefore, we also had a time constraint.

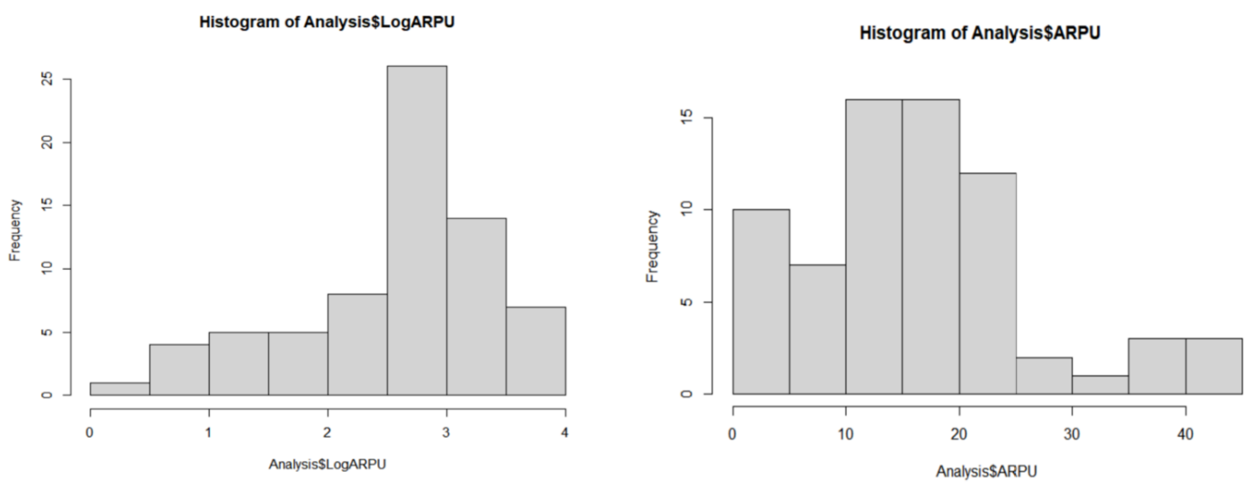
To meet the objectives of the research, it was decided to use quantitative methods. We applied econometric modelling, specifically, the hedonic approach. As mentioned by Corrado and Ukhaneva (2016), hedonic techniques are usually considered for modelling international price differences in telecom services. The hedonic approach use cases were thoroughly reviewed in the previous chapter. Normally, researchers use four hedonic function forms (Tochaiwat and Likitanupak 2019):

- linear form;

- log-linear form;
- linear-log form;
- log-log form.

In most of the reviewed models in Chapter 1, researchers preferred the log-linear and log-log forms of equation. For all models in this research, we have tested both linear, log-linear and log-log models and found that the log-linear and log-log ones fit our data better. One of the explanations for this can be seen from the below histograms. The log transformation helps to change a rather skewed ARPU variable into more normalized data (although with a visible right skewness):

Fig 4. Histogram of the logarithm of ARPU vs ARPU



In the scope of this research, we constructed two models. For simplicity reasons, we will refer to them as Model A (the ARPU Model) and Model B (the Bundle Prices model). When analyzing the econometric results of both models, we adopted the approach by Díaz-Pinés and Fanfalone (2015) who used different specifications of the model by adding or excluding certain variables. For example, they started with a rather simple specification of a model and built further on it by adding more variables. Nevertheless, the number of variables cannot be infinite. According to Harrell (2015), it is required to have at least 10 observations per each estimated parameter to build a robust model.

In this research, we used 4 specifications for Model A and 10 specifications for Model B. They are thoroughly discussed in Chapter 3. This Chapter explains the main variables in the models and describes the samples.

Model A defines the relationship between ARPU and a set of indicators that can be grouped into the external and internal factors:

$$LogARPU = \beta_0 + \beta_1 BundlePlay + \beta_2 Services + \beta_3 MarketEnvironment + \beta_4 MarketShare + \varepsilon$$

where

LogARPU is a log-transformed ARPU variable that was converted to USD using the purchasing power parity (PPP) conversion rate.

BundlePlay is one of the several bundle compositions (n-plays) described in the literature review: double-play (including its two variations), triple-play (including its two variations) and quadruple-play. This is a dummy variable. The information on the variations of the n-play is available in Appendix (Table 5).

Services includes core telecommunication services (such as mobile internet, landline, TV) and non-core services (such as entertainment packages, financial or security services, etc.). This is a dummy variable.

MarketEnvironment is a control variable used to account for market-specific features. It is either GPD per capita (the logarithm) or the income level of the country (according to the World Bank classification).

MarketShare is a control variable used to account for operator-specific features. It is determined as the market share of the company. The calculation of this variable is discussed in the next section.

ε is a random variable.

Model A draws on the studies by Boylaud and Nicoletti (2000) and McCloughan and Lyons (2006). Contrary to McCloughan and Lyons (2006) who did not include many bundle-related variables, our model complements their approach by focusing on the internal factors rather than on external (macroeconomic) ones. This shift in focus helps to derive managerial implications instead of recommendations for regulators and investors.

In the ARPU model, the independent variables are mostly dummy variables (except for the GDP per capita and the market share). The dummy variables were introduced according to the approach taken by Summers (1973) who used the country product dummy variables (CPD) for comparing prices across countries. In Summers' CPD regression model, several dummies are used to represent unique service specifications (e.g., availability of double-play offers). As noted by Corrado and Ukhaneva (2016), the CPD model is an example of a modified hedonic model whereas traditional hedonic models use service's characteristics (e.g., the download speed).

Since the first model uses mostly dummy variables, it is not a typical hedonic model. Nevertheless, Triplett (2004) mentions that it is a valid substitute for a usual hedonic function. This modification was also used by Corrado and Ukhaneva (2016) in their research.

Model B describes the relationship between the bundle price and the bundle characteristics on a deeper level. While Model A focused mainly on the dummy variables (presence or absence of a specific feature), Model B investigates the relationship between the bundle price and the bundle specification:

$$LogPrice = \beta_0 + \beta_1 BundlePlay + \beta_2 Services + \beta_3 BundledCharacteristics \\ + \beta_4 Operator + \beta_5 Country + \varepsilon$$

where

LogPrice is a log-transformed price variable that was converted to USD using the purchasing power parity (PPP) conversion rate.

BundlePlay is one of the two most used bundle compositions i.e. double-play or triple-play. The variable was coded as a factor in R to distinguish between these two variations.

Services includes dummy variables for the services that constitute the double- or triple-play such as mobile services, TV, broadband internet and fixed telephone services (landline).

BundledCharacteristics include variables that describe the characteristics of each of the four services such as a number of call minutes, gigabytes, SMS, the speed of the broadband internet, etc.

Operator is a factor variable to account for the differences between operators.

Country is a factor variable to account for differences between countries.

ε is a random variable.

This model draws on the study by Díaz-Pinés and Fanfalone (2015). Similar to other hedonic pricing models reviewed in Chapter 1, Model B focuses on the internal bundle characteristics using the country and operator variables only as control variables. Following the example of Díaz-Pinés and Fanfalone (2015), the variables are described and added to different model specifications in a structured way. For example, the mobile dummy indicator is characterized by several mobile-related variables such as the mobile internet data allowance, SMS or family-friendly features. This multi-level approach helps to build several regressions (specifications) to understand a broader picture.

2.2. Data collection

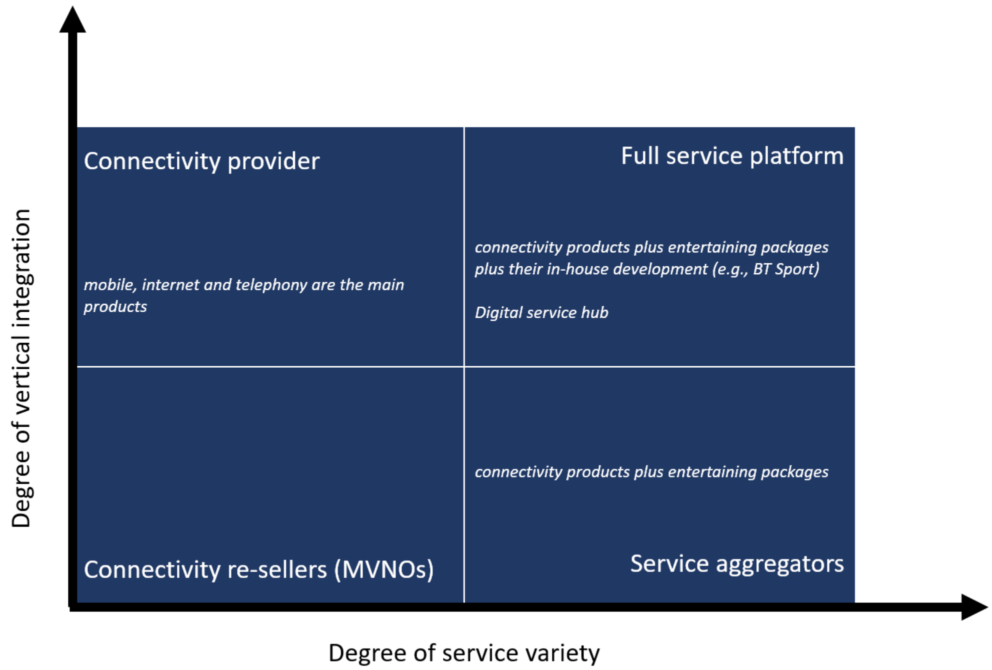
As mentioned by Forenbacher, Perakovic and Husnjak (2016), it can be problematic to obtain data on historic prices directly from telecom providers since they operate in a rather competitive market where such information is considered to be strategically important (Magnien 2003). Therefore, in this research, it was decided to use data only for the year 2020.

To test the econometric models specified in the previous section, we manually assembled two datasets based on the publicly available information from the operator's official websites, financial statements and annual reports.

ARPU Dataset

The first cross-sectional dataset (70 observations) spans over 49 countries and 22 operators. The breakdown per country and operator is included in the Appendix (Table 1 and Table 2). The constructed ARPU dataset included information on the ARPU indicators per operator in 2020. To make these indicators comparable, each ARPU was converted to USD using the purchasing power parity (PPP) conversion rate that is published by the World Bank. The dataset also contains information on the composition of the bundles (double-play, triple-play or quadruple-play), the services included in these compositions (landline, TV, mobile, fixed internet), macroeconomic factors (country's income category according to the World Bank classification and GPD per capita) and the degree of the vertical integration (according to the below matrix Fig 5).

Fig 5. Matrix of telecom's integration. Adopted from STL Partners (2020)



Since this research focuses only on telecom providers, the dataset does not contain any observations on connectivity re-sellers (MVNOs). The matrix categories (integration and types of services[1]) were added and coded to account for the strategic differences between operators. Moreover, this matrix is also a good illustration of the current convergence trend happening in the telecommunication market. Despite its importance, to our knowledge, there are no studies that include this trend in their models, although there are several survey results that advocate for telecom's integration and variety of offerings.

The data structure consists of two levels, namely, company and country. Therefore, we have also collected data for two controlling variables to mitigate the effects of country-specific

[1] By types of services, we mean either core telecommunication services or non-core ones. For example, as it can be seen from the matrix, full service platforms provide not only core services but also entertaining packages and in-house developed products (such as financial or security services or their own TV channel).

and operator-specific characteristics. All the variables collected in this dataset are described in the subsequent section.

A rather limited size of the dataset can be explained by the time and capacity constraints. In similar studies, researchers were provided with data by large organizations such as Merrill Lynch, OECD, IMF, International Telecommunications Union, etc. Besides, only a few operators disclosed their ARPU indicators. Many operators view this information as strategically important and do not publish it in open sources. At the same time, rough estimations that are published by consulting firms are either not publicly available or raise concerns regarding their accuracy.

Bundle Prices Dataset

The second cross-sectional dataset (100 observations) spans over 5 countries and 12 operators. The countries were chosen based on their GDP per capita to make sure that the comparison is meaningful. There are the following countries in the dataset: Russia, Ukraine, Belarus, Kazakhstan and Bulgaria (Table 4 is provided below). The breakdown per operator is provided in the Appendix (Table 3).

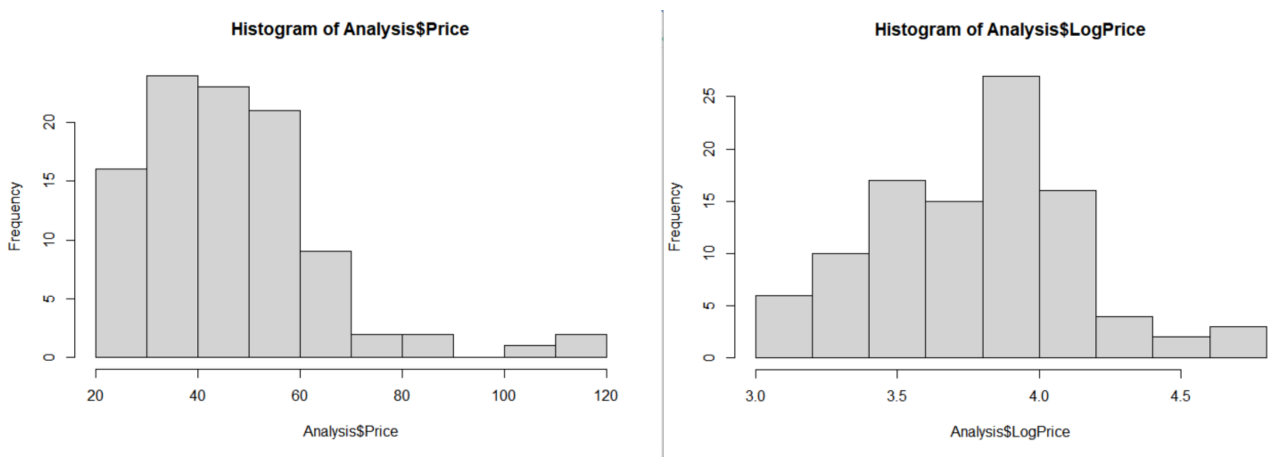
Table 4. Breakdown per country (the Bundle Prices dataset)

	Russia	**Ukraine**	**Belarus**	**Kazahstan**	**Bulgaria**
Observations	34	19	21	18	8
Proportion	34%	19%	21%	18%	8%
Code as in model	1	2	3	4	5

These five countries were also chosen because many operators in other countries are offering customized solutions to their clients. For example, before disclosing information on the price, they ask to provide the home address to make sure that they can deliver the services to the potential customer. This has complicated the data collection process. Besides, on some websites, the information on bundles is available only to current customers and the system requires the user to log in to their private account. Moreover, surprisingly, some websites do not work in the Russian Federation without a VPN service which made the data collection process more time-consuming. Taking into consideration all of these limitations, it was decided to focus on relatively similar countries in terms of their GDP per capita indicator. Furthermore, the websites of these operators are available in the Russian language which made it easier to retrieve some details on the bundle plans specified in the additional documentation (for example, whether the WiFi hotspot rent is included in the price or not).

As observed from the ARPU dataset (Appendix Table 5), quadruple-play offers are still not very widespread among operators, therefore, the constructed dataset has either double- (61%) or triple-play (39%) offers that were coded as factors in R. Similar to the ARPU indicator, the bundle prices were converted to USD using the purchasing power parity (PPP) conversion rate. The prices were collected from the operator's official websites in respective countries in February 2021. We did not take into accounts any discounts or promotion campaigns. For the analysis purposes, we used the logarithm of the Price to transform skewed data to a more normalized one:

Fig 6. Histogram of the bundle price and the logarithm of the bundle price



The Bundle Prices dataset also contains information on the services provided by the operator (landline, TV, mobile, fixed internet). Contrary to the ARPU dataset, the second dataset contains the characteristics of these services (data allowances and limits). Both datasets are exhaustive as no missing data was allowed.

2.3. Data description

This section provides descriptions and summary statistics for the variables used in Model A and Model B. The data were analyzed using the R language.

The ARPU Dataset

The ARPU dataset consists of several sets of variables with the logarithm of ARPU as a dependent variable. The list below describes the independent variables that were collected for the regression analysis and explains why these variables were included and how they were codified.

Independent variable:

ARPU was collected in national currency and converted to USD using the purchase power parities (PPP) conversion rate. The ARPU indicator was collected only for the companies that published their mobile ARPU indicator. Some companies published their average revenue per line[2] (ARPL) and average revenue per mobile subscriptions as two independent indicators. The ARPL indicator was not taken into account because most of the telecom subscribers are mobile customers. ARPU was transformed into a natural logarithm.

Company control variable:

Market share. At first, all 22 companies were coded as factors and assigned an individual number. Since the dataset is rather limited, the inclusion of these variables had a negative effect on the overall quality of the models. Therefore, it was decided to omit these factor variables and use the market share instead. Usually, the market share is calculated by dividing sales by the total industry revenues, but the total industry revenues are not publicly available information for all countries. Therefore, in this research, another proxy was calculated. To calculate the market share, we divided the number of mobile subscribers per company by the total mobile subscribers in the country. Most of the telecom's subscriptions are wireless (mobile) and operators publish these numbers in their annual reports. The information on the total mobile subscribers in the country was downloaded from the World Bank database.

Integration. This variable was introduced based on the STL Partners Matrix (for more details please refer to Figure 5 in section 2.2). This variable describes the level of vertical integration of the telecom providers and was coded as a dummy variable where 1 defines a full vertical integration and 0 stands for a partial vertical integration. This variable was added to account for strategic differences between operators.

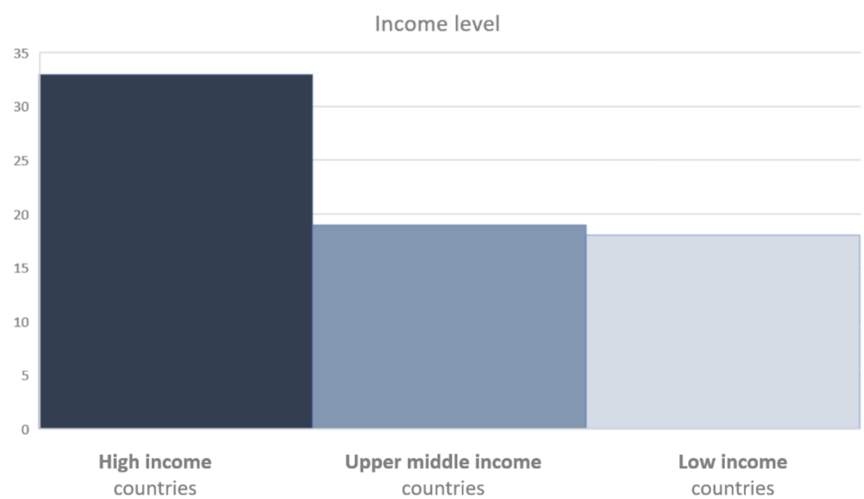
[2] ARPL is used for fixed services. For more information, please refer to section 1.2.

Country control variables:

To control for the market environment, it was decided to use either of the two variables.

Country category. According to the World Bank classification, all countries were divided into three groups i.e., high income, upper middle income and low income. This variable was coded as a factor and assigned the following codes: high income (1), upper middle income (2), low income (3). The low-income countries include the lower-middle-income countries (such as India, Philippines or Mongolia) as well as a small fraction of low-income countries (such as Afghanistan, Uganda, Liberia).

Fig 7. The distribution of income categories in the dataset



GDP per capita. We have also collected information on the GDP per capita from the World Bank database for all 49 countries. For calculations, we used the logarithm of this number. The reasons for using a logarithm were discussed earlier in this chapter.

Service-specific variables:

The service-specific variables were added to identify the impact of bundled services on the ARPU indicator. They can be grouped as follows:

- *Bundle n-play* defines a type of bundle which can be either double-play, triple-play or quadruple-play. The bundle play was coded as a factor.
- *Services* were divided into two groups, namely, core and non-core telecommunication services:

- *Core-telecommunication services* are four main services provided by telecom companies that form a bundle n-play. They include landline, mobile services, fixed broadband internet, TV and were coded as dummy variables where 1 means that the company provides a particular service and 0 means that the service is not provided.
- *Non-core telecommunication services* included two variables that were coded as *fun* and *in-house development*. By the *fun* variable, we mean additional entertainment services such as a discount on a Netflix or Warcraft account. By *in-house development*, we mean additional unique services that were developed by the company such as security services, e-wallet, car insurance, finance-related smartphone app, etc. These dummy variables were introduced based on the STL Partners Matrix that was described in section 2.2.

For detailed information about the summary statistics on the variables including the sources of these variables, please refer to Table 4 and Table 5 in the Appendix.

The Bundle Prices Dataset

The second dataset also consists of several sets of variables with the logarithm of Price as a dependent variable. The list below describes the independent variables that were collected for the regression analysis and explains why these variables were included and how they were codified.

Independent variable:

Price was collected in national currency and converted to USD using the purchase power parities (PPP) conversion rate. Similar to the ARPU model, the price was transformed into a natural logarithm.

Control variables:

Operator and *Country*. Since the dataset contains information on 12 operators, they were coded as factors and included in the regression mode. A similar approach was taken for the country variable (5 countries). They were also coded as factors.

Bundle indicators:

The bundle indicators can be divided into two groups:

- *TypeCode* is a factor variable that defines if the bundle can be categorized as a double- or triple-play. Quadruple-play bundles were not included in the dataset because they are not very widespread.
- *Services* indicators include dummy variables for the four major core telecommunication services such as mobile services, TV, broadband internet, fixed telephone (landline).

Bundle characteristics indicators:

This set of variables provides a deeper level of the influence of the bundle characteristics on the price and, hence, on the revenues. They can be grouped into three categories according to the types of services outlined above.

Mobile-specific:

- *Family* is a dummy variable that describes if a mobile service has a family-friendly feature. For example, an opportunity to share data allowance with other family members or to connect several phone numbers to one subscription plan.
- *UnlimitedGB* and *UnlimitedCalls* were two dummy variables introduced to the model as per recommendation by Díaz-Pinés and Fanfalone (2016) who tried to avoid multicollinearity concerns and some limitations in the way unlimited data allowance is codified (these limitations will be described below).
- *GB* describes the amount of data included in the mobile services. Its codification raised some questions. For example, some of the bundles had unlimited mobile data allowance. According to some research, 100 GB is a practically unlimited amount of data for mobile services (Rogerson 2021). Therefore, the unlimited allowance was codified with 100 GB. Since this is not an ideal solution, the *UnlimitedGB* dummy variable was introduced (as described above).
- *Calls* describes the number of minutes included in the mobile services. Similar to the data allowance problem, some plans have an unlimited number of minutes. They were also codified with a very high number (e.g., 10,000 minutes).

- *UnlimitedCalls* variable was introduced similar to the *UnlimitedGB* variable.
- *SMS* describes the number of SMS included in the service.

TV-specific:

- *Channels* is the number of channels included in the TV service. Only interactive TV services were included in the analysis for consistency reasons. Overall, there are several types of TV services such as digital, satellite and interactive ones. For those bundles, where TV services were not included, this variable is equal to zero. Therefore, this variable was not transformed into a natural logarithm as the data has some zero values.
- *TVBox* is a dummy variable that defines if TV box rent was already included in the bundle price or if the customer is expected to pay extra.

Internet-specific:

- *Speed* is the speed of the fixed broadband internet in Mbit/sec. For those bundles, where internet services were not included, this variable is equal to zero. Therefore, this variable was not transformed into a natural logarithm as the data has several zero values.
- *Wifi* is a dummy variable that defines if Wi-Fi hotspot rent was included in the bundle or if the customer is expected to pay extra.

For detailed information about the summary statistics on the variables including the sources of these variables, please refer to Table 6 and Table 7 in the Appendix.

CHAPTER 3. ECONOMETRIC ANALYSIS

This chapter looks into the econometric analysis of both models A and B and the results. The limitations and suggestions for future research are described in the Conclusion.

3.1. Econometric results and discussion of the ARPU drivers

For the ARPU dataset, we adopted the methodology of Díaz-Pinés and Fanfalone (2015) who built 12 regressions (specifications) including different sets of variables. In the scope of this exercise, 4 regressions were constructed:

Regression 1. ARPU vs a bundle n-play (incl. GDP per capita and market share as control variables):

$$LARPU = \beta_0 + \beta_1 doubleplay + \beta_2 tripleplay + \beta_3 quadplay + \beta_4 LogGDP + \beta_5 MarketShare + \varepsilon$$

Regression 2. ARPU vs core and non-core telecom services (incl. GDP per capita and market share as control variables):

$$LARPU = \beta_0 + \beta_1 telephone + \beta_2 TV + \beta_3 mobile + \beta_4 internet + \beta_5 integration + \beta_6 fun + \beta_7 in\text{–}house + \beta_8 MarketShare + \beta_9 LogGDP + \varepsilon$$

In Regression 2, two variables were dropped due to their insignificance:

- *Internet* variable might be insignificant due to the fact that according to most observations in the constructed dataset if the operator is providing TV services, they also provide fixed broadband internet services. Therefore, these two services are closely related. To understand which of them has a stronger impact on telecom's revenues, a more detailed analysis of their individual drivers should be performed. This analysis is described in section 3.2 (Model B).
- *Mobile services* were dropped because in the constructed dataset all operators provide these services. Therefore, we can conclude that these services are expected by telecom's clients and are provided by all operators regardless of the macroeconomic environment or any other factors.

Table 5. Summary of Regressions 1-2 (the ARPU dataset)

Variables	Description	Regression 1	Regression 2
		Coefficient	Coefficient
Intercept		-4.545*** (0.367)	-3.498*** (0.659)
LogGDP	GDP per capita	0.701*** (0.043)	0.615*** (0.060)
MarketShare	Subscribers base	0.002 (0.005)	
	Bundle play		
doubleplay11	Landline + internet	0.253*** (0.021)	
doubleplay21	Internet + TV	0.105** (0.044)	
tripleplay11	Landline + internet + TV	(dropped)	
tripleplay21	Mobile + internet + TV	-0.056 (0.173)	
quadplay1	Mobile + TV + internet + landline	-0.254*** (0.071)	
	Core services		
Mobile1	Mobile services		(dropped)
Internet1	Fixed internet		(dropped)
TV1	TV		0.211* (0.109)
Telephone1	Fixed phone/landline		0.001 (0.087)
	Non-core services		
Integration1	Full vertical		(dropped)
Fun1	Entertainment		-0.208*** (0.018)
In-house1	Other services		-0.083 (0.240)
Multiple R^2		0.815	0.803
Adjusted R^2		0.798	0.788
F-statistic		46.359***	52.216***
Notes	*, ** and *** denote significance levels at 10%, 5% and 1% respectively. Observations – 70. Numbers in parentheses are standard errors. They are robust to heteroskedasticity and clustered by country's income level (category code). Results are based on the author's data collection, February 2021.		

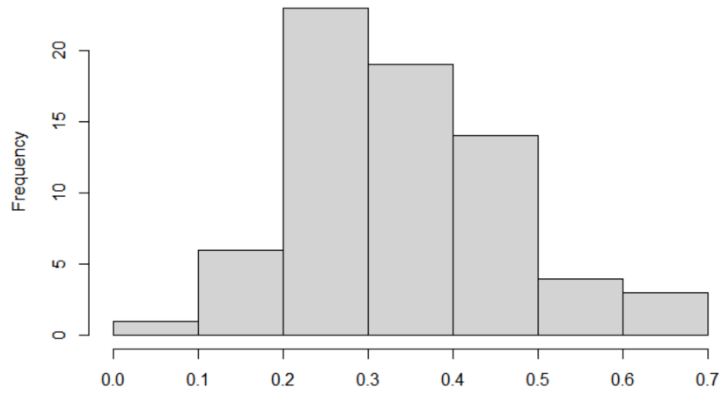
Since the dataset is limited (70 observations) and according to Harrell (2015), the model should have at least 10 observations per parameter, in Regression 1 and 2 we used the logarithm of GDP per capita instead of the income category as a market-related indicator. The summary of both regressions is presented in the table above. The reasons for including market control variables were discussed in section 1.2.

Following the approach by Calzada and Martínez-Santos (2016), we calculated robust standard errors clustered by country's income level using a stargazer package in R. Therefore, we can say that both models are robust. According to F-test, both models are overall significant. They also have significant coefficients. The goodness-of-measures indicate that both regressions are relatively well-determined with the adjusted R^2 between 78.8% and 79.8%.

We also performed the VIF tests to ensure that there are no multicollinearity concerns. The average VIF value for Regression 1 is 1.44 and for Regression 2 is 1.75. For more details, please refer to Table 8 in Appendix. According to the results of the VIF test, it was decided to drop *tripleplay11* in Regression 1 (its VIF score exceeded 5). The high VIF score for this variable can be explained by the specifics of the constructed dataset (Table 5 in Appendix). Both *tripleplay1* and *tripleplay2* variables have the same number of observations. In Regression 2, *integration* was dropped due to a very high VIF score. Originally, this variable was added to reflect the telecom's evolution as per the STL Partner's matrix (Fig 5 in section 2.1) but since the model already has a *quadruple-play* variable, it is better to omit the *integration* variable because the full integration is achieved when the company offers all four core services.

From the summary table above, we can also see that the market share is not significant in both regressions. The market share (the percentage of mobile subscribers) was used as a control variable to accommodate for the differences between operators. One of the reasons for its insignificance in both regressions may be that this is not a reliable market share proxy and a more robust indicator should be used (e.g., firm's sales as a share of the overall industry revenues). As explained in the previous section, the overall industry revenues were not publicly available, therefore, this indicator was not calculated in this research. Another possible reason for the market share insignificance is the limited dataset. According to the below histogram the majority of the companies in the dataset have between 20% and 50% of the market share.

Fig 8. Histogram. The market share distribution



According to the performed analysis, several variables appear to be important determinants of ARPU:

- GDP per capita
- Availability of double-play and quad-play offers
- TV services
- Entertainment services (partnerships with OTT services)

Since most of the variables are dummy variables, we can interpret their coefficients as the percentage difference in ARPU between firm's that have a particular characteristic and those that do not (Crocioni and Correa 2012).

According to our analysis, two variables have a negative impact on telecom's revenues (entertainment services and quadruple-play offers). For example, a partnership with OTT providers can decrease telecom's ARPU by 21%. This is an interesting finding since it is generally believed that these partnerships are a way for telecom to boost their ARPU. There can be several explanations:

- Partnerships with OTT companies were introduced as an attempt to increase declining revenues but their benefits might not have been well assessed by the companies.
- Netflix or similar subscriptions are usually provided for a discount only for one month. Customers may not see much value in subscribing to a rather expensive bundle for a short-term discount.

- The partnership is a long-term project and the analysis requires a longer time series for conclusions for the long term.
- If two services are significantly different from the company's competencies, customers are not interested in buying this bundle (Lipowski 2015) which will drive the ARPU indicator down.

According to Regression 1, quadruple-play offers decrease ARPU by approx. 25%. Having a closer look at the dataset will reveal several insights:

- There are no quadruple-play offers in low-income level countries.
- There are only 4 quadruple-play offers in upper-middle-income level countries.
- There are 15 quadruple-play offers in high-income level countries.

Therefore, the decrease of 25% is relevant for high-income level countries. From one side, it is obvious that the quadruple-play offers are not widespread even in developed economies. On another side, it is important to keep in mind that the dataset takes into account only one year. To offer a quadruple-play bundle, the operators had to make significant investments (for example, by acquiring smaller telecom companies). Therefore, to understand if there is indeed a negative impact, a panel dataset with observations spanning over several years should be used since the benefits of the quadruple-play bundles can be long-term. Contrary to the quadruple-play offers, we can see that double-play offers have a positive impact on ARPU (an increase of 10-25% depending on the type of the double-play bundles). They have also been used in the telecom industry for several decades already.

As expected, there is a positive relationship between ARPU and macroeconomic indicators (GPD per capita and the income level). As for Regressions 1 and 2, since both variables (the dependent and the independent ones) are log-transformed, we can interpret the coefficient as the percent change in the response variable. Therefore, a 1% increase in GDP can lead to approx. 62-70% increase in ARPU.

The dataset contains information on ARPU indicators from countries with very different economic situations (e.g., the USA and Nigeria). Therefore, we have also re-built Regression 1 using the Income category level instead of the GDP per capita.

Table 6. Summary of Regressions 3 (the ARPU dataset)

Variables	Description	Regression 3
		Coefficient
Intercept		3.134 *** (0.203)
CategoryCode2	Upper middle income	-0.475 *** (0.064)
CategoryCode3	Low income	-1.538 *** (0.208)
MarketShare	Subscribers base	-0.003 (0.011)
doubleplay11	Landline + internet	0.102 (0.089)
doubleplay21	Internet + TV	0.125 (0.127)
tripleplay11	Landline + internet + TV	(dropped)
tripleplay21	Mobile + internet + TV	0.085 (0.143)
quadplay1	Mobile + TV + internet + landline	-0.222 *** (0.124)
Multiple R^2		0.688
Adjusted R^2		0.652
F-statistic		19.507***
Notes	*, ** and *** denote significance levels at 10%, 5% and 1% respectively. Observations – 70. Numbers in parentheses are standard errors. They are robust to heteroskedasticity and clustered by country's income level (category code). Results are based on the author's data collection, February 2021.	

Regression 3 is overall significant with coefficients similar to Regression 1 which means that both models are robust (McCloughan and Lyons 2006). There are also no issues with multicollinearity (see Table 7 below).

Table 7. The VIF test for Regression 3 (the ARPU dataset)

```
> ols_vif_tol(reg3)
      Variables Tolerance      VIF
1 CategoryCode2 0.7454092 1.341545
2 CategoryCode3 0.4603206 2.172399
3   MarketShare 0.8932152 1.119551
4    doubplay11 0.7737617 1.292388
5    doubplay21 0.6018507 1.661542
6    tripplay21 0.6838725 1.462261
7     quadplay1 0.7271324 1.375265
```

In this case, only the ARPU indicator is log-transformed. To understand the change in ARPU, we need to exponentiate the coefficient and then calculate the percent change by subtracting one from the obtained number and multiplying it by 100. The results suggest that on average, the ARPU indicator in low-income level countries is approximately 79% lower than in high-income countries. This finding suggests that telecommunication services are still an example of superior goods meaning that the expenditures on telecom's services are rising when the income level is increasing.

TV services are also one of the significant determinants of the ARPU indicator. There might be two explanations:

- The consequence of the pandemic. Since the data takes into account only the 2020 year, customers who were confined in their houses opted for TV services but this demand is expected to decrease as soon as the lockdown restrictions are lifted (Hart and Fischer 2020).
- These services are provided when the operator has fixed broadband internet. Therefore, in the next section, we will provide a more detailed analysis of the drivers for both services (TV and broadband internet).

From the results, we can see that not all core services are driving ARPU in an equal manner. It is interesting to note that all operators in the dataset provide mobile services. This is in line with the S&P Global Market Intelligence report that noticed that there were fewer mobile-only or fixed-only operators (Colakides, Hamza and Ryazantsev 2020). Moreover, fixed telephone (landline) is often not advertised on the website and is included in the bundle with no additional charge as a complimentary service, therefore, it does not have any significant influence on the ARPU indicator. As the result, mobile indicators were dropped from Regression 2 while fixed phone services did not have any statistically significant impact on ARPU.

Another interesting observation from this analysis is that practitioners do not follow academic definitions of bundles. Although the academic literature distinguishes between double-play, triple-play and quadruple-play bundles, operators do not follow these definitions strictly and often mix different services as can be seen from Table 5 in the Appendix. Besides, most operators offer their clients a customized solution where they can choose the number and type of services included in the bundle without following the double-triple-quadruple-play structure described in the academic literature.

Since the results for the *fun* variable were surprising, we built an additional regression (Regression 4) with six interaction terms coded as dummy variables:

- *FunHigh* is a dummy variable that indicates those companies that have entertaining services and are located in high-income countries (FunHigh is equal to 1, otherwise to 0).
- *FunMiddle* is a dummy variable that indicates those companies that have entertaining services and are located in upper-middle-income countries (FunMiddle is equal to 1, otherwise to 0).
- *FunLow* is a dummy variable that indicates those companies that have entertaining services and are located in low-income countries (FunLow is equal to 1, otherwise to 0).
- *DevHigh* is a dummy variable that indicates those companies that have in-house developments and are located in high-income countries (DevHigh is equal to 1).
- *DevMiddle* is a dummy variable that indicates those companies that have in-house developments and are located in upper-middle-income countries (DevMiddle is equal to 1).
- *DevLow* is a dummy variable that indicates those companies that have in-house developments and are located in low-income countries (DevLow is equal to 1).

Table 8. Regression 4 variables (the ARPU dataset)

	0	**1**
FunHigh	64.3%	35.7%
FunMiddle	74.3%	25.7%
FunLow	81.4%	18.6%
DevHigh	70%	30%
DevMiddle	81.4%	18.6%
DevLow	80%	20%

Table 9. Summary of Regression 4 (the ARPU dataset)

Variables	Regression 4
	Coefficient
Intercept	2.877*** (0.138)
FunHigh1	0.095 (0.263)
FunMiddle1	0.187 (0.464)
FunLow1	-0.609*** (0.205)
DevHigh1	0.356 (0.225)
DevMiddle1	-0.439*** (0.046)
DevLow1	-0.874*** (0.324)
MarketShare	-0.004 (0.011)
Multiple R^2	0.676
Adjusted R^2	0.639
F-statistic	18.473***
Notes	*, ** and *** denote significance levels at 10%, 5% and 1% respectively. Observations – 70. Numbers in parentheses are standard errors. They are robust to heteroskedasticity and clustered by country's income level. Results are based on the author's data collection, February 2021.

Similar to previous regressions, the standard errors were clustered by country income category and are robust to heteroskedasticity. According to F-test, the model is significant and also have significant coefficients. The goodness-of-measure indicates that the model is relatively well-determined with the adjusted R^2 being equal to 63.9%. We also performed the VIF test to ensure that there are no multicollinearity concerns. The average VIF value for Regression 4 is 2.51. For more details, please refer to the below table.

Table 10. The results of the VIF test for Regression 4 (the ARPU dataset)

```
> ols_vif_tol(reg4)
    Variables Tolerance      VIF
1    FunHigh1 0.5016700 1.993342
2     FunLow1 0.3727357 2.682866
3  FunMiddle1 0.2367125 4.224534
4    DevHigh1 0.6082394 1.644090
5     DevLow1 0.3383928 2.955146
6  DevMiddle1 0.3387974 2.951616
7 MarketShare 0.9162955 1.091351
```

According to the results of Regression 4, there is a relation between the additional services in a specific economic environment and the ARPU. For example, additional services (both entertaining and in-house developed ones) have a negative impact on ARPU in low-income countries. This finding is in line with the previous statement about telecom services still being a superior good. Although the model did not confirm a positive relationship between high-income countries and the provision of non-core services, we can still assume that the negative coefficient for the *fun* variable in Regression 2 might have been mostly influenced by low-income level countries that constitute 26% of the dataset (Appendix Table 5) and have rather low ARPU indicators (see comparison below, Table 11).

Table 11. Average ARPU comparison between countries categories (the ARPU dataset)

	Average ARPU in USD PPP	**No. of observations**
High-income countries	24.13	34
Upper-middle-income countries	14.74	19
Low-income countries	4.73	18

3.2. Econometric results and discussion of the bundle prices drivers

Adopting the approach taken in studies by Crocioni and Correa (2012) and Díaz-Pinés and Fanfalone (2016), we built a hedonic model with several specifications. By constructing these regressions, we kept in mind the findings by Díaz-Pinés and Fanfalone (2016) who noticed that the estimated coefficients for operators coded variables are statistically significant when country dummy variables are not used in the same regression. Our data analysis confirmed these findings, therefore, we used either country or operator variables in each of the regression. We also adopted the approach by Calzada and Martínez-Santos (2016) who calculated robust standard errors clustered by country (similar to what we did in the previous section).

In the scope of this research, ten regressions were constructed. The meaning of each variable is explained in section 2.3. The first two specifications only considered the bundle composition (e.g., double- or triple-play). The 3rd and 4th specification considered the bundled services. The 5-8 specifications also considered the characteristics of these services: download speed, data allowance, number of minutes and TV channels. Regressions 9 and 10 are similar to regressions 5-8 but they included both control variables, namely, the *CountryCode* and the *OperatorCode*.

Regression 1: $LogPrice = \beta_0 + \boldsymbol{\beta_1 CountryCode} + \beta_2 TypeCode + \varepsilon$

Regression 2: $LogPrice = \beta_0 + \boldsymbol{\beta_1 OperatorCode} + \beta_2 TypeCode + \varepsilon$

Regression 3: $LogPrice = \beta_0 + \boldsymbol{\beta_1 CountryCode} + \beta_2 Mobile + \beta_3 TV + \beta_4 Internet + \varepsilon$

Regression 4: $LogPrice = \beta_0 + \boldsymbol{\beta_1 OperatorCode} + \beta_2 Mobile + \beta_3 TV + \beta_4 Internet + \varepsilon$

In regressions 3 and 4, the fixed telephone and *TypeCode* variables were dropped because they are not significant. One of the reasons for fixed telephone's insignificance may be that only a limited number of bundles included this service.

Regression 5: $LogPrice = \beta_0 + \boldsymbol{\beta_1 CountryCode} + \beta_2 Family + \beta_3 GB + \beta_4 Calls + \beta_5 SMS + \beta_6 Channels + \beta_7 TVBox + \beta_8 Speed + \beta_9 Wifi + \varepsilon$

Regression 6: $LogPrice = \beta_0 + \boldsymbol{\beta_1 OperatorCode} + \beta_2 Family + \beta_3 GB + \beta_4 Calls + \beta_5 SMS + \beta_6 Channels + \beta_7 TVBox + \beta_8 Speed + \beta_9 Wifi + \varepsilon$

In regressions 5 and 6, *mobile*, *TV*, *internet* and *fixed telephone* variables were dropped because of the multicollinearity issue. The included variables already characterize these three services on a deeper level.

Regression 7: $LogPrice = \beta_0 + \boldsymbol{\beta_1 OperatorCode} + \beta_2 Family + \beta_3 UnlimitedGB + \beta_4 UnlimitedCalls + \beta_5 SMS + \beta_6 Channels + \beta_7 TVBox + \beta_8 Speed + \beta_9 Wifi + \varepsilon$

Regression 8: $LogPrice = \beta_0 + \boldsymbol{\beta_1 CountryCode} + \beta_2 Family + \beta_3 UnlimitedGB + \beta_4 UnlimitedCalls + \beta_5 SMS + \beta_6 Channels + \beta_7 TVBox + \beta_8 Speed + \beta_9 Wifi + \varepsilon$

In regressions 7 and 8, *GB* and *Calls* were swapped for two dummy variables i.e. *UnlimitedGB* and *UnlimitedCalls*. For a detailed explanation, please refer to section 2.3.

Regression 9: $LogPrice = \beta_0 + \boldsymbol{\beta_1 OperatorCode} + \boldsymbol{\beta_2 CountryCode} + \beta_3 Family + \beta_4 GB + \beta_5 Calls + \beta_6 SMS + \beta_7 Channels + \beta_8 TVBox + \beta_9 Speed + \beta_{10} Wifi + \varepsilon$

Regression 10: $LogPrice = \beta_0 + \boldsymbol{\beta_1 OperatorCode} + \boldsymbol{\beta_2 CountryCode} + \beta_3 Family + \beta_4 GB + \beta_5 Calls + \beta_6 SMS + \beta_7 Channels + \beta_8 TVBox + \beta_9 Speed + \beta_{10} Wifi + \varepsilon$

To ensure that there is no multicollinearity issue we performed the VIF (Variance Inflation Factor) tests for each regression. The mean VIF was calculated for all 10 regressions and is presented in Table 12 below. The test was used to determine whether the models were correctly specified or whether some variables should be excluded. The results were satisfactory because the mean VIF largely remained between 2 and 4. The problem occurred when we tried to use country and operator factor variables in the same specification. Therefore, it was decided not to use Regressions 9 and 10 for the discussion of the results. As we can see from the table, by introducing *UnlimitedGB* and *UnlimitedCalls* variables in Regressions 7 and 8, we have slightly decreased the VIF indicator compared to Regressions 5 and 6. For the detailed summary of the VIF tests, please refer to Tables 9 and 10 in Appendix.

Table 12. The results of the VIF tests for Regressions 1-10 (the Bundle Prices dataset)

	Average VIF	Maximum VIF
Regression 1 (w/ country code)	1.286303	1.426275 (CountryCode3)
Regression 2 (w/ operator code)	1.385418273	1.796468 (OperatorCode8)
Regression 3 (w/ country code)	1.2955815	1.507102 (Mobile1)
Regression 4 (w/ operator code)	1.422082077	1.794779 (OperatorCode8)
Regression 5 (w/ country code)	1.904558833	3.282199 (GB)
Regression 6 (w/ operator code)	2.367844167	4.986489 (GB)
Regression 7 (w/ operator code)	2.215823	3.680606 (SMS)
Regression 8 (w/ country code)	1.793859583	2.781647 (SMS)
Regression 9	Inf	Inf (several countries and operators)
Regression 10	Inf	Inf (several countries and operators)

From the correlation matrix (Table 13 below), we can also notice a positive relationship between the price of the bundle and the speed of the broadband internet as well as the number of calls. It might be explained as follows: to provide these services, telecom companies need to heavily invest in their infrastructure. Therefore, they need to replenish their investments in the technology that helps provide these services.

One of the interesting findings is a negative correlation between the price of the bundle and the number of SMS. It can be explained as follows: operators might be adding SMS to their package to make the price more justifiable and appealing to the buyer when in fact the price is driven by other services. Another explanation might be that SMS service is being replaced with mobile internet. Therefore, a positive correlation between GB and the price is balanced by the negative relation between the price and the number of SMS.

Table 13. The correlation matrix (the Bundle Prices dataset)

```
               Price         GB       Calls         SMS   Channels     Speed
Price     1.00000000  0.1549975  0.4333321 -0.02046998  0.1922393 0.4505868
GB        0.15499755  1.0000000  0.4966656  0.71589701 -0.1916836 0.2126103
Calls     0.43333210  0.4966656  1.0000000  0.16705381 -0.1700963 0.1087826
SMS      -0.02046998  0.7158970  0.1670538  1.00000000 -0.1930315 0.2270972
Channels  0.19223926 -0.1916836 -0.1700963 -0.19303148  1.0000000 0.2228291
Speed     0.45058675  0.2126103  0.1087826  0.22709719  0.2228291 1.0000000

             LogPrice         GB       Calls          SMS   Channels     Speed
LogPrice  1.000000000  0.1415924  0.3701397 -0.003733746  0.1895977 0.3866892
GB        0.141592402  1.0000000  0.4966656  0.715897006 -0.1916836 0.2126103
Calls     0.370139743  0.4966656  1.0000000  0.167053813 -0.1700963 0.1087826
SMS      -0.003733746  0.7158970  0.1670538  1.000000000 -0.1930315 0.2270972
Channels  0.189597689 -0.1916836 -0.1700963 -0.193031478  1.0000000 0.2228291
Speed     0.386689221  0.2126103  0.1087826  0.227097193  0.2228291 1.0000000
```

Overall, there were several insights from the 8 regressions. A detailed summary of all regressions is available in the Appendix (Tables 11-13). For brevity purposes, here we included only a fraction of the summary that has bundle-related coefficients without country or operator variables. It is important to note that since all the regressions are multi-level factor models that have several categorical variables, R automatically uses the first categorical variables as a baseline (for the intercept calculation). Although this impacts the interpretation of the operator-specific and country-specific variables' coefficients, this does not influence the bundle-related coefficients that are the focus of the current research.

Table 14. The summary of regressions 1-4 (the Bundle Prices dataset)

Variables	**Regression 1**	**Regression 2**	**Regression 3**	**Regression 4**
	Coefficient	Coefficient	Coefficient	Coefficient
Intercept	3.47130 *** (0.036)	3.51679 *** (0.131)	2.49524 *** (0.098)	2.47960 *** (0.114)
TypeCode3	0.23464 *** (0.103)	0.33785 *** (0.084)	(dropped)	(dropped)
Mobile1			0.31066 ** (0.120)	0.36964 *** (0.128)
TV1			0.31559 *** (0.087)	0.27224 *** (0.082)
Internet1			0.64418 *** (0.052)	0.76939 *** (0.057)
Telephone1			(dropped)	(dropped)
Multiple R^2	0.3779	0.42	0.4377	0.4444
Adjusted R^2	0.3448	0.3475	0.3949	0.3604
F-statistic	11.42 ***	5.793 ***	10.23 ***	5.291 ***
Notes	*, ** and *** denote significance levels at 10%, 5% and 1% respectively. Observations – 100. Numbers in parentheses are standard errors. They are robust to heteroskedasticity and clustered by country. Results are based on the author's data collection, February 2021.			

Although Regressions 1-4 are relatively simple, they reveal some interesting results. The variables describing the bundle n-play type (double- or triple-play) and the bundled services (TV, internet and mobile) are significant and can explain some variations in the bundle price. The adjusted R^2 lies between 34.48 – 39.49%. For the interpretation of the coefficients, we will use the approach proposed by Halvorsen and Palmquist (1980). In our model, the dependent variable is log-transformed. To understand the change in the ARPU indicator, we need to exponentiate the coefficient and then calculate the percent change by subtracting one from the obtained number and multiplying it by 100.

For example, according to Regressions 1-2, the triple-play bundles can be 26.44% – 40% more expensive than a double-play package. This result is rather predictable and is in line with the results of the previous studies. Another interesting finding of Regressions 3-4 is the impact of the bundled services on the price. For example, we can see that in general, the inclusion of internet services can almost double the price compared to the bundle that has no broadband internet service. Moreover, according to the results of the regressions, the addition of TV services increases the price up to 30% but not as much as the inclusion of mobile services that can drive the price up to 43.33%. This can help determine the main revenue-generating telecom services with fixed internet being the first one on the list.

Table 15. The summary of regressions 5-8 (the Bundle Prices dataset)

Variables	**Regression 5**	**Regression 6**	**Regression 7**	**Regression 8**
	Coefficient	Coefficient	Coefficient	Coefficient
Intercept	2.92794889*** (0.033)	3.22132397*** (0.198)	3.22128229*** (0.188)	2.95039180 *** (0.040)
Family1	0.07425789 (0.078)	0.10015347 (0.162)	0.15541983 (0.173)	0.12142939 (0.102)
GB	0.00127502 (0.001)	0.00366663*** (0.0005)	(dropped)	(dropped)
UnlimitedGB	(dropped)	(dropped)	0.38375880 *** (0.051)	0.15988526 (0.099)
Calls	0.00003688*** (0.00001)	0.00005789*** (0.00001)	(dropped)	(dropped)
UnlimitedCalls	(dropped)	(dropped)	0.51684700 *** (0.090)	0.23509010* (0.139)
SMS	0.00018656 (0.0001)	-0.00054468*** (0.0002)	-0.00046577 *** (0.0002)	0.00014184 (0.0002)
Channels	0.00143909*** (0.0003)	0.00136509*** (0.0004)	0.00124711 *** (0.0005)	0.00134005 *** (0.0004)
TVBox1	0.10812338 (0.113)	-0.07530813 (0.209)	-0.07173265 (0.206)	0.10918357 (0.119)
Speed	0.00075428*** (0.0001)	0.00069875*** (0.0001)	0.00073192 *** (0.0001)	0.00078193 *** (0.0001)
Wifi1	-0.04551672 (0.088)	-0.04969907 (0.119)	-0.02970643 (0.107)	-0.04908848 (0.084)
Multiple R^2	0.8064	0.7847	0.7782	0.79
Adjusted R^2	0.7797	0.7369	0.729	0.761
F-statistic	30.19***	16.4 ***	15.79 ***	27.27 ***
Notes	*, ** and *** denote significance levels at 10%, 5% and 1% respectively. Observations – 100. Numbers in parentheses are standard errors. They are robust to heteroskedasticity and clustered by country. Results are based on the author's data collection, February 2021.			

Regressions 5-8 were built with a set of more detailed variables that replaced bundle compositions indicators with specific service characteristics. The inclusion of the detailed variables helped increase the adjusted R-squared up to 73-78%. The most interesting findings are as follows:

- The amount of GB and Calls have a positive effect on the bundle price. For example, a package with unlimited gigabytes can be up to 39% more expensive than a package with a limited data allowance. At the same time, the addition of unlimited calls can increase the price by up to 52%. This can be explained by the fact the unlimited data allowance is usually included in the family-friendly packages to make it easier for the clients to share data among their network.
- Surprisingly, the addition of 100 SMS in the package can drive the price down by approximately 4.6%. This might be explained as follows: SMS services are no longer popular with customers. Moreover, the provision of these services can be taxing on the telecom’s infrastructure.
- Another driver of bundle price is the speed of broadband internet. The increase of 100 Mbit/sec is accompanied by a 7.55% increase in price. This finding is similar to the results of Regressions 3-4 where fixed internet service was identified as one of the main drivers of telecom’s revenues.

3.3. Summary

In this chapter, we examined the drivers of ARPU. As expected, our econometric analysis confirmed that there is a difference in ARPU depending on the income level of the country. For example, the ARPU indicator is approximately 79% lower in low-income countries compared to high-income ones.

Surprisingly, we have found out that TV services are also one of the significant determinants of the ARPU indicator although the literature review suggested that these services are playing a diminishing role in the telecom’s industry. One of the reasons for this positive relationship might be the consequence of the pandemic. In 2020, customers who were dealing with the lockdown looked for different ways to spend their time at home and opted for TV services.

Another interesting finding was the negative impact of additional non-core telecommunication services on the ARPU indicator (in particular, the entertainment services). To test this relationship further, we introduced several interaction terms. Our analysis revealed that additional services (both entertaining and in-house developed ones) have a negative impact on ARPU in low-income countries.

Therefore, the results of the first econometric analysis suggest the following:

- telecom services are still being a superior good and not a utility.
- TV services are still an important revenue driver for the telecom's industry.
- the academic classification of n-play bundles is outdated.

In this chapter, we also analyzed the drivers of bundle prices by using the hedonic pricing approach. We constructed 10 regressions with different bundle-related variables and identified the impact of each service on the bundle price. The analysis revealed the following:

- one of the main drivers of the bundle price is broadband internet followed by mobile services.
- although TV services are an important price driver, they have a lower impact on telecom's revenue than mobile and fixed broadband internet services.
- landline services are no longer driving the telecom's revenue and are mostly included in the bundle as free-of-charge services.
- the bundles with an unlimited data allowance for mobile services can significantly increase the price of the bundle (up to 39-52%). One of the reasons might be that the bundles with unlimited data allowance are usually family-friendly and encourage clients to introduce their family and friends to the operator's services. Therefore, these unlimited features can be one of the main drivers for telecom's revenue and customer acquisition rate.

By confirming that fixed broadband internet service is one of the main drivers of telecom's revenue, we also accidentally encountered another trend that has been emerging in the telecommunication industry for a while. This finding is similar to the results of the recent study that pointed out the emergence of a so-called "quad-play" (Frost & Sullivan 2014). According to this survey, telecom customers are becoming increasingly interested in two access services, fixed-line and wireless internet, and show a declining interest in voice (fixed telephone) and video (TV) services. The Frost & Sullivan survey based on the insights from 2035 respondents from North America revealed that customers are using fixed-line and mobile internet to access voice and video apps instead of paying for these services as part of a bundle. This indicates possible future developments in the telecommunication market (Arnason 2014) and also relates back to the issue briefly discussed in Chapter 1 and generally known as a “dumb pipeline” problem (Kim, Nam and Ryu 2020).

CONTRIBUTION AND CONCLUSION

This paper adds to the pricing and bundling academic research and also derives some practical implications that can be used to guide telecom operators on how to manage their revenue management strategies. Although bundling plays an important role in telecommunication services, the empirical economic literature (and especially with regard to the company's financial performance) is rather limited (for more details, please see Chapter 1). One of the reasons is that the analysis relies on the information that is often viewed by operators as strategically important and confidential. Therefore, the in-depth research of this topic is a complicated exercise but it is vital for a better understanding of telecom's revenue drivers and ways to improve these indicators.

In the scope of this paper, we built two models (Chapter 2) to examine how bundled services affect telecom's revenue. The first model (Model A or ARPU Model) looked at the high-level relationship between bundled services and ARPU and operated mainly with dummy variables. The second model (Model B or Bundle Prices Model) looked at what service characteristics are driving bundle prices and to what extent. The paper analyzed the relationship between external and internal factors and ARPU as well as identified the main determinants of bundle prices. Since most of the telecom services are offered in bundles, we refer to these bundle price drivers as bundle revenue drivers.

The ARPU drivers analysis conducted in Chapter 3 provides an overview of how telecommunication services affect the ARPU indicator across 49 countries. In this section, we introduced a novel approach to the determination of ARPU drivers by including not only core telecommunication services (such as broadband internet or TV) but also indicators for the non-core ones (such as entertainment services or in-house developments[3]).

One of the conclusions was that non-core services do not necessarily drive ARPU and even lead to decreasing revenues in low-income countries meaning that ARPU depends on the income level of the country. This is one of the reasons why telecom services should be still treated as a superior good and not as a utility:

[3] The entertaining services include the subscription to Netflix, Spotify, Warcraft accounts, etc. The in-house developments include the products developed by the telecom provider (for example, e-wallet smartphone app, security services, a sports channel, etc.).

- ARPU is approx. 37.8% lower in upper-middle-income countries (such as Russia, Kazakhstan, Belarus, Brazil) compared to the high-income ones (such as Germany, the UK, Denmark). For more details, please refer to Table 6 in section 3.1.
- An inclusion of non-core services (both entertaining and in-house developed ones) has a negative impact on ARPU in low-income countries (a decrease of approx. 60.9% - 87.4%). For more details, please refer to Table 9 in section 3.1.

Moreover, the analysis in Chapter 3 revealed that the academic classification of n-play bundles is not flexible enough to accommodate the latest developments in the telecommunication industry (e.g., the shift towards customization).

The bundle price analysis conducted in the second half of Chapter 3 is one of the common hedonic modelling exercises. Contrary to previous studies, we included the Russian telecommunication market in this research. One of the conclusions was that fixed internet services are the main driver of the telecom bundle prices and, consequently, revenues. The second important driver is mobile services. This finding corresponds to the observations of some researchers who noted that telecom was being treated as an infrastructure provider rather than a content provider (Frost & Sullivan 2014).

The analysis also confirmed that TV services are still an important price and revenue driver although they have a lower impact on telecom's revenue than mobile and fixed broadband internet services. One of the reasons might be the consequence of the pandemic. Since our data takes into account only the year 2020, customers who were confined in their houses opted for TV services. This demand will possibly decrease as soon as the COVID-19 restrictions are lifted.

Also, the bundles with an unlimited data allowance for mobile services can significantly increase the price of the bundle (up to 39-52%). These services are often included in family-friendly bundles and encourage the network effect. Family-friendly bundles are bundles where the customer has an opportunity to connect more than one phone number or account to the plan.

Contrary to previous studies, it was revealed that landline services are no longer driving telecom's revenues and bundle prices. This is a new result compared to the studies that were carried out 3-4 years ago where this variable was still significant.

Academic contribution

This paper continues the wide research of bundling in the telecommunication industry but also contributes to a rather limited body of the revenue management (RM) literature in this industry. Moreover, this research examined bundling in the financial performance (revenue management) context instead of the more commonly used marketing perspective. Contrary to the large body of existing papers, the current research provides implications not for regulatory authorities or investors but for managers of telecommunication companies.

In previous studies, academics mostly focused on the developing countries such as the US or the EU markets or on some specific developing regions (such as Africa or India). The current research includes data from the Russian market as well as ARPU indicators from over 40 countries around the world.

The current research complemented the existing academic literature in two more ways:

- Inclusion of the non-core telecom services. To our knowledge, there are no papers that explore the relationship between ARPU and non-core services.
- Analysis of the ARPU determinants. There is a rather limited body of research (only three papers) on the ARPU determinants in the telecommunication industry.

Managerial implications

There are some risk zones for telecom managers, namely, the strategy of bundling different services and products together and the rush to enter new businesses. Although there might be a positive relationship between the variety of services provided and ARPU, the research has shown that the inclusion of entertainment services has a negative effect on the ARPU indicator in the short term (especially, in low-income countries). Therefore, the role of non-core offerings in telecommunication revenue management deserves special attention. Although non-core services are enjoying increasing popularity, this does not necessarily mean that they are one of telecom's revenue drivers.

The ARPU model results indicated that there is a link between the economic situation in the country and ARPU. When assessing the financial performance of the subsidiary, managers should pay attention to the macroeconomic environment of the country where this subsidiary is based. If some services are driving revenues in Germany, they might not be driving revenues in Bangladesh or might even have an adverse effect on them.

To successfully address regulators' concerns, managers can use the hedonic pricing models to demonstrate to regulators what services are driving the price increase. For example, instead of mentioning that their investments are growing, telecom companies can communicate another idea to the regulators and the society such as: "The price for a specific bundle increased because we added 20 new TV channels." According to the results of this study, the price increase can also be justified as a change in the internet or mobile services proposition. These services and their characteristics (such as data allowance or broadband internet speed) are the main price drivers.

Using a hedonic pricing model, managers can single out company's revenue streams and identify for which services the company can charge more and, thus, finance their other investments. Nevertheless, these results should be combined with the internal information about the costs involved in the provision of additional services. Overall, the constructed hedonic pricing models can help operators refine their investment decision-making process.

Limitations

Although we consider this paper a small contribution to the large research enterprise dedicated to analyzing the impact of bundling practices on the telecom's revenue, the current research has several limitations:

- Since both datasets were constructed manually, there is a possibility of a selection bias. Besides, not all operators published their ARPU indicators, therefore, the research findings can be generalized only to a certain extent.
- The datasets contain only publicly available data that are advertised online. The results would have been more robust when combined with internal data and customer-oriented surveys. For example, it would be valuable to know how many subscribers each plan has. The estimations can be imprecise and, as a result, the calculated effects may be either bigger or smaller in reality.
- Both datasets focus exclusively on the residential plans. Telecom's operators are offering a variety of services to their business customers. It would be interesting to see the difference between determinants for the average revenue per user (ARPU) and the

average revenue per line (ARPL). For more details about these two indicators, please refer to section 1.3.

- Bundle prices vary across different regions within one country due to the network capacity and coverage. In the scope of this research, we used only prices for capital cities without considering smaller cities or rural areas.
- The data collection process for the bundle prices was based on the prices published on the websites and did not include information on any discounts (e.g., connected with a specific marketing campaign or with an individual agreement between the operator and the customer).

Future research

For future research, it would be valuable to look at a longer time series data spanning over several periods. The results can be completely different. For example, partnerships with OTT service providers might have a positive effect on ARPU in the long run.

It might be interesting in the future to use prices of different bundles instead of dummy variables (in model A). This would help identify if an increase or decrease in the bundle price leads to changes in the ARPU indicator.

Moreover, an improved hedonic pricing model can use specifications of the bundle characteristics not only for the core telecommunication services (such as data allowance) but also for the non-core ones. For example, information about what discounts are available or what in-house developments were introduced.

The current research revealed that family-friendly features have a significant effect on telecom's revenue. Therefore, a more detailed analysis of these services would help reach a deeper understanding of the latest trends in the telecommunication industry. Overall, we believe that complemented by internal information, the specified models can be improved further to provide more insights into operators' strategic behavior.

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APPENDIX

Table 1. Breakdown per operator (the ARPU dataset)

No.	**Operator**	**No. of observations**
1	A1 Telekom Austria	6
2	América Móvil	7
3	AT&T	1
4	Deutsche Telekom	3
5	Drei	1
6	KT	1
7	LG Uplus	1
8	Liberty Global	1
9	lifecell	1
10	MTN	10
11	MTS	1
12	NTT Docomo	1
13	Orange	4
14	SKT	1
15	SoftBank	1
16	Tele2	1
17	Telecom Italia	1
18	Telefonica	3
19	Telenor	8
20	Telia Company	6
21	VEON	7
22	Vodafone	4
	Total	**70**

Table 2. Breakdown per country (the ARPU dataset)

No.	Country	No. of observations
1	Afghanistan	1
2	Algeria	1
3	Argentina	1
4	Austria	2
5	Bangladesh	2
6	Belarus	1
7	Belgium	1
8	Brazil	3
9	Bulgaria	1
10	Chile	1
11	Colombia	1
12	Croatia	1
13	Denmark	2
14	Ecuador	1
15	Estonia	1
16	Finland	2
17	France	1
18	Germany	3
19	Ghana	1
20	Italy	1
21	Japan	2
22	Kazakhstan	1
23	Lithuania	1
24	Malaysia	1
25	Mexico	2
26	Netherlands	1
27	Nigeria	1
28	North Macedonia	1
29	Norway	2
30	Pakistan	2
31	Peru	1
32	Poland	1
33	Russia	3
34	Rwanda	1
35	Slovenia	1
36	South Africa	1
37	South Korea	3
38	Spain	1
39	Sudan	1
40	Sweden	2
41	Syria	1
42	Thailand	1
43	Uganda	1
44	Ukraine	3
45	United Kingdom	3
46	USA	1
47	Uzbekistan	1
48	Yemen	1
49	Zambia	1
	Total	**70**

Table 3. Breakdown per operator (the Bundle Prices dataset)

No.	**Operator**	**No. of observations**
1	A1	8
2	AlmaTV	8
3	Megafon	1
4	Beeline	18
5	Beltelecom	15
6	Kyivstar	4
7	Megafon	7
8	MTS	12
9	Rostelekom	10
10	Tenet	8
11	Vivacom	3
12	Volia	7
	Total	**100**

Table 4. Variable sources and summary statistics (the ARPU dataset)

Variable	***Source***[4]	***Mean***	***Min.***	***Max.***	***Obs.***
LogARPU	(3)	2.5505	0.4684	3.7377	70
ARPU	(1)	16.485	1.597	42.000	70
LogSub	(3)	16.33	13.48	18.33	70
Subscriptions	(1)	21676001	715914	91003982	70
Total Subscriptions	(2)	76435976	1921013	442457000	70
Log Total Subscriptions	(3)	17.23	14.47	19.91	70
GDP per capita	(2)	31221	1139	70006	70
LogGDP	(3)	9.962	7.038	11.156	70
MarketShare	(1), (2), (3)	34.686	4.076	63.300	70

[4] (1) – financial reports and annual statements, (2) – World Bank, (3) – own calculations

Table 5. Dummy and factor variables sources and summary statistics (the ARPU dataset)

Variable	***Description***	***Value***	***Frequency***	***Proportion***
Category	High income	1	33	0.471
	Upper middle income	2	19	0.271
	Low income	3	18	0.257
DoublePlay1	Fixed telephone + internet	0	53	0.757
		1	17	0.243
DoublePlay2	Internet + TV	0	35	0.5
		1	35	0.5
TriplePlay1	Internet + TV + fixed telephone	0	46	0.657
		1	24	0.343
TriplePlay2	Internet + TV + mobile services	0	46	0.657
		1	24	0.343
Quadplay	Internet + TV + mobile services +	0	51	0.729
	fixed telephone	1	19	0.271
Fixed telephone		0	34	0.486
		1	36	0.514
Mobile services		0	0	0
		1	70	1
Fixed internet		0	23	0.329
		1	47	0.671
TV		0	23	0.329
		1	47	0.671
Fun	additional entertaining services	0	14	0.2
	(partnerships with OTT providers)	1	56	0.8
In-house	in-house development	0	22	0.314
		1	48	0.686
Vertical	partial vertical integration	0	35	0.5
Integration	full vertical integration	1	35	0.5

Table 6. Variable sources and summary statistics (the Bundle Prices dataset)

Variable	***Source***[5]	***Mean***	***Min.***	***Max.***	***Obs.***
Price	(4)	46.78	20.62	118.36	100
LogPrice	(3)	3.779	3.026	4.774	100
GB	(4)	24.99	0.00	100.00	100
Calls	(4)	761.5	0.00	10000.0	100
SMS	(4)	70.1	0.00	500.0	100
Channels	(4)	131.2	0.00	250.0	100
Speed	(4)	223.46	0.00	1000.00	100

[5] (1) – financial reports and annual statements, (2) – World Bank, (3) – own calculations, (4) – official websites

Table 7. Dummy and factor variables sources and summary statistics (the Bundle Prices dataset)

Variable	*Description*	*Value*	*Frequency*	*Proportion*
TypeCode	Double-play	2	61	0.61
	Triple-play	3	39	0.39
Mobile	Mobile services indicator	0	64	0.64
		1	36	0.36
Family	Mobile service characteristic	0	86	0.86
	A feature to connect several phone numbers to data allowance package	1	14	0.14
UnlimitedGB	Mobile service characteristic	0	77	0.77
	Unlimited GB allowance	1	23	0.23
UnlimitedCalls	Mobile service characteristic	0	96	0.96
	Unlimited call minutes	1	4	0.04
TV	TV services indicator	0	10	0.1
	(interactive television)	1	90	0.9
TVBox	TV services indicator	0	72	0.72
	(if TV box rent is included in the bundle price)	1	28	0.28
Internet	Fixed internet services indicator	0	1	0.01
		1	99	0.99
Wifi	Fixed internet services indicator	0	81	0.81
	(if WiFi hotspot rent is included in the bundle price)	1	19	0.19
Telephone	Fixed telephone services indicator	0	86	0.86
		1	14	0.14

Table 8. VIF tests for Regression 1 and 2 (the ARPU dataset)

```
> ols_vif_tol(reg1)
    Variables Tolerance      VIF
1      LogGDP 0.5436683 1.839357
2 MarketShare 0.8489382 1.177942
3  doubplay11 0.8022681 1.246466
4  doubplay21 0.6307952 1.585301
5  tripplay21 0.6786816 1.473445
6   quadplay1 0.7539081 1.326422
```

```
> ols_vif_tol(reg2)
   Variables Tolerance      VIF
1     LogGDP 0.4833134 2.069051
2       fun1 0.9285911 1.076900
3  platform1 0.9299715 1.075302
4        TV1 0.3823889 2.615139
5 telephone1 0.5226562 1.913304
```

Table 9. VIF tests for Regression 1-8 (the Bundle Prices dataset)

```
> ols_vif_tol(reg1)
     Variables Tolerance      VIF
1 CountryCode2 0.7896001 1.266464
2 CountryCode3 0.7011272 1.426275
3 CountryCode4 0.7803376 1.281497
4 CountryCode5 0.8435380 1.185483
5    TypeCode3 0.7862887 1.271797
> ols_vif_tol(reg2)
        Variables Tolerance      VIF
1   OperatorCode2 0.6815796 1.467180
2   OperatorCode3 0.7738066 1.292313
3   OperatorCode4 0.7041098 1.420233
4   OperatorCode5 0.8501085 1.176320
5   OperatorCode6 0.7492802 1.334614
6   OperatorCode7 0.7715852 1.296033
7   OperatorCode8 0.5566478 1.796468
8   OperatorCode9 0.7147841 1.399024
9  OperatorCode10 0.7147841 1.399024
10 OperatorCode11 0.8625176 1.159397
11      TypeCode3 0.6671137 1.498995
```

```
> ols_vif_tol(reg3)
     Variables Tolerance      VIF
1 CountryCode2 0.7812224 1.280045
2 CountryCode3 0.7058851 1.416661
3 CountryCode4 0.7486041 1.335820
4 CountryCode5 0.8010883 1.248302
5      Mobile1 0.6635250 1.507102
6          TV1 0.7932263 1.260674
7    Internet1 0.9576246 1.044251
> ols_vif_tol(reg4)
        Variables Tolerance      VIF
1   OperatorCode2 0.6577590 1.520314
2   OperatorCode3 0.7571402 1.320759
3   OperatorCode4 0.6638769 1.506303
4   OperatorCode5 0.7616206 1.312990
5   OperatorCode6 0.7361595 1.358401
6   OperatorCode7 0.7559736 1.322797
7   OperatorCode8 0.5571717 1.794779
8   OperatorCode9 0.6824177 1.465378
9  OperatorCode10 0.6824177 1.465378
10 OperatorCode11 0.8434321 1.185632
11        Mobile1 0.5672838 1.762786
12            TV1 0.7147468 1.399097
13      Internet1 0.9324422 1.072453
```

```
> ols_vif_tol(reg5)
      Variables Tolerance      VIF
1  CountryCode2 0.6197583 1.613532
2  CountryCode3 0.5298301 1.887397
3  CountryCode4 0.5850629 1.709218
4  CountryCode5 0.7837194 1.275967
5       Family1 0.4556021 2.194898
6            GB 0.3046738 3.282199
7         Calls 0.5681162 1.760203
8           SMS 0.3542058 2.823218
9      Channels 0.7573982 1.320309
10       TVBox1 0.6150390 1.625913
11        Speed 0.6493958 1.539893
12        Wifi1 0.5488599 1.821959
```

```
> ols_vif_tol(reg6)
        Variables Tolerance      VIF
1   OperatorCode2 0.3911847 2.556337
2   OperatorCode3 0.5153615 1.940386
3   OperatorCode4 0.4379994 2.283108
4   OperatorCode5 0.6535962 1.529997
5   OperatorCode6 0.5408889 1.848809
6   OperatorCode7 0.4633205 2.158333
7   OperatorCode8 0.4869462 2.053615
8   OperatorCode9 0.5279576 1.894091
9  OperatorCode10 0.5986842 1.670330
10 OperatorCode11 0.6441618 1.552405
11        Family1 0.3360636 2.975627
12             GB 0.2005419 4.986489
13          Calls 0.4608348 2.169975
14            SMS 0.2441976 4.095045
15       Channels 0.6493653 1.539965
16         TVBox1 0.3249607 3.077295
17          Speed 0.6416363 1.558515
18          Wifi1 0.3661833 2.730873
```

```
> ols_vif_tol(reg7)
         Variables Tolerance      VIF
1    OperatorCode2 0.3889716 2.570882
2    OperatorCode3 0.5475085 1.826456
3    OperatorCode4 0.4416623 2.264173
4    OperatorCode5 0.6764891 1.478220
5    OperatorCode6 0.5525838 1.809680
6    OperatorCode7 0.4771983 2.095565
7    OperatorCode8 0.4901268 2.040288
8    OperatorCode9 0.5289668 1.890478
9   OperatorCode10 0.5999900 1.666694
10  OperatorCode11 0.6309318 1.584957
11         Family1 0.3576508 2.796023
12     UnlimitedGB1 0.2952882 3.386522
13 UnlimitedCalls1 0.5605612 1.783927
14             SMS 0.2716944 3.680606
15        Channels 0.6560291 1.524323
16          TVBox1 0.3234013 3.092134
17           Speed 0.6381741 1.566970
18           Wifi1 0.3537424 2.826916
```

```
> ols_vif_tol(reg8)
         Variables Tolerance      VIF
1     CountryCode2 0.6222348 1.607110
2     CountryCode3 0.5304605 1.885155
3     CountryCode4 0.5963596 1.676840
4     CountryCode5 0.7859090 1.272412
5          Family1 0.4856306 2.059178
6     UnlimitedGB1 0.3995696 2.502693
7  UnlimitedCalls1 0.6942872 1.440326
8              SMS 0.3594992 2.781647
9         Channels 0.7576132 1.319935
10          TVBox1 0.6161300 1.623034
11           Speed 0.6585699 1.518442
12           Wifi1 0.5436133 1.839543
```

Table 10. VIF tests for Regression 9-10 (the Bundle Prices dataset)

```
> ols_vif_tol(reg9)
        Variables  Tolerance       VIF
1     CountryCode2 0.00000000       Inf
2     CountryCode3 0.02987010 33.478293
3     CountryCode4 0.18071574  5.533552
4     CountryCode5 0.03966612 25.210434
5    OperatorCode2 0.29679489  3.369330
6    OperatorCode3 0.28107372  3.557786
7    OperatorCode4 0.24618137  4.062046
8    OperatorCode5 0.00000000       Inf
9    OperatorCode6 0.00000000       Inf
10   OperatorCode7 0.00000000       Inf
11   OperatorCode8 0.04001975 24.987663
12   OperatorCode9 0.04642310 21.541001
13  OperatorCode10 0.53449917  1.870910
14  OperatorCode11 0.07175727 13.935871
15         Family1 0.31815947  3.143078
16              GB 0.17545878  5.699344
17           Calls 0.22899795  4.366851
18             SMS 0.18837542  5.308548
19        Channels 0.61437583  1.627668
20          TVBox1 0.25353649  3.944205
21           Speed 0.59866042  1.670396
22           Wifi1 0.19800732  5.050318
```

```
> ols_vif_tol(reg10)
         Variables  Tolerance       VIF
1     CountryCode2 0.00000000       Inf
2     CountryCode3 0.02247398 44.495907
3     CountryCode4 0.16803798  5.951035
4     CountryCode5 0.03376920 29.612785
5    OperatorCode2 0.29611566  3.377059
6    OperatorCode3 0.28018666  3.569049
7    OperatorCode4 0.23625457  4.232722
8    OperatorCode5 0.00000000       Inf
9    OperatorCode6 0.00000000       Inf
10   OperatorCode7 0.00000000       Inf
11   OperatorCode8 0.03082641 32.439715
12   OperatorCode9 0.03978933 25.132367
13  OperatorCode10 0.53935159  1.854078
14  OperatorCode11 0.06537741 15.295803
15         Family1 0.32650142  3.062774
16     UnlimitedGB1 0.21604802  4.628601
17  UnlimitedCalls1 0.21174468  4.722669
18              SMS 0.19999666  5.000084
19         Channels 0.61572368  1.624105
20           TVBox1 0.24557854  4.072017
21            Speed 0.60348315  1.657047
22            Wifi1 0.19795535  5.051644
```

Table 11. Regressions 1-4 summary (the Bundle Prices dataset)

Variables	Regression 1	Regression 2	Regression 3	Regression 4
	Coefficient	Coefficient	Coefficient	Coefficient
Intercept	3.47130 *** (0.036)	3.51679 *** (0.131)	2.49524 *** (0.098)	2.47960 *** (0.114)
CountryCode2	0.23577 *** (0.007)		0.22084 *** (0.008)	
CountryCode3	0.36161 *** (0.042)		0.52732 *** (0.051)	
CountryCode4	0.24011 *** (0.019)		0.24401 *** (0.041)	
CountryCode5	0.65618 *** (0.036)		0.67248 *** (0.071)	
OperatorCode2		0.18056 (0.153)		0.14665 (0.150)
OperatorCode3		-0.22231 ** (0.099)		-0.25429 ** (0.075)
OperatorCode4		-0.04932 (0.116)		-0.08933 (0.079)
OperatorCode5		-0.09162 (0.094)		-0.16065 ** (0.069)
OperatorCode6		0.10924 (0.094)		0.08891 (0.085)
OperatorCode7		0.32604 *** (0.110)		0.29861 *** (0.088)
OperatorCode8		0.11071 (0.067)		0.42160 *** (0.139)
OperatorCode9		0.60588 *** (0.143)		0.60145 *** (0.146)
OperatorCode10		0.26197 ** (0.131)		0.25754 * (0.139)
OperatorCode11		0.52006 *** (0.131)		0.51562 *** (0.139)
TypeCode3	0.23464 *** (0.103)	0.33785 *** (0.084)	(dropped)	(dropped)
Mobile1			0.31066 ** (0.120)	0.36964 *** (0.128)
TV1			0.31559 *** (0.087)	0.27224 *** (0.082)
Internet1			0.64418 *** (0.052)	0.76939 *** (0.057)
Telephone1			(dropped)	(dropped)
Multiple R^2	0.3779	0.42	0.4377	0.4444
Adjusted R^2	0.3448	0.3475	0.3949	0.3604
F-statistic	11.42 ***	5.793 ***	10.23 ***	5.291 ***
Notes	*, ** and *** denote significance levels at 10%, 5% and 1% respectively. Observations – 100. Numbers in parentheses are standard errors. They are robust to heteroskedasticity and clustered by country. Results are based on the author's data collection, February 2021.			

Table 12. Regressions 5-8 summary (the Bundle Prices dataset)

Variables	Regression 5	Regression 6	Regression 7	Regression 8
	Coefficient	Coefficient	Coefficient	Coefficient
Intercept	2.92794889*** (0.033)	3.22132397*** (0.198)	3.22128229*** (0.188)	2.95039180 *** (0.040)
CountryCode2	0.44471291*** (0.049)			0.45254723 *** (0.057)
CountryCode3	0.77888830*** (0.037)			0.77605988 *** (0.040)
CountryCode4	0.50264663*** (0.039)			0.47698831 *** (0.041)
CountryCode5	0.62902259*** (0.044)			0.61384250 *** (0.052)
OperatorCode2		-0.11728508 (0.142)	-0.10211857 (0.137)	
OperatorCode3		-0.35625204 (0.222)	-0.29923670 (0.219)	
OperatorCode4		-0.18405719 (0.209)	-0.17210287 (0.199)	
OperatorCode5		0.02528934 (0.208)	0.04678117 (0.202)	
OperatorCode6		0.12668186 (0.237)	0.17327412 (0.236)	
OperatorCode7		0.42333680* (0.246)	0.46683271 * (0.256)	
OperatorCode8		0.53772683** (0.220)	0.54965611 ** (0.219)	
OperatorCode9		0.55035083** (0.251)	0.55390674 ** (0.247)	
OperatorCode10		0.29043628 (0.225)	0.29998742 (0.223)	
OperatorCode11		0.34490365* (0.180)	0.32295379 * (0.193)	
Family1	0.07425789 (0.078)	0.10015347 (0.162)	0.15541983 (0.173)	0.12142939 (0.102)
GB	0.00127502 (0.001)	0.00366663*** (0.0005)	(dropped)	(dropped)
UnlimitedGB	(dropped)	(dropped)	0.38375880 *** (0.051)	0.15988526 (0.099)
Calls	0.00003688*** (0.00001)	0.00005789*** (0.00001)	(dropped)	(dropped)
UnlimitedCalls	(dropped)	(dropped)	0.51684700 *** (0.090)	0.23509010* (0.139)
SMS	0.00018656 (0.0001)	-0.00054468*** (0.0002)	-0.00046577 *** (0.0002)	0.00014184 (0.0002)
Channels	0.00143909*** (0.0003)	0.00136509*** (0.0004)	0.00124711 *** (0.0005)	0.00134005 *** (0.0004)
TVBox1	0.10812338 (0.113)	-0.07530813 (0.209)	-0.07173265 (0.206)	0.10918357 (0.119)
Speed	0.00075428*** (0.0001)	0.00069875*** (0.0001)	0.00073192 *** (0.0001)	0.00078193 *** (0.0001)
Wifi1	-0.04551672 (0.088)	-0.04969907 (0.119)	-0.02970643 (0.107)	-0.04908848 (0.084)
Multiple R^2	0.8064	0.7847	0.7782	0.79
Adjusted R^2	0.7797	0.7369	0.729	0.761
F-statistic	30.19***	16.4 ***	15.79 ***	27.27 ***

Table 13. Regressions 9-10 summary (the Bundle Prices dataset)

Variables	Regression 9	Regression 10
	Coefficient	Coefficient
Intercept	2.78822831 *** (0.130)	2.79037166 *** (0.137)
CountryCode2	0.69446949*** (0.074)	0.73542458 *** (0.735)
CountryCode3	0.61534471 (0.421)	0.81350815 ** (0.371)
CountryCode4	0.57759639 *** (0.073)	0.55823312 *** (0.096)
CountryCode5	0.56810885 (0.380)	0.77779725 ** (0.340)
OperatorCode2	0.03021129 (0.060)	0.03422981 (0.066)
OperatorCode3	0.12754191 (0.114)	0.16740783 (0.115)
OperatorCode4	0.21499754** (0.103)	0.21064079 ** (0.099)
OperatorCode5	-0.17240427 (0.112)	-0.20330299 (0.139)
OperatorCode6	-0.15302234*** (0.057)	-0.17670167 ** (0.074)
OperatorCode7	(dropped)	(dropped)
OperatorCode8	0.30497030 (0.405)	0.10705935 (0.382)
OperatorCode9	0.35609684 (0.366)	0.14276209 (0.371)
OperatorCode10	0.14452483 ** (0.065)	0.16241810 ** (0.074)
OperatorCode11	-0.11360675 (0.420)	-0.35175399 (0.425)
Family1	0.17074651 (0.130)	0.20535463 ** (0.160)
GB	0.00178308* (0.001)	(dropped)
UnlimitedGB	(dropped)	0.16485165 (0.134)
Calls	0.00004430 (0.00003)	(dropped)
UnlimitedCalls	(dropped)	0.22768407 *** (0.083)
SMS	-0.00006910 (0.0003)	0.00006748 (0.0004)
Channels	0.00131363** (0.001)	0.00127662 ** (0.001)
TVBox1	0.12775727 (0.116)	0.13083040 (0.117)
Speed	0.00075155*** (0.0001)	0.00077789 *** (0.0001)
Wifi1	0.05097546 (0.044)	0.06621474 (0.043)
Multiple R^2	0.8612	0.8453
Adjusted R^2	0.8238	0.8037
F-statistic	23.05 ***	20.3 ***