Ex-post evaluation of mobile telecommunication entry: the Italian case.

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Abstract

This research aims to deeply examine and evaluate the effect of a new policy introduced by the European Commission in Italy, to safeguard competition when assessing merger requests. The Wind-Tre merger has been conditioned, by the EC, on a new structural remedy: the entry of a new mobile network operator. Iliad, after being selected, started to strongly compete with the incumbent operators. To estimate the effect of this new policy we use the Difference in Differences estimator. For the first time, a very accurate counterfactual, for a merger from 4 to 3 MNOs followed by an entry, has been available. Two MNOs in the United Kingdom sent a merger request in the same year the Italian MNOs did it: the UK one has been blocked while the Italian one has been cleared with the new remedy experimentation. To evaluate the same treatment we also used Finland, the classical control country in which nothing occurred. Finally, Ireland has been used as a control country for evaluating the effect of the new remedy compared to the previous ones. All these estimations are consistently indicating that the treatment had a huge price-decreasing effect: between 43% and 66% using the UK as the control country.

Contents

1. Introduction

Mergers and entries in mobile telecommunication markets represent a very good context for the application of econometric techniques: indeed, many researchers have studied the economical effects of such structural changes. Companies competing in this type of market must obtain licenses to operate and use mobile telecommunication infrastructures. These entry barriers could encourage collusion and cooperative behaviors among incumbent firms. In this context, one of the European Commission's goals is to regulate these markets to protect consumers' welfare: if two mobile telecommunication operators, want to merge, they have to submit a request to the EC, which can clear, clear with remedies, or block the request. Studies have been conducted to perform ex-post evaluations of the European Commission's decisions. On one hand, the body of literature we refer to is useful to understand the real consequences of mergers and entries. On the other hand, these findings can improve the European Commission's decision-making process.

Our work is inspired by this growing literature: we want to estimate the effect of a few market dynamics changes on prices in the Italian mobile telecommunication market. The Italian case is unique because of the merger's structural remedy imposed by the European Commission: the entry of a new competitor, Iliad. This event appeared to have resulted in prices reduction, thus increasing consumer welfare. Many other European markets experienced mergers, but the remedies imposed in those cases did not have such a huge effect. Thanks to the two events which affected the Italian market in 2016 and 2018, namely a merger between Wind and Tre (Hutchison) and the entry of Iliad, we can estimate different causal effects depending on the chosen control country: the first one is the effect of a merger and an entry in a market in which a merger request has been submitted to the EC; the second one is the effect of an entry as a remedy in a market in which a merger occurred; the third is the effect of a merger and an entry in a market in which nothing has happened.
We build our analysis starting from the inspection of our dataset, which is built using data from the European Union's resources about the pricing of usage baskets in each Member State. Then, we use the Difference in Differences (DiD) estimator, which is able (if used in the right conditions) to extract the causal effect of an event in a specific context. We tackle these problems by accurately analyzing the mobile telecommunication market history and by comparing our ideas with many other approaches presented in published papers.

This report is structured as follows: Section 2 contains a summary of the main findings of the papers we review, and from which we take important insights about both different mobile telecommunication markets and methodological approaches. Moreover, we introduce a previous work of ours regarding a before-after analysis of the entry of Iliad into the Italian mobile telecommunication market, using granular data. Section 3 illustrates the economical principles underlying oligopolies and collusion, the context in different Member States' markets, and, lastly, it goes deeper into the Italian mobile telecommunication market. Section 4 concerns the dataset and the empirical approaches: this part is dedicated to a meticulous and detailed study of the techniques we use and the potential pitfalls and obstacles we could encounter during the analysis. Section 5 shows the results we get from our DiD estimators and Section 6 offers a set of robustness checks to validate our estimations. Section 7 concludes the report with a summary highlighting the most important findings. In the Appendix (Section 8), we report other analyses we perform, in particular descriptive statistics and output tables of robustness checks.

2. Literature review

In this Section, we present published papers regarding the impact on prices of mergers, entries, and acquisitions. We also present our previous work, discussing the price/quantity ratio changes in the Italian mobile telecommunication market due to the entry of Iliad.

2.1. *Published papers*

Most of the body of literature focuses on the impact mergers have on prices, quality of services, and investments. Even if the focus is not on market entries, taking into consideration these studies is important. Markets should be seen in all their development to be able to differentiate possible effects on prices. Moreover, this literature makes great use of DiD in the same context as our work. This stream of papers aims to make merger assessment a more conscious procedure and, most importantly, to safeguard competition.

(BEREC, 2018) estimates the price effect of three mergers in the European mobile market: the Hutchison/Orange merger in Austria in 2013, the Hutchison/Telefónica merger in Ireland in 2014, and the Telefónica/KPN merger in Germany in 2014. The authors use two approaches: standard DiD and synthetic control group. They use tariff data provided by IDATE/Tarifica, which altogether consists of 20000 observations from 48 operators on a semi-annual basis in 13 European countries from 2012 to 2016. These tariffs are then grouped in baskets, which represent different types of customers and types of usage. They study mergers in markets going from 4 to 3 MNOs, and they find evidence that prices for new customers increased due to the merger. However, this main result can differ a bit from country to country. This report also discusses other aspects, such as mandatory remedies that the companies involved in the merger have to implement, and the difficulties derived from trying to establish quality effects.

(Aguzzoni et al., 2018) analyses the effects on prices of two merger instances: the T-Mobile/tele.ring merger in Austria in 2006 and the T-Mobile/Orange merger in the Netherlands in 2007. This analysis is performed using DiD. The authors derive a price index by measuring the monthly expenditure of consumers in different baskets from 2004 to 2010: this is possible by collecting data from different sources, namely Teligen, Telecompaper, and the Austrian Chamber of labor. Regarding the Austrian case, the authors do not find any significant effect on prices in that market. The Dutch case, however, differs from the Austrian one: indeed, the authors find a positive effect on prices but, since the merger happened two years after another merger (KPN/Telfort), this deviation could potentially be addressed to both the first merger and the second.

(Mariuzzo et al., 2016)'s work focuses on studying merger retrospectives in the European context. In particular, the authors bring together the body of literature on ex-post evaluation of European merger decisions. By doing so, it provides a summary of the corpus of studies, highlighting what the research community has learned from European merger control. Moreover, it tries to understand whether or not merger control works. Lastly, it identifies the areas in which improvements are needed, including the methodological approaches. By selecting the most important and relevant literature from the whole body, this work has three key findings. Firstly, the authors look at the covariation of prices impacts of mergers with the type of the agency's (or authority) decision: from this analysis, they are capable of finding that, on average, remedied mergers are not followed by a price increase, indicating that the European merger control intervention is effective. Second, the authors look at the variation of the estimates in the corpus, and they find that highly concentrated markets are prone to have a positive and higher price increase after a merger. In addition, they argue that most econometric analyses are performed taking into account short-run effects, thus these estimates could change as the market adapts in the long run. Lastly, the work explains how each merger decision is evaluated in light of the changes in prices. In around half of the cases, it seems that the agency's decision is erroneous if compared to the respective retrospective (ex-post analysis) estimates. This could be the case for two reasons: genuine errors in the decisions and other factors, such as random error, faulty evidence, and non-price effects having a higher priority than price effects.

In the following, we list other works in the literature which assess both the problem of evaluating the effect on prices of a merger and the problem of evaluating the effect on prices of an entry.

(Csorba and Pápai, 2015) estimates the price effects of both mergers and entries using DiD. In particular, the authors examine different frameworks and market characteristics, including the number of active operators and, if the case study consists of an entry, the type of entrant. The key finding is that the effect of entry crucially depends on the number of existing operators in the national market and the type of entrant. This work also divides the effect into short-run effects (first year), medium rum effects (second year), and from the third year onwards. They find positive significant effects on prices two years after the entry of a multinational telecommunication company, and negative significant effects on prices the same year of the entry of a local telecommunication company. These results are obtained using Teligen tariffs data from 2003 to 2010, grouped into three baskets defined by OECD.

Another empirical work that uses DiD to estimate a price change is (Houngbonon, 2015). To select the control country for each treated country, he implements PCA (Principal Component Analysis) on a different dataset containing variables representing various factors of mobile telecommunication markets. PCA is used to evaluate the similarity of many mobile telecommunication markets across multiple countries. In particular, he studies the entry of Free (Iliad) in France in 2012 and the merger of Hutchison/Orange in Austria in 2012. Using Italy and Korea as controls for Austria and France respectively, he finds that after the Austrian merger, the prices in the market are lower than before the merger. On the contrary, after the entry of Free, the prices in the French mobile telecommunication market increased. To derive these results, he uses the usual Teligen dataset from 2013 (first quarter) to 2014 (third quarter) and basket grouping. This result is quite singular since many works discover negative effects on prices when a disruptive firm enters a mobile telecommunication market: indeed, the author uses only tariffs from incumbent mobile telecommunication companies as a control group. However, in the case of France, incumbent companies fought the new entrant with other subsidiary fighting brands, which were marketed as "more affordable" and "cheaper". Thus, the expected effect could be hidden in the fact that more economic tariffs were offered in these sub-brands, and their exclusion could have led to the opposite estimate of what is expected.

The paper proposed by (OFCOM, 2016) explains how to define a "disruptive" firm in the mobile telecommunication context, and the effect it causes when it is present. They use data from Teligen and Tarifica (between 2010 and 2015) to construct a dataset, including also bundles with an handset[1]. The main finding OFCOM presents is that, when a disruptive player is present in the market, prices are lower between 10.7% and 12.4% compared to markets with no disruptive firm.

many other works address the problem of estimating the impact of mergers and entries without using DiD: one of them is (Bourreau et al., 2021). Indeed, the methodology used in this paper is an empirical oligopoly model with differentiated products. The authors study the context created by the entry of Free Mobile (Iliad) in 2012 in France, which played a disruptive role in the French telecommunication market. They used data from Kantar, a UK-based market research firm, from 2011 to 2014. This data is related to the consumption of mobile services in France. The main finding of this research is that the entry of Free Mobile has made a large contribution to consumer surplus, which is due to both the increased variety from the new entrant and the additional gains from fighting brands.

Many works in the literature focus on the estimation of the effect of mergers: with this paper, we want to explore another type of market change, namely the entry of a new firm. In particular, our effort will contribute to the existing scenario by providing an empirical analysis of the entry of Iliad into the Italian mobile telecommunication market. Expanding the body of literature with the addition of specific-country analysis contributes also to the overall picture, as seen in (Mariuzzo et al., 2016).
It is worth mentioning that reduced-form econometric techniques, largely used in

[1]This particular fact is quite relevant since the other papers presented in this Section exclude those bundles which include a handset in the offer.

labor economics, have only recently begun to be implemented also in market dynamics evaluation. Indeed, the US literature has already substantial applications of these econometric techniques while the European literature makes only a little, but growing, use of them.

2.2. *Previous work*

This Subsection explains briefly a previous analysis we performed on Italian micro-data[2].

Our previous work, "Empirical analysis on price in Italian mobile telecommunication market: the Iliad effect" provides an in-depth analysis of price/quantity ratio changes in the Italian mobile telecommunication market due to the entry of Iliad. To test our hypothesis, we built a micro-data dataset by web-scraping an Italian tariff comparison website, collecting details about tariffs from 2012 to early 2020. Using the Regression Discontinuity Design (RDD) technique we evaluated that the causal effect of the entry of Iliad on prices is negative, huge, statistically significant, and robust.

3. Study context

Mobile telecommunication markets in Europe, but also in almost all the OECD countries, are very similar, being subject to similar restrictions and dynamics. Different events, such as merger acquisitions and entries, can influence these markets' dynamic efficiency, thus leading to higher or lower competition. Prices, quality, and investments are the obvious important outcomes that can be affected by market developments. In the three following subsections, we describe what characterizes these markets (especially focusing on Italy and Europe) and what theory and previous empirical works can tell us about these effects.

3.1. *Theoretical framework and empirical evidence*

Perfect competition with a large number of suppliers and consumers results in prices equal to marginal costs, efficient use of resources and it would maximize total welfare for society. On the contrary, oligopolistic settings, thus markets with only a few suppliers of goods or services and many customers, could produce a very

[2]Few parts in this Section are a literal transcription of our work "Empirical analysis on price in Italian mobile telecommunication market: the Iliad effect".

different and worse outcome due to the possibility of the firms to influence price and quantity. In oligopolistic markets prices are typically above marginal cost, there are often allocative inefficiencies and they are not likely to maximize social welfare. Two scenarios are then possible in this setting: non-collusive or collusive outcome. While collusive outcomes (tacit or not) are for sure illegal and negative from the consumer's viewpoint, non-collusive outcomes could be different.

> Non-collusive oligopolies can in principle deliver dynamic efficiency, particularly in industries where innovation and investment associated with substantial risks play a major role. As telecommunications firms face manifold risks, such as uncertain demand or exogenous technological developments, an oligopolistic structure might be well suited to lead to a dynamically efficient outcome (BEREC, 2015).

Certain oligopolistic market structures, instead, cause inefficient market outcomes without any explicit collaboration or tacit collusion observed.

> In such a setting the undertakings unilaterally adopt a behavior that forms a self-sustaining reduction in competition and prevents the development of competitive outcomes. In contrast to tacit collusion, this market outcome does not require any form of stability mechanism such as penalties. The equilibrium is non-cooperative and stable, as it results from each undertaking individual best reaction to its competitors' behavior (BEREC, 2015).

This kind of oligopoly is called *tight oligopoly* (ineffective oligopolistic competition without tacit collusion) and it is opposed to the previous setting called *effective oligopolistic competition*. Among the features that boost the rising of a tight oligopoly, there are: high market concentration, high entry barriers and no significant new entrants, mature technologies, capacity constraints, low price elasticity, and low growth of demand. The market scenario established before the entry of Iliad in Italy is strongly characterized by all these traits.

Previous works on ex-post evaluation already quoted in Section 2.1 show that mergers and entries differ a lot on the relevant outcome variables depending on some crucial factors. Price increase after mergers is on average zero where the market concentration is low, while it is significantly large in concentrated ones. Another important factor is the presence of remedies as a condition for the merger: where remedies are not imposed the price increase is significantly higher (Mariuzzo et al., 2016). Even the type of entrant has a significantly different effect on prices. It has been shown that while local entrants have more beneficial (negative) effect on prices in the first year, the multinational entrants have on average no effect on prices in the first year, but from the second year onwards they have a decreasing effect (Csorba and Pápai, 2015). Another important categorization of the entrant refers to its disruptive behavior. *Disruptive entrants* are the ones that do not follow the crowd and actively disturb existing market dynamics.

> Disruption is a strategic choice made by firms and is something that happens exogenously. However, once it emerges, we are keen to protect disruption to retain the consumer benefits associated with it. These benefits may take the form of lower retail prices or improved product offerings (OFCOM, 2016).

In conclusion, (Csorba and Pápai, 2015) also showed that the effect of entry crucially depends on the number of active operators: 2 to 3 entries have no robust effect, while 3 to 4 entries tend to have a significant decreasing price effect.

3.2. *The European mobile telecommunication market*

The mobile telecommunication markets in Europe have very similar characteristics. Almost all the countries have a number of Mobile Network Operators (MNOs) of 3-4 and a little share of the market covered by Mobile Virtual Network Operators (MVNOS): under 13% of the total share in every country with only Germans and Dutch MVNOs' share of respectively 20% and 17%. The companies (MNOs) present in the European markets are often the same. For example, Vodafone is present in 13 European countries, Deutsche Telekom and H3G in 9, Liberty Global in 8, and Orange and Telefonica in 6.
Mobile Network Operators are the ones provided with a complete infrastructure, meaning those with their own network. The Mobile Virtual Network Operators are instead those operators which do not own a network: they need to find an agreement for the utilization of MNOs networks. European mobile telecommunication markets are all characterized by an oligopolistic structure where new competitor entries are pretty rare.

> The telecommunication sector represents a typical case in which markets take oligopolistic assets by virtue of the existence, among other things of high entry costs due to expensive infrastructure network investments. In the specific case of mobile services, market operators provided with a complete infrastructure are regulated by a mechanism

> of licenses released through competitive processes (i.e. auctions) which entitles the right of using radio frequencies (a public and scarce good) (Ardovino and Delmastro, 2020).

In the European mobile telecommunication markets, in recent years, there have been some important developments in market dynamics: few market entries and a substantial number of merger requests. From 2008 to 2018 the European countries experiencing an MNO entry are Slovenia from 3 to 4 MNOs (2008), Poland from 4 to 6 (2009), Iceland from 3 to 4 (2010), France from 3 to 4 (2012), The Netherlands two entries from 3 to 4 (2012 and 2015), Luxembourg from 4 to 5 (2014), Slovak Republic from 3 to 4 (2015), Lithuania from 3 to 4 (2016), Hungary from 3 to 4 (2017) and finally Italy from 3 to 4 (2016-2018). These events are mostly due to 4G spectrum auctions and the same is expected for 5G auctions. Among these entries, there is one that is especially important in our analysis: Free Mobile (Iliad) in France. This event is completely analogous to our treatment of interest. When Iliad entered the Italian market, it applied the same disruptive behavior. The incumbent operators responded in the same way, using subsidiary fighting brands to accommodate the newcomer in the low-end segment, which it would not want to serve otherwise. The effect of this event has already been evaluated by Marc Bourreau et al., which showed how breaking a tacit collusion setting pre-existing among the 3 incumbents MNOs greatly increased consumer welfare.

> The total consumer surplus gains from the changes in market structure amount to 4.6 billion (with a standard error of 0.9). To put this figure in perspective, the size of the gains is equivalent to 7.7% of the total 60.1 billion industry retail sales (Bourreau et al., 2021).

From 2008 Europe went through a process of market consolidation: there have been a lot of requests for mergers to the competent competition authority. The 3 to 2 mergers have been denied because of the great increase in concentration. The remaining merger requests have been approved either without conditions or with some remedies to be applied, such as divestiture of the spectrum, sites and infrastructures, MVNOs access, network sharing, and others. The European countries which asked for mergers are Switzerland from 4 to 3 (2008, cleared), Estonia from 5 to 4 (2010, cleared), Sweden from 5 to 4 (2010, cleared), Switzerland from 3 to 2 (2010, blocked), United Kingdom from 5 to 4 (2010, with remedies), Norway from 5 to 4 (2011, cleared), Estonia from 4 to 3 (2012, cleared), Greece from 3 to 2 (2012, blocked), Austria from 4 to 3 (2013, with remedies), Ireland from 4 to 3 (2014, with remedies), Germany from 4 to 3 (2014, with remedies), Norway from 4 to 3 (2015, with remedies), Denmark from 4 to 3 (2015, abandoned), United Kingdom from 4 to 3 (2016, blocked), Italy from 4 to 3 (2016, with new MNO). It is important to notice that in the same period in which Wind and H3G asked permission to merge in Italy, 5 other countries experienced the same request (period 2014-2016). In Ireland, Germany, Norway, Denmark, and United Kingdom there has been the willingness to switch from 4 to 3 MNOs: this makes these countries good control candidates for our empirical evaluation. The European countries subject to European Commission decisions in competition matters, share the same criteria used for determining merger approvals, and if and which remedies should be imposed as a condition. Until 2015, the European Commission has always allowed mergers from 4 to 3 MNOs. The difference lay in the presence or absence of remedies and their typology. After 2015 the European Commission, like most of the OECD countries, has become more reluctant to approve mergers (James Allen, 2017). Intended mergers that would have taken place otherwise (from four to three players) were prevented. Such is the case of Denmark in 2015 and the United Kingdom in 2016 (Fanfalone, 2021). In this new setting, a very peculiar case is the Wind/H3G merger in Italy.

3.3. *The Italian market*

The Italian telecommunication market has always been characterized by the presence of at most 4 MNOs. This market is, like almost all the mobile telecommunication markets, regulated by a mechanism of licenses that entitles the right of using radio frequencies. From 2003, when H3G entered the market, to 2016 there have been the same 4 MNOs (Tim, Vodafone, Wind, and Tre) and a niche of small MVNOs. In this period no important structural shocks happened to the competitive structure.

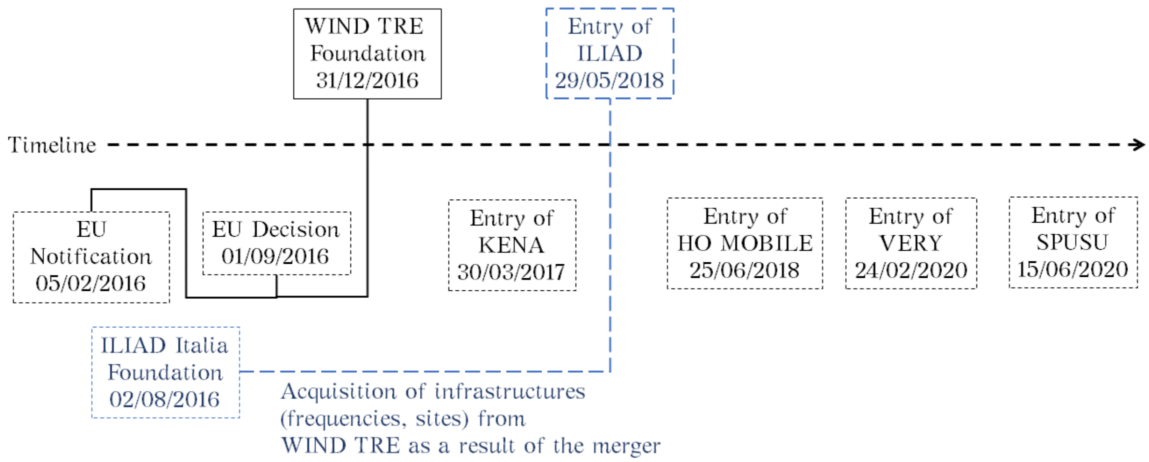

Figure 1. Timeline market dynamics.

On 5th July 2016 Wind and Tre notified their willingness to merge that, after the European Commission decision, led on 31st December 2016 to the WindTre foundation. This merger is peculiar because it was allowed under the new reluctant approach of the European Commission on 4 to 3 mergers: the previous two requests from Denmark and United Kingdom have not been approved. However, it has been conditioned on a new structural measure to safeguard competition instead of classical remedies. During the merger authorization procedure (case M.7758) the European Commission, in close coordination with Agcom, pointed out that the merger, without corrective measures, would not only have weakened competition between incumbents (MNOs, from 4 to 3) but would also have harmed virtual mobile operators (MVNOs) since the number of independent networks able to provide transmission capacity was reduced. The merger was therefore conditioned on the entry of a new MNO, which would have used part of the frequency spectrum and sites previously held by Wind and H3G, to order to be fully able to compete at a national level. Iliad was the company chosen by the competent authorities which debuted in the market on 29th May 2018. Iliad is a multinational and disruptive firm that immediately started an intense price war to which the incumbent MNOs responded with subsidiary fighting brands.

4. Data and empirical approach

This Section shows the dataset we used for our analysis, the methodology, and other peculiar facts about DiD estimators, namely their assumptions and pitfalls.

4.1. *Data*

Before describing how data is structured and built, it is necessary to explain two concepts: bundle and basket. One of the difficulties met in many works in this field is that prices are defined on a set of products put together (i.e. 100 SMS, 100 minutes for calls, and 5 GB): this set of mobile telecommunication services offered is called *bundle*. A mobile telecommunication subscriber, to be able to access services, must pay a monthly charge for the tariff plan chosen, set-up and connection fees (if there are any), and possible additional services consumed and not included in the bundle. To be able to compare one offer to another (also across countries) and to derive a one-dimensional price index to measure the "price level", we use *baskets*. Baskets are usage profiles, describing a consumption pattern for different types of users (BEREC, 2015). Many other works in the literature have adopted this data setup (Aguzzoni et al., 2018), (BEREC, 2015), (BEREC, 2018), (Csorba and Pápai, 2015).

Contrarily to other paper cited in Section 2, we could not get specific data about every single offer and mobile operator in each country, because this data has to be requested from data collection entities, such as Teligen[3], and this procedure requires a lot of time to be completed. Instead of working on tariff-level data, we collect basket-level datasets from the European Union website, which have also been used in Mobile Broadband prices reports ((Consultants, 2015), (Consultants, 2016), (Empirica, 2017), (Empirica, 2018), (Empirica, 2019) and (Empirica, 2020)). In particular, we aggregate data from 2015 (EU, 2015), 2016 (EU, 2016), 2017 (EU, 2017), 2018 (EU, 2018), 2019 (EU, 2019) and 2020 (EU, 2020). The most important difficulty to notice is that basket definitions change through the years, as user consumption and needs evolve. Indeed, the European Commission reports use different basket specifications according to the best user consumption representation. To be able to compare baskets across years, we analyze how each of them repre-

[3]https://www.strategyanalytics.com/access-services/service-providers/tariffs—mobile-and-fixed/

sents a specific level of consumption, and we aggregate different baskets in a new basket specification of our choice, according to quantities described in each original basket and to our evaluation of how consumption evolved across years. Figure 2 represents details about the original baskets and our basket specification. Having constant basket specification through time is very important to prevent changes in the consumption pattern from influencing the tariffs price series (Aguzzoni et al., 2018).

2015

Basket	Data volume	Voice (# calls)	SMS
1	100 MB	30	100
2	500 MB	100	140
3	1 GB	300	225
4	2 GB	900	350
5	2 GB	100	140

2016

Basket	Data volume	Voice	SMS
1	100 MB	30	100
2	500 MB	100	140
3	1 GB	300	225
4	2 GB	900	350
5	2 GB	100	140
6	5 GB	900	350

2017

Basket	Data volume	Voice	SMS
1	100 MB	30	100
2	500 MB	100	140
3	1 GB	300	225
4	2 GB	900	350
5	2 GB	100	140
6	5 GB	100	140
7	10 GB	100	140

2018

Basket	Data volume	Voice	SMS
1	100 MB	30	100
2	500 MB	100	140
3	1 GB	300	225
4	2 GB	900	350
5	2 GB	100	140
6	5 GB	100	140
7	10 GB	100	140

2019

Basket	Data volume	Voice	SMS
1	100 MB	30	20
2	500 MB	100	40
3	1 GB	300	80
4	2 GB	900	160
5	5 GB	Unlimited	Unlimited

2019 High Data

Basket	Data volume	Voice	SMS
1	0.5 GB	30	10
2	2 GB	100	20
3	5 GB	300	40
4	10 GB	900	80
5	20 GB	Unlimited	Unlimited

2020

Basket	Data volume	Voice
1	500 MB	30
2	1 GB	30
3	2 GB	100
4	5 GB	300
5	20 GB	300
6	5 GB	30
7	20 GB	100

Our specification

Basket	Color
Very low	
Low	
Medium low	
Medium high	
High	
Very high	

Figure 2. Baskets through years.
Each table list how the official European Commission report build basket specifications in each edition. The last table shows our basket specification and how we aggregate official baskets (baskets having the same color belong to the same basket in our specification).

The datasets provided by the EU have a very wide geographical coverage, indeed they have data from the 28 EU Member States, Iceland, Japan, South Korea, the United States, and Turkey. Moreover, the EU does not collect all tariffs from all mobile operators, but they select

> at least the two largest mobile network operators per country, based on the number of mobile broadband subscribers (i.e. market shares). If this information is not available, operators have been selected based on the number of mobile subscriptions (including voice, SMS, and data). If the combined market share of these two operators is below 70%, the third largest operator has also been included in the sample. In any case, no more than three operators are considered, whatever their combined market share would be. Discount brands of the mobile operators in the sample are only taken into account when they are linked with the network operators brand and website and when their market share is considered significant (i.e. at least 5% of the total number of mobile (broadband) subscriptions) (Consultants, 2015).

For each basket, the EU includes only the cheapest tariffs for each mobile operator to represent in the best way what a consumer would rationally choose to satisfy his or her needs; this choice is also made by the above-cited works using baskets. Furthermore, we consider tariffs including smartphones to be very attractive for some customer categories. We do not exclude tariffs including handsets (contrarily to other works in the literature, such as (Aguzzoni et al., 2018) and (Csorba and Pápai, 2015)). Moreover, we identify outliers in the final dataset without removing them, because drastic price decreases can happen in the mobile market (Csorba and Pápai, 2015).

In Table 1, we list and describe every variable collected in the dataset.

Variable name	Type	Description
Year	Numeric {2015, 2016, 2017, 2018, 2019, 2020}	Year in which the offer has been registered. It is important to register only the offers available at a certain point in time and not those which cannot be subscribed anymore by customers (Aguzzoni et al., 2018).
Country	String	Country in which the offer is available.
Currency	String	The currency used in the country in which the offer is present.
Region	String	Region to which the country belongs.
VAT	Numeric (%)	Value added tax specific for each country in a specific year.
Mobile operator	String	Name of the mobile operator to which the offer belongs.
Name of the offer	String	Name used by the mobile operator to indicate the specific offer.
Type of the offer	String	Whether the offer is a prepaid offer (you pay for your mobile telecommunication service upfront) or a postpaid offer (you pay at the end of the month based on your usage).
Contract duration	Numeric (# months)	How many months the contract is supposed to last.
4G LTE or speed of at least 20Mbps	Numeric {0, 1}	Whether or not the offer includes the use of 4G technology or at least a download speed of 20 megabit per second.

Variable name	Type	Description
Data Volume	Numeric (MB/month)	How many megabytes are included in the offer each month (other name: Data volume included).
Smartphone	Numeric {0, 1}	Whether or not the offer includes a smartphone among the other services (Smartphone included in the offer).
Price	Numeric (EUR/PPP)	Monthly recurring charges per month. This indicator is chosen because, as opposed to total recurring charges per month, it is available in each year and country studied. Total recurring charges per month is a price index including one-off charges, monthly subscription charges, overage charges, discounts, charges related to the equipment, any specific taxes.
Outlier	Numeric {0, 1}	Whether or not the observation is an outlier. This distinction is made by selecting those offers having price smaller than $3rd\_quartile - 1.5 * (3rd\_quartile - 1st\_quartile)$ or larger than $3rd\_quartile + 1.5 * (3rd\_quartile - 1st\_quartile)$, where quartiles are with respect to the associated price distribution for specific basket, year and country.
Basket	Numeric {1, 2, 3, 4, 5, 6}	The basket the offer belongs to.

Variable name	Type	Description
GDP	Numeric (US dollars/capita)	Gross Domestic Product for specific country and year. It is representative of the demand factor.
GDP Growth	Numeric (Growth Rate Previous Period, Seasonally Adjusted)	Gross Domestic Product by Expenditure in Constant Prices: Total Gross Domestic Product for each country (GDP growth rate). It is a proxy for changes in demand conditions (Aguzzoni et al., 2018).
MTR	Numeric (rates per voice minute, EUR cents/min)	The mobile termination rate is one of the three components in the cost of providing telephone service, and the one subject to the most variation. It is representative of the supply factor since it is due for each call to other mobile networks (off-net), they can be considered as a proxy for marginal costs of voice calls (Aguzzoni et al., 2018). It is registered for each year and country.

Table 1: List of all variables collected to perform the econometric analysis.
Source for GDP data: OECD webpage.
Source for GDP growth rate data: FRED webpage.
Source for MTR definition: Wikipedia.
Source for MTR data for 2015: BEREC webpage; 2016: BEREC webpage; 2017: BEREC webpage; 2018: BEREC webpage; 2019: BEREC webpage; 2020: BEREC webpage.

To conclude, our dataset is composed of 14620 observations representing offers in 35 countries from 2015 to 2020.

4.2. *Methodology*

This Section illustrates which tools and methods we use to get the wanted causal effect estimates.

4.2.1. *Model definition*

The model we use is the Difference in Differences estimator. Difference in Differences consists in a comparison between trends followed by two groups, namely the treatment group and control group, and between a "before" period and an "after" period. This technique is very useful to determine the effect a policy (or a naturally occurring phenomenon) could have on a specific context. To identify the causal effect of an event, DiD computes the difference between after and before values of the variable of interest in both the treatment group (composed of observations that have been affected by the event) and the control group (including observations that have not been affected by the treatment). Afterward, a difference is computed between the two differences obtained in the previous step. The causal effect of interest can be identified in the result of this final calculation. To apply DiD, it is necessary to check if the assumptions are met, as explained in Sections 4.4.1, 4.4.2 and 4.4.3. DiD estimator can be expressed as a regression equation, which can be estimated through OLS and takes the following standard form.

$$Y_{gt} = \alpha + \gamma TG_g + \lambda After_t + \delta(TG_g * After_t) + \varepsilon_{gt} \tag{1}$$

Y_{gt} indicates the variable of interest measured in specific group and time; α is the intercept; TG_g is the dummy variable for the treatment group observations and γ is its coefficient in OLS estimation; $After_t$ is the dummy indicating post policy periods and λ is its coefficient; $(TG_g * After_t)$ is the dummy indicating the treatment group's observations during the treatment years, and δ is the causal effect of interest. Finally, ε_{gt} is the residual error term.

Now we explain how the general regression DiD can be adapted in our context. In particular, we focus on three main objectives:

1. estimating the effect of having an entry after a merger against having asked for a merger that has been blocked;
2. estimating the effect of having an entry after a merger against having a merger conditioned on remedies, not including an entry of a new competitor;
3. estimating the effect of having an entry after a merger against neither having asked for a merger nor having an entry.

All these three estimation problems can be solved using OLS with the following regression DiD.

$$\begin{aligned}\log price = {} & \alpha + \gamma treated\_country_s + \lambda treatment\_year_t + \\ & + \delta(treated\_country_s * treatment\_year_t) + \\ & + \beta year2016_t + \eta gdp\_growth\_rate_{st} \\ & + \theta mtr_{st} + \mu data\_included\_month + \\ & + \rho smartphone\_included + \varepsilon_{st}\end{aligned} \tag{2}$$

One crucial point in DiD is to identify the correct control group and treatment group. For this purpose, we choose observation from Italy to be the treatment group in all three regression DiD specifications: indeed, Italy had a merger in 2016 and an entry in 2018. Then, we select other three countries which serve as control group countries in the problems: the United Kingdom, Ireland, and Finland are identified as candidates for solving problems 1, 2, and 3 respectively. Indeed, the United Kingdom had requested a merger in 2016 but the request has been blocked by the European Commission; Ireland had a merger in 2014 with other types of assigned remedies different from an entry; Finland experienced neither a merger nor an entry in the period of interest. Greater details on the country selection procedure are shown in Section 4.3.

It is necessary to accurately select which data to use to estimate our causal effects. In particular, we cannot include all years in our regression equation 2. Since our observations are registered in February, even if the entry of Iliad occurred in 2018, we consider as "treated observation" the offers registered from 2019. Because February 2018 observations were taken during the development of the treatment, the merger, and the entry (from 31/12/2016 to 29/05/2018), they have been excluded. Only for problem 2, for which the treatment is the entry alone, observations from 2017 and 2018 could be included. Furthermore, as explained in (Aguzzoni et al., 2018) and (BEREC, 2018), we would observe anticipatory effects in prices in 2018 observations, as it is checked in Section 6. Moreover, as one can see in Figure 15, Italian observations in 2017 are from only one operator and are very homogeneous (Figure 16): this fact invalidates those observations since they are not representative of the whole market scenario in that year. A similar motivation leads us to exclude observations from 2020. Excluding 2017, 2018, and 2020, we need to include in the DiD regression only two dummy variables as time-fixed effects: $year2016_t$ and $treatment\_year_t$ in Equation 2, and the last one represents 2019.

$gdp\_growth\_rate_{st}$ and mtr_{st} are included as proxies for changes in demand conditions and marginal costs of voice calls (offer conditions) respectively. Looking at the data, Italy had the same MTR in 2015 and 2016, thus we have to remove mtr_{st} from Equation 2 because it would be collinear with time-fixed effects. Since the MTR change occurred in coincidence with the treatment, someone could argue that the estimated effect could be due to this change. However, this is not possible because the change is very little and a similar change is present in almost every year. This pattern is a coincidence produced by the selection of years 2015, 2016, and 2019. To visually notice this trend, see Figure 3.

$data\_included\_month$ is an important variable in the regression because it can reflect, with higher precision, the change in data volume offered through years; unfortunately, baskets include all offers presenting at least what the basket specifies, but they cannot take into account the real change in data volume offered, especially in recent years. This variable is useful to represent those offers (having a very high data volume) that baskets cannot entirely depict. Contrarily to all the other selected countries, Finland does not have complete and reliable information about data volume, thus this variable has to be discarded when estimating Equation 2 using Finland as the control group country.
$smartphone\_included$ is additional information that we have to describe even more an offer, and it could explain changes in prices due to the inclusion of smartphones in offered bundles.

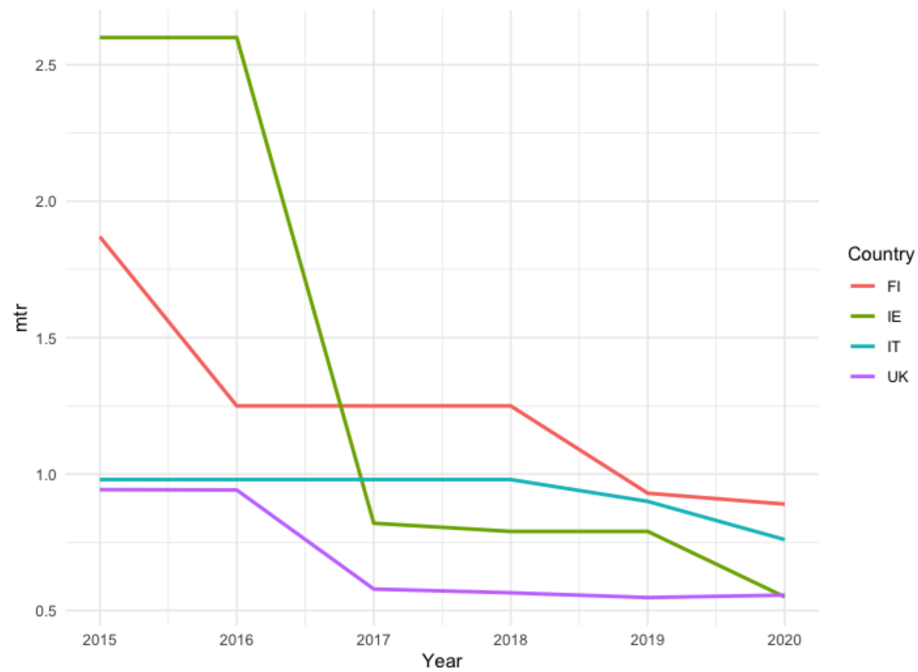

Figure 3. Mobile Termination Rate.
Each line depicts MTRs registered from 2015 to 2020 in different countries: Italy (IT), Finland (FI), Ireland (IE), and the United Kingdom (UK).

4.3. *Control country choice*

In Section 4.2.1 we introduce the fact that we select three particular countries whose observations are the control group for the three estimation problems we want to solve. This Section shows how we select these countries.

Our objective is to choose countries that are the most similar to Italy, and at the same time they have to serve as a good control for the three problem specification we have. The selection process is performed on a dataset describing both the history and the characteristics of mobile telecommunication markets in different countries. In particular, we can collect the variables listed in Table 2.

Variable	Type	Description
Share of MVNO subscription over mobile subs. 2018	Numeric (%)	Percentage of MVNO mobile subscriptions in 2018. This is a proxy for the MVNOs market size over the MNOs market size in a specific country.
Number of MVNOs 2018	Numeric	Number of active MVNO in 2018 in a specific country.
Share of MNO subscription over mobile subs. 2018	Numeric (%)	Percentage of MNO mobile subscriptions in 2018. This is a proxy for the MNOs market size over the MVNOs market size in a specific country.
Common ownership	Numeric {0, 1}	Whether or not there are multiple MNOs partially owned by the same company in a specific country.
Hutchinson (3)	Numeric {0, 1}	Whether or not Hutchison (3) is an MNO in a specific country. Obtained by searching on Wikipedia historical pages.
Vodafone	Numeric {0, 1}	Whether or not Vodafone is a MNO in a specific country. Obtained by searching on Wikipedia historical pages.
Iliad (Free)	Numeric {0, 1}	Whether or not Iliad (Free) is an MNO in a specific country. Obtained by searching on Wikipedia historical pages.
Penetration Growth Rate (2006-2017)	Numeric (%)	Mobile penetration growth rate computed from 2006 to 2017 in a specific country.
2017 penetration	Numeric (%)	Mobile penetration rate in 2017 in a specific country.
MNO number 2017 Q4	Numeric	Number of active MNO in quarter 4 2017 in a specific country.
Average year of MNO existence	Numeric	Average MNO age in a specific country. Computed by searching for the year of foundation of the respective MNO.
Growth rate MTR (2013-2017)	Numeric (%)	Mobile termination rate growth computed from 2013 to 2017 in a specific country.

Variable	Type	Description
MTR 2017	Numeric (%)	Mobile termination rate in 2017 in a specific country.
Growth rate advanced 3G coverage rural (2013-2017)	Numeric (%)	Growth rate of the 3G technology for mobile telecommunication services geographical coverage, specifically rural areas, computed from 2013 to 2017, in a specific country.
Advanced 3G coverage rural 2017	Numeric (%)	3G technology for mobile telecommunication services geographical coverage, specifically rural areas, registered in 2017, in a specific country.
Growth rate advanced 4G coverage rural (2013-2017)	Numeric (%)	Growth rate of the 4G technology for mobile telecommunication services geographical coverage, specifically rural areas, computed from 2013 to 2017, in a specific country.
Advanced 4G coverage rural 2017	Numeric (%)	4G technology for mobile telecommunication services geographical coverage, specifically rural areas, registered in 2017, in a specific country.
Growth rate advanced 4G coverage (2013-2017)	Numeric (%)	Growth rate of the 4G technology for mobile telecommunication services geographical coverage, computed from 2013 to 2017, in a specific country.
Advanced 4G coverage 2017	Numeric (%)	4G technology for mobile telecommunication services geographical coverage, registered in 2017, in a specific country.
Growth rate advanced 3G coverage (2013-2017)	Numeric (%)	Growth rate of the 3G technology for mobile telecommunication services geographical coverage, computed from 2013 to 2017, in a specific country.

Variable	Type	Description
Advanced 3G coverage 2017	Numeric (%)	3G technology for mobile telecommunication services geographical coverage, registered in 2017, in a specific country.

Table 2: Source for Share of MVNO subscription over mobile subs. 2018, Number of MVNOs 2018, Share of MNO subscription over mobile subs. 2018, Common ownership, MNO number 2017 Q4 : OECD digital economy paper.
Hutchinson (3), Vodafone, Iliad (Free): Wikipedia and web research.
Source for Penetration Growth Rate (2006-2017), 2017 penetration, : The World Bank.
Source for Growth rate MTR (2013-2017), MTR 2017, Growth rate advanced 3G coverage rural (2013-2017), Advanced 3G coverage rural 2017, Growth rate advanced 4G coverage rural (2013-2017), Advanced 4G coverage rural 2017, Growth rate advanced 4G coverage (2013-2017), Advanced 4G coverage 2017, Growth rate advanced 3G coverage (2013-2017), Advanced 3G coverage 2017: Digital Agenda Scoreboard Key Indicator.

The first problem is estimating the effect of having an entry after a merge against having asked for a merge that has been blocked. First, we filtered out countries that have not asked for a merger or countries which have an entry in the period following 2010. Second, we put a preference on countries that have asked for a merger near 2016, as Italy has done, and with the number of MNOs going from 4 to 3. This step leads us to choose between the United Kingdom and Denmark. The final country is then chosen by identifying the nearest country to Italy, according to distances obtained through MultiDimensional Scaling (MDS). MDS takes market characteristics of the previously selected countries (in 2017), computes the distance matrix, and applies a dimensionality reduction technique to get the most important components which explain the distance matrix the most. With a distance score of 5.68 (against Danish's 6.84), the United Kingdom has the most similar mobile telecommunication market compared to the Italian one. the first plot in Figure 4 depicts MDS's space and the selected countries.
The United Kingdom is a very peculiar control country because it asked for the merger in the very same year of Italy without approval. This gives us the lucky possibility to use a control country in which the market dynamics were going in the same direction: a merger. The other papers did not have this possibility for 4 to 3 mergers. Furthermore, two of the MNOs are H3G and Vodafone, exactly as in Italy

The second problem is estimating the effect of having an entry after a merger against having a merger but other remedies not including an entry of a new competitor. The selection process is similar to the previous one, with the only exception that the control country must have had an approved merger, as near in time as possible to 2016. The selected countries are Germany, Ireland, and Norway. Performing MDS on these countries, we have the following results: Germany has a distance score of 7.32, Ireland has a score of 5.07 and Norway has a score of 6.74. The final country we choose for this specification is Ireland. The second plot in Figure 4 depicts MDS's space and the selected countries. Two of the Irish MNOs are even in this case H3G and Vodafone.
The remedies the Irish merger has been conditioned on are: MVNO access, divestiture of the spectrum, and network sharing.

The third problem is estimating the effect of having an entry after a merger against neither having asked for a merger nor having an entry. Again, the selection process is similar to the previous processes but, this time, countries must neither have asked for a merger nor have an entry after 2010. Many countries meet this feature: Belgium, Bulgaria, Croatia, Cyprus, Czech Republic, Finland, Malta, Portugal, Romania, and Spain. Distances scores are, respectively: 6.90, 7.16, 6.86, 8.44, 7.05, 5.63, 6.87, and 6.16. Finland is the selected country for this specification. Figure 4, third plot, depicts MDS's space and the selected countries.

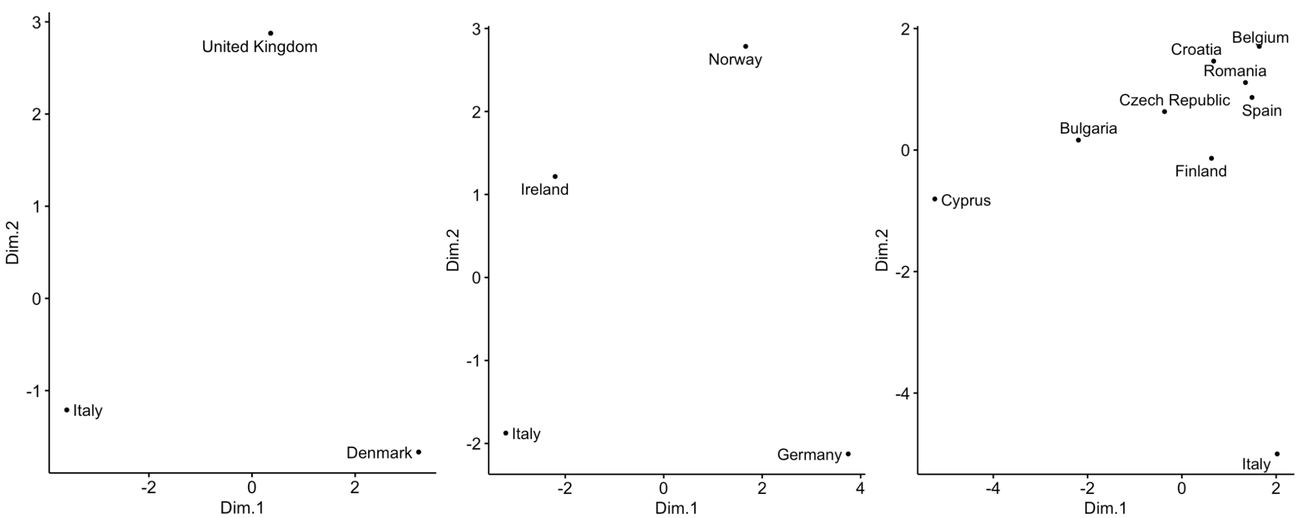

Figure 4. MultiDimensional Scaling applied for the three different sets of selected countries. The first, second, and third plots depict countries selected for the first, second, and third estimation problems in a new dimensional space output by MDS.

4.4. *Assumptions*

In this Section, we analyze the three fundamental assumptions of the Difference in Differences estimator. Each assumption is formally presented, discussed, and validated (where possible) in our setting.

4.4.1. *Common trend assumption*

The first and most crucial assumption of Difference in Differences estimator is the common trend assumption. Defining t_1 the period after the treatment occurs and t_0 the period before, the formulation of the assumption is:

$$E[Y_{0,t_1} - Y_{0,t_0}|D = 1] = E[Y_{0,t_1} - Y_{0,t_0}|D = 0] \tag{3}$$

We assume that in the absence of the treatment, the outcomes in the two groups would have followed parallel trends. This is an assumption because we cannot observe $E[Y_{0,t_1}|D = 0]$, but it is fundamental because the credibility of a DiD estimation hinges on it. The violation of this assumption makes it impossible to disentangle the causal effect of the policy from the effect of the specific different macro trends. If treated and untreated states have different macro trends, the DiD estimates will be biased.

Luckily, the common trend is not simply assumed, but it can be partially tested using pre-policy data. We can test if before the treatment occurred the outcome variables in treatment and control groups were following parallel trends.

Three methods are applied to validate the common trend assumption in our work: visual inspection, slopes comparison, and placebo test. The validity of this analysis is limited in our specific framework because the available data is yearly collected and we have only two observations in the pre-treatment period.

Visually comparing the pre-treatment trends in Figures 5, 6 and 7 we can already say that while Ireland doesn't seem to have the same slope as Italy, the United Kingdom and Finland slopes appear close. To validate this comparison we have to look at Table 3: if the estimated Italian slope is not included in the three control countries' slope confidence intervals we can reject the hypothesis that they have parallel trends.

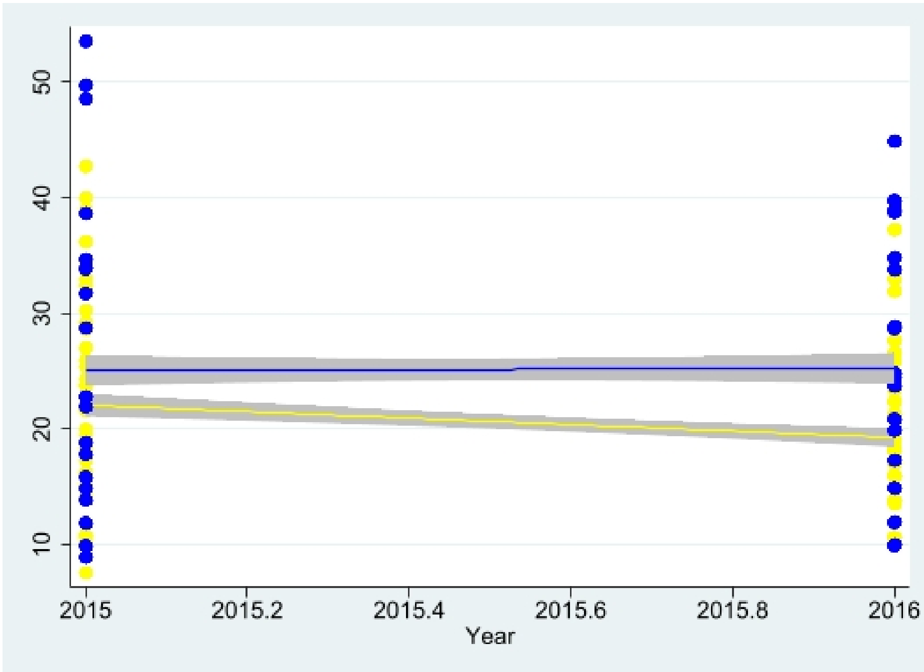

Figure 5. Slopes comparison: Italy - United Kingdom.
Each point depicts the price related to a specific offer available in a year and the lines represent the slopes with the 95% confidence interval between 2015 and 2016. Italy is in blue and United Kingdom is in yellow.

Country	Slope	SE	CI left	CI right
Italy	0.0291	0.0959	-0.1611	0.2192
UK	-0.0977	0.0734	-0.2431	0.0477
Ireland	0.1752	0.0636	0.0492	0.3012
Finland	-0.0262	0.0427	-0.1107	0.0582

Table 3: Slopes comparisons for common trend assumption.
Column "Slope", for each country, depicts the estimated slopes from 2015 to 2016.

While we cannot reject the parallel trend hypothesis for the United Kingdom and Finland with respect to the Italian one (they are indeed very similar), we can reject it for Ireland. The last test we can perform to further validate the common trend assumption is the placebo test. It consists in performing an additional difference-in-differences estimation using a fake treatment group, that is, a group of observations we know was not affected by the policy. In our case, the

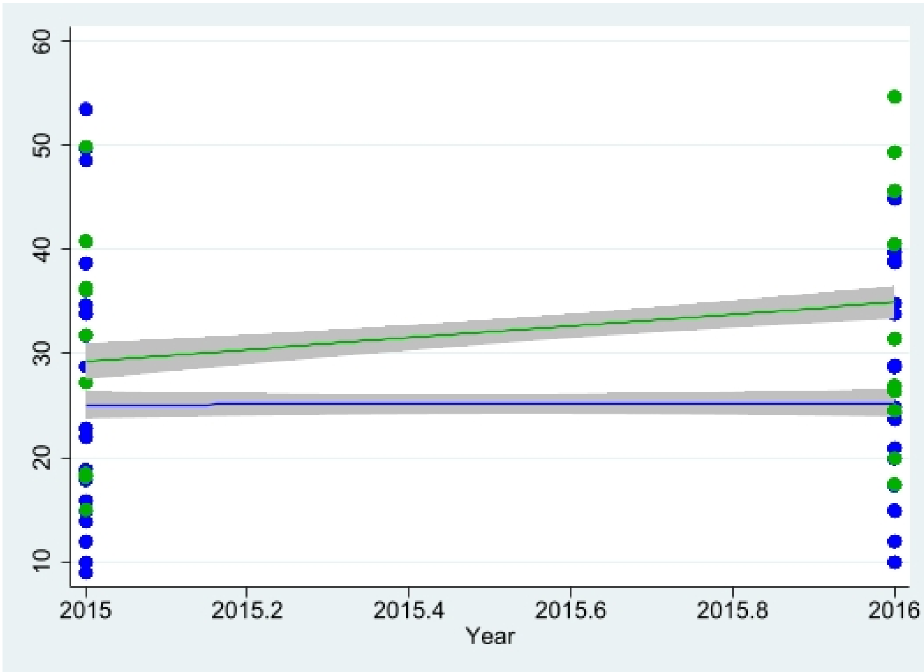

Figure 6. Slopes comparison: Italy - Ireland.
Each point depicts the price related to a specific offer available in a year and the lines represent the slopes with the 95% confidence interval between 2015 and 2016. Italy is in blue and Ireland is in green.

fake treated observations are the ones in 2016. If the estimated causal effect of the policy is significantly different from zero we are convinced that the parallel trend assumption is not met.

Country	Causal Effect	SE	t	Pvalue	CI left	CI right
UK	0.0155	0.0404	0.3800	**0.7010**	-0.0638	0.0948
Ireland	-0.2123	0.0541	-3.9200	**0.0000**	-0.3186	-0.1061
Finland	0.0554	0.0534	1.0400	**0.3000**	-0.0494	0.1601

Table 4: Placebo test for common trend assumption.
DiD causal effect's regression coefficient performed setting 2016 as the year with treated observations, instead of 2019.

The placebo test results from Table 4 show that, with the awareness of the sample limitations, the United Kingdom and Finland are reasonably good controls when it comes to common trend assumption. A more in-depth discussion is needed

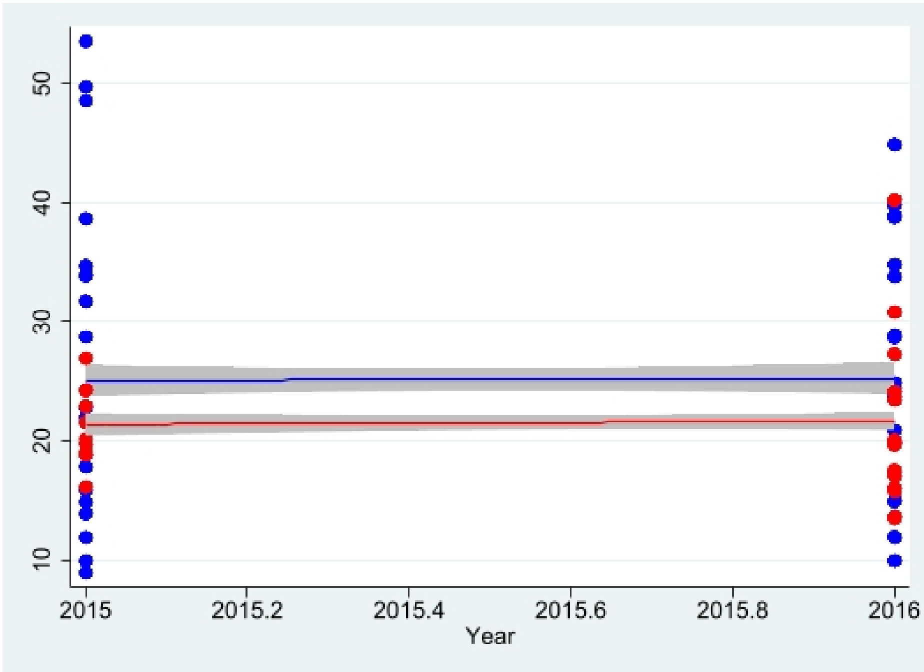

Figure 7. Slopes comparison: Italy - Finland.
Each point depicts the price related to a specific offer available in a year and the lines represent the slopes with the 95% confidence interval between 2015 and 2016. Italy is in blue and Finland is in red.

concerning Ireland. As explained in Section 4.2.1, each one of these control countries is used to estimate a different effect. We use Ireland to estimate the effect of a merger (from 4 to 3) followed by a structural remedy (the entry of Iliad) in comparison to the effect of a merger followed by traditional remedies. The perfect control country would have been one experiencing a merger from 4 to 3 MNOs in the same year of Italy (2016) conditioned on classical remedies. The problem is that it does not exist because of the change of approach after 2015 (as written in Section 3.2). Ireland experienced the merger in the 3rd quarter of 2014. To tackle this issue a shift in the timeline to make them overlap would have been appropriate. Again, this is not possible because of the lack of observations before 2015. We choose to still use Ireland as a control to try to estimate this specific effect because, as we can see from Figure 14, the major price increase probably due to the merger has been experienced in 2017: the same year in which Italy experienced it. The effect on price after a merger may not occur always at the same pace. In Italy, there has been an increase in prices immediately after the merger, while in Ireland prices were progressively increasing in 2016 and 2017. Indeed, what we estimate with

the placebo test with Ireland is an increase in prices between 10% and 31% the year after the merger, using as the control country Italy, in which nothing occurred in 2014 e 2015.
In conclusion, the United Kingdom and Finland are pretty good control countries for estimating the effect we want, while Ireland is the best we can find for estimating that specific effect. We will comment on the results with the awareness of this limitation.

4.4.2. *No selection on idiosyncratic shocks*

No selection on idiosyncratic shocks is the second very important assumption on which DiD is based. Observations selected for treatment may have experienced different idiosyncratic shocks with respect to those that were not treated. If this happens we have:

$$E[\varepsilon_{st}|D_{st} = 0] \neq E[\varepsilon_{st}|D_{st} = 1] \tag{4}$$

For example, if we wanted to estimate the effect of an increment in the unemployment benefit in a country, we could not simply use a country that DiDn't experience it as a control. The treated country could have been subject to the treatment because it experienced higher demand for it, and the control may not have experienced the same variation. By assuming that participation in treatment is independent of idiosyncratic shocks, this term is assumed to be zero:

$$E[\varepsilon_{st}|D_{st}] = 0 \tag{5}$$

This assumption has different degrees of validation depending on which of the three treatments we are talking about.

Using the United Kingdom as control, the treatment is: having experienced a merger from 4 to 3 and an MNO entry, after having asked permission for the merger, instead of having asked and being blocked. After having changed approach (2015), the European Commission blocked every requested merger from 4 to 3 (Denmark and United Kingdom), while it experimented with a new remedy in Italy. Thus, the reason why Italy experienced the entry and the United Kingdom didn't is completely exogenous, and the assumption is completely met.

Using Ireland as control, the treatment is: having experienced a merger from 4 to 3 and an MNO entry, after having asked permission for the merger, instead of experiencing a merger with the classical remedies after asking for permission. The reason why the treatment occurred in Italy and not in Ireland is that the latter had the merger immediately before the European Commission started to be reluctant on approving this kind of merger. The treatment is completely exogenous also in this setting, even if it is clear that the UK setting is more robust: the UK asked permission in the same year as Italy.

Using Finland as control, the treatment is: having experienced a merger from 4 to 3 and an MNO entry, after having asked permission for the merger, instead of not even having asked permission for a merger. In this setting, to validate the exogeneity of the treatment, we have to claim that asking for a merge or not, does not depend on variables that can affect our outcome variable (prices). All the papers using the same methodology we discussed in Section 2.1, estimate the effect of mergers on prices by selecting control countries that didn't even ask for a merger. Alternatives for mergers from 4 to 3 didn't exist because they were never blocked, but the possibility of evaluating mergers from 3 to 2 was available. In these papers, they all assumed that the reasons for the request for a merger were exogenous: we doubt the goodness of this assumption. If in the mobile telecommunication market, two MNOs wanted to merge, there could be different reasons. One could be that the two players were already working together, maybe colluding. Another one could also be that one of the two players was about to fail, and in order not to leave the most valuable asset (the licenses for the infrastructures), they decided to merge. These are a few examples, but they are enough to doubt the validity of the assumption because the described events are very likely to have some effects on the output variable (prices). However, we will use also Finland to try to estimate this specific effect, being aware of this limitation.

4.4.3. *Absence of compositional changes between groups*

The third assumption, the absence of compositional changes between groups, is very important when we have repeated cross-sectional data, as we have. The idea of DiD is to compare the same groups over time: if the groups are not the same in terms of composition, any observed difference in average outcomes may be simply due to compositional changes. We need to make sure that the characteristics of the control and treated groups do not change across periods.

This assumption is the easiest to assess, but also very difficult to obtain when the observations are mobile plans and not people. It is easy to assess because you simply need to look if the composition is the same, while is difficult to obtain because customers' needs, technologies, and accessibility change, making some offers obsolete over time. It is not simple to have every year in the market of every country a representation of the same offers. Luckily, the observations composing each year for each country of our dataset have been chosen to be the most representative possible following the OECD methodology.

As we can see in Figure 8 the proportion of observations for each basket among countries is the same. The basket composition changes over time because of the introduction of new baskets with higher volumes. For this reason, the DiD estimation has been done on every basket separately, on the first 4 together (as they are present in each year) and only the last one including all the baskets. Even if we already know that our observations are indeed chosen to try to meet this assumption, a more in-depth analysis of the variable that we have would be useful. We would validate even more this assumption and know if control variables must be added to the regression.

The two main variables of which we have to check the composition are $Smartphone$ and $DataVolume$. As we explained in Section 4.1 we included in the sample both plans including and not including the smartphone. However, it is important to control for this variable if the composition is not constant, because when the offers include a smartphone they are typically more costly. Looking at Figure 9 we can see that, luckily enough, we have data on this variable only in the relevant years for our regression (2015, 2016, and 2019). The composition doesn't change too much, but still, it can introduce bias in our estimation: the variable $Smartphone$ is included in any regression. Concerning the variable $DataVolume$ a deep discussion will follow in Section 4.5.2. However, in this section, quickly looking at Figure 10 we can see that the composition is not constant. This happened even if the offers are chosen in different baskets with different lower bounds. We certainly have to include $DataVolume$ as a control variable in each regression. Knowing how mobile plans have been chosen and controlling for these two compositional differences, we are reasonably convinced that the best we could do, to validate the compositional assumption in this kind of research setting, has been done.

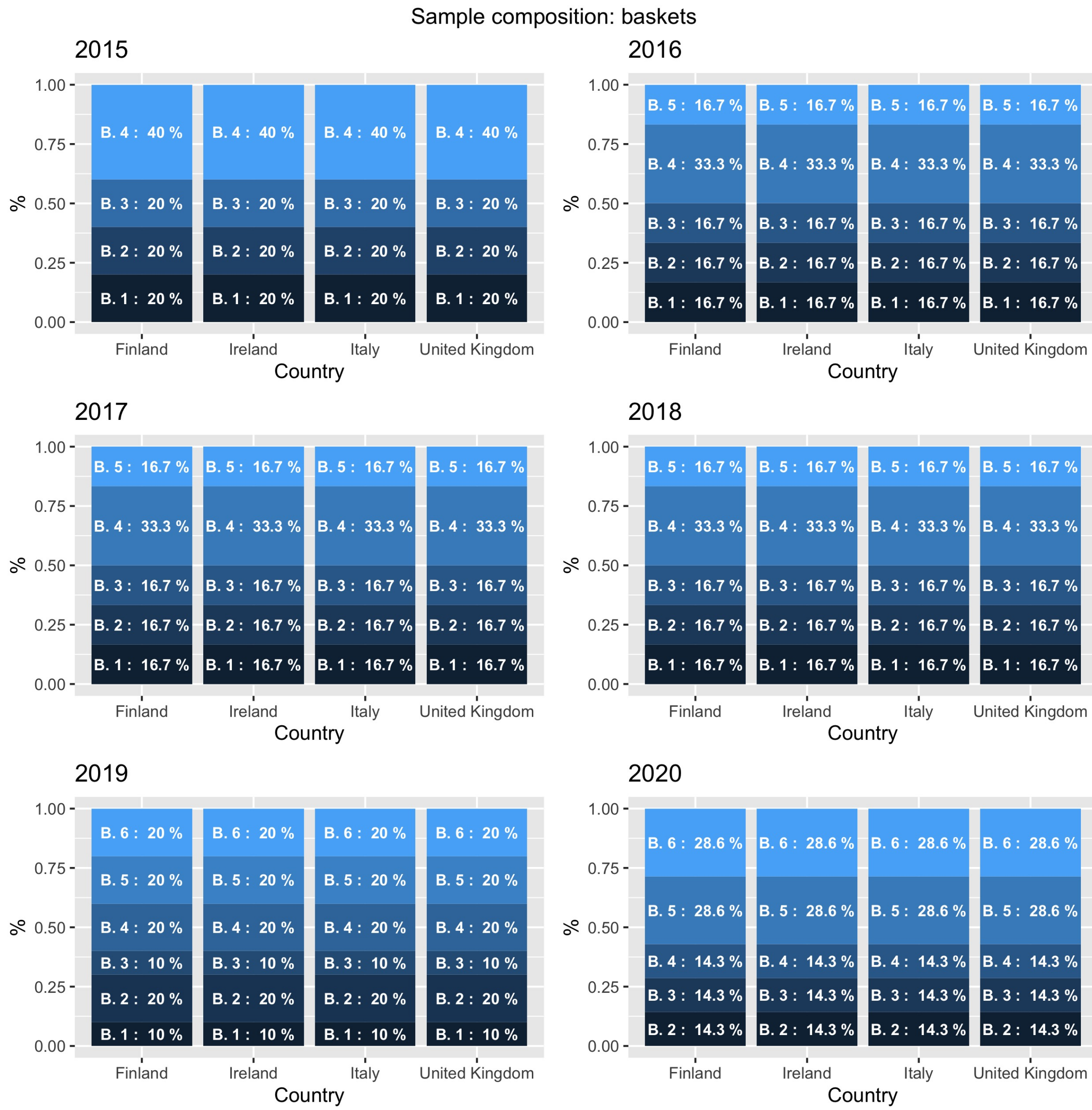

Figure 8. Sample composition: basket specification.
Each bar depicts how observations distribute across baskets in specific years and countries.

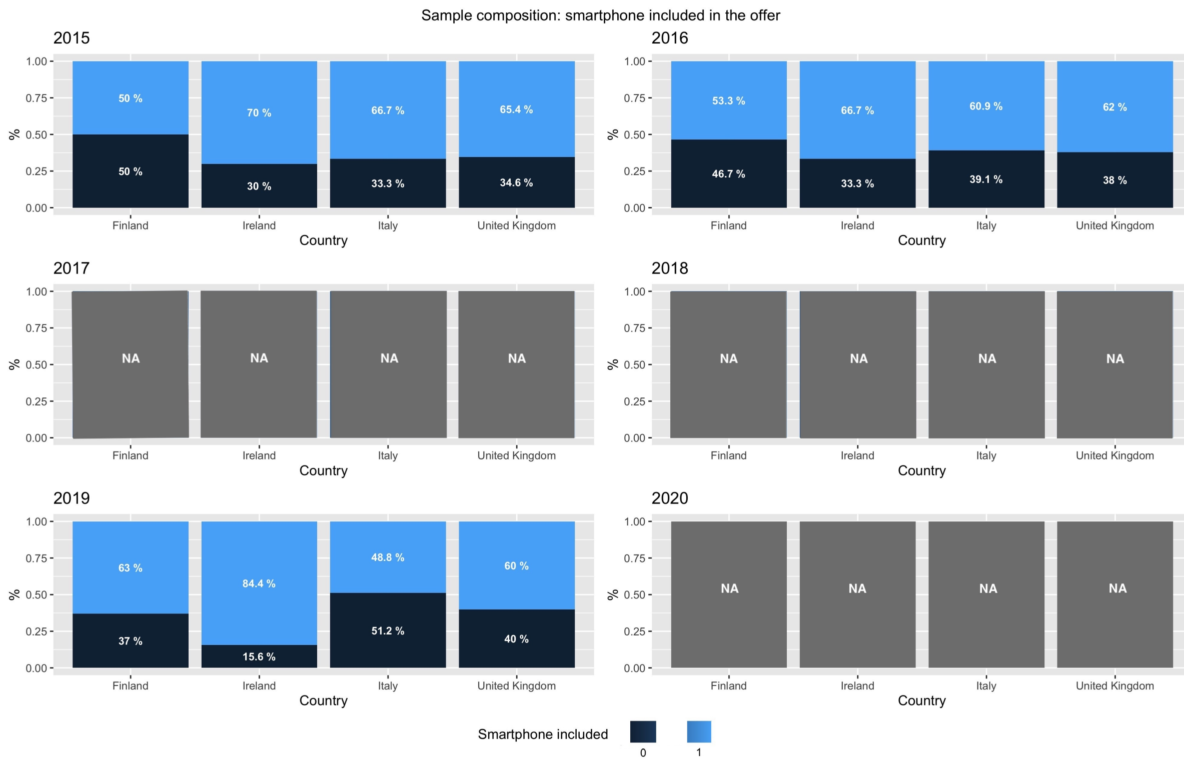

Figure 9. Sample composition: smartphone included in offers.
Each bar depicts the percentage of offers including a smartphone in a specific year and country. 2017, 2018, and 2020 do not have the necessary information to derive this specification.

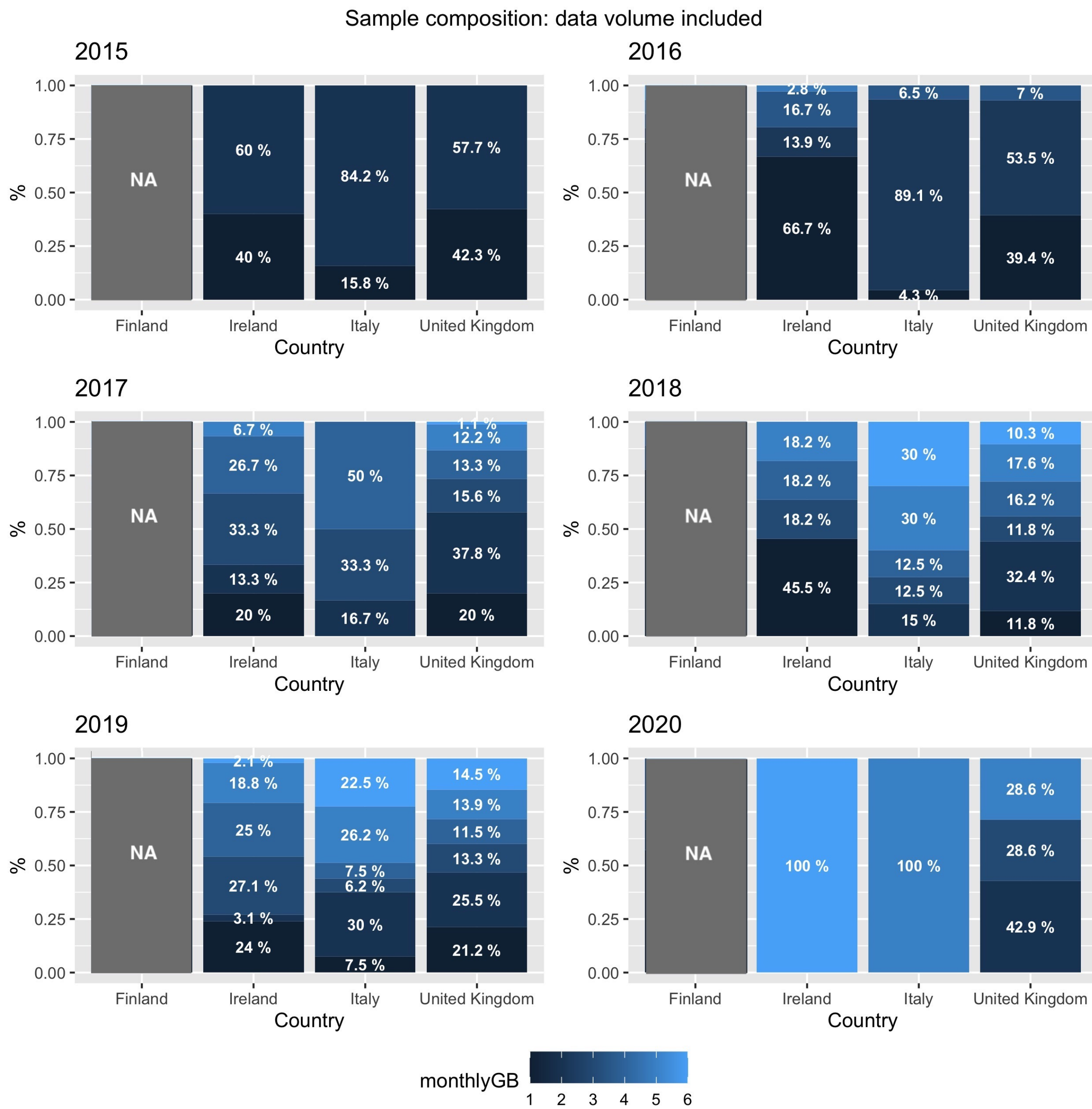

Figure 10. Sample composition: data volume (GB) per month specification.
Each bar depicts the percentage of observations offering gigabytes within a certain range in a specific year and country. Finland has not the necessary information to create its plot.
The ranges of gigabytes included in each categorization are: lower than 1GB (1), between 1GB and 5GB (2), between 5GB and 10GB (3), between 10GB and 20GB (4), between 20GB and 35GB (5) and higher than 35GB (6).

4.5. *Potential pitfalls*

In this Section, we present the most important pitfalls in a Difference in Differences estimation with respect to our specific setting. In Subsection 4.5.1 we discuss what happens when some of the assumptions fail, while in Subsection 4.5.2 we discuss the source of underestimation in our research.

4.5.1. *Methodology pitfalls*

In this Subsection, we discuss what happens when the assumptions are violated and other typical pitfalls in we may incur. Let's start with the common trend assumption violation. Suppose that there is a macro trend λ_t, but the two countries have different trends, according to a state-specific parameter κ_s. The observed outcome Y_{st} can be written as:

$$Y_{st} = \alpha + \delta D_{st} + \gamma_s + \kappa_s \gamma_t + \epsilon_{st} \tag{6}$$

We have (assuming no selection on idiosyncratic shocks and no compositional change between groups):

$$DiD = \delta + (\kappa_{TS} - \kappa_{CS})(\gamma_{T_1} - \gamma_{T_0}) \tag{7}$$

The term $(\kappa_{TS} - \kappa_{CS})(\gamma_{T_1} - \gamma_{T_0})$ is the biased introduced. The bias is zero if $\kappa_{TS} = \kappa_{CS}$, that is, if the common trend assumption holds. As we understood from Section 4.4.1 with the awareness of the sample limitation, this bias is probably negligible in the estimated effect from the United Kingdom and Finland. This bias could be instead substantial in the case of Ireland.

When there is a violation of the second assumption, thus having selection on idiosyncratic shocks (assuming common trend and no compositional changes within groups), we have:

$$DiD = \delta + (E[\epsilon_{TS,T_1} - \epsilon_{TS,T_0}|D_{st}] - E[\epsilon_{CS,T_1} - \epsilon_{CS,T_0}|D_{st}]) \tag{8}$$

The term $(E[\epsilon_{TS,T_1} - \epsilon_{TS,T_0}|D_{st}] - E[\epsilon_{CS,T_1} - \epsilon_{CS,T_0}|D_{st}])$ is the biased introduced. As already said in Section 4.4.2, this bias could occur only in the case of Finland: this assumption is very strongly validated for the other two cases.

The last assumption violation we have to discuss about is the absence of compositional changes within groups. With compositional changes, the state-specific fixed effect does not cancel out when taking differences over time. This creates an endogeneity issue (assuming common trend and no selection on idiosyncratic shocks):

$$DiD = \delta + [(E[\gamma_{TS}|D_{TS,T_1}] - E[\gamma_{TS}|D_{TS,T_0}]) - (E[\gamma_{CS}|D_{CS,T_1}] - E[\gamma_{CS}|D_{CS,T_0}])] \quad (9)$$

The term $[(E[\gamma_{TS}|D_{TS,T_1}] - E[\gamma_{TS}|D_{TS,T_0}]) - (E[\gamma_{CS}|D_{CS,T_1}] - E[\gamma_{CS}|D_{CS,T_0}])]$ is the bias introduced by the violation. As shown in Section 4.4.3 we expect this bias to be very little. A little higher bias is introduced concerning the estimated effect with Finland as a control, because of the lack of information for variable $DataVolume$ to use as an additional control variable.

Usually, in Difference in Differences estimation, another great source of bias is introduced by spillover effects. The occurrence of the treatment in the treated countries could affect the outcome variable even in the control countries. In our setting, however, spillover effects are very unlikely to take place. The entry of Iliad into the Italian mobile telecommunication market is very unlikely to affect mobile plan prices in the United Kingdom, Finland, and Ireland. Mobile telecommunication markets are independent across countries, because, to offer services in a country, you need to be entitled to national licenses. It is always possible to think of some complex ways in which spillover effects may occur, but no significant one comes to mind when reasoning about our specific treatment.

(Csorba and Pápai, 2015) argue that DiD's standard errors can be serially correlated, leading to biased standard errors. Serial correlation could be expected in price trends: indeed, (Csorba and Pápai, 2015) solves this potential pitfall by taking the first difference. Unfortunately, we cannot perform a similar procedure, since we would lose another year for the causal effect estimation. Going from 3 years to 2 years, in our case, would impact too much the reliability of our results.

4.5.2. *Sources of underestimation*

In our work there are some important limitations. Some of them have already been discussed, while in this Subsection we analyze how the sample we managed to obtain would affect the estimation. Both underestimation and overestimation are possible, but in our case, we have mainly strong sources of underestimation.

Exactly as it happened when Iliad entered the French market, in Italy the incumbents (Tim, Vodafone, WindTre) used subsidiary fighting brands (MVNOs) to compete with Iliad. Kena Mobile, Ho Mobile, and Very Mobile are respectively owned by Tim, Vodafone, and WindTre. The highest competitive pressure effect was then between these three subsidiaries and Iliad. As already said in Section 4.1, our dataset is composed of observations only of the 2/3 largest MNOs: we have only the observations of Tim, Vodafone, and WindTre. We will then only estimate the effect on prices on the incumbents' MNOs. This would lead to a strong underestimation of the general effect on prices.

The competition, after the entry of Iliad, has been strongly characterized by discriminating offers.
The win-back offers have been largely used to try to make the client come back to the previous operator after leaving for the new convenient competitor. In some cases, preemptive offers, have been done to customers which are very likely to change operator (having higher churn rate (Ardovino and Delmastro, 2020)), to keep them. All these offers had a price lower or equal to the Iliad ones (5.99 Euros, 30 gigabytes, unlimited SMS and call minutes). They have been offered through direct calls or SMS to the customers and they were not included in the public price list.
In our sample we have only offers that are in the public price list. We then only estimate the effect on public prices, thus leading to a strong underestimation of the general effect on prices.

In Italy, immediately after the treatment, most of the plans including less than 20 gigabytes disappeared. A lot of offers contain very high quantities of SMS, call minutes, and gigabytes. This is mainly due to the fact that as the high volume plans started to cost as the old very low volume offers, there remained little market space for them: customers who used the smartphone very little, mainly the elderly people (Ardovino and Delmastro, 2020). Our dataset is based on OECD baskets. As one can see in Figure 2, the baskets present in all the years needed for the estimation require very little volume as lower bound to be included. In the control countries, this process did not happen: the higher volume plans portion of the market increased slowly and less, as visible in Figures 14 and 10. To overcome this issue, a control variable $DataVolume$ has been included in the regressions. However, we do not have the necessary data for this variable in Finland's observations. This would probably lead to an underestimation of this specific effect. The biggest problem, however, is that we never have basket including the plans with 30, 50, 70, 100, or unlimited gigabytes. Because they are the baskets in which the price reduction effect has been greater, this would lead to a substantial underestimation of the general effect on prices.

5. Econometric results

In this Section, Difference in Differences estimation outputs are illustrated and discussed in light of what has been highlighted in previous Sections.

	United Kingdom		**Ireland**		**Finland**	
lnprice	**1-2-3-4**	All	**1-2-3-4**	All	**1-2-3-4**	All
Causal Effect	**-0.5461*****	-0.5378***	**-0.7267*****	-0.7061***	**-0.4560*****	-0.4431***
	(0.0570)	(0.0532)	(0.0546)	(0.0467)	(0.0408)	(0.0341)
Country	0.6255***	0.6308***	-0.4203***	-0.4160***	-0.0369	-0.0428
	(0.1693)	(0.1556)	(0.0638)	(0.0567)	(0.0934)	(0.0898)
2016	0.0888*	0.0922**	0.0369	0.0406	0.0345	0.0377
	(0.0486)	(0.0450)	(0.0348)	(0.0320)	(0.0298)	(0.0278)
2019	0.8555***	0.8671***	0.2871***	0.2839***	0.0143	0.0101
	(0.2201)	(0.2037)	(0.0625)	(0.0556)	(0.1311)	(0.1238)
GDP Growth	1.7970***	1.8172***	-0.0355**	-0.0351***	-0.3980	-0.4034
	(0.6551)	(0.6101)	(0.0141)	(0.0130)	(0.3663)	(0.3435)
Data Volume	0.0000***	0.0000***	0.0000***	0.0000***		
	(0.0000)	(0.0000)	(0.0000)	(0.0000)		
Smartphone	0.3988***	0.4470***	0.3026***	0.3586***	0.2612***	0.3190***
	(0.0166)	(0.0135)	(0.0207)	(0.0171)	(0.0200)	(0.0167)
_cons	1.5605	1.5161	3.3233	3.2820	3.1089	3.0782

Table 5: DiD regression output coefficients on $lnprice$**, with Italy as treatment group country**.
Each column, which refers to the control group's observations belonging to a specific country, depicts coefficients related to two types of regressions: "1-2-3-4" indicates that baskets 5 and 6 are not included; "All" indicates that all baskets are included. Standard errors are indicated in parenthesis.*** p<0.01, ** p<0.05, * p<0.1

Table 5 shows the main DiD estimations: the ones with the first 4 baskets, which are present in each year, and all the control variables included. Regression output including all baskets, even if two of them are not present every year, is also presented in this table only to show the consistency of the results.

Looking at the first regression output, using the United Kingdom as the control country, and including only the first 4 baskets, we get the first effect's estimation. This effect is associated with a specific treatment: a merger followed by an entry. The estimated reduction in prices due to this treatment is between 43% and 66%. These analytical results are graphically shown in Figure 11.
This estimation is the most robust among the three because, as discussed in Section 4.4, all the assumptions are strongly validated. The estimated effect is not only statistically significant but also of great effect size. However, because of what we have remarked in Section 4.5.2, we are almost surely underestimating the overall effect on prices. We are estimating the effect only on a specific portion of prices which are: offered by incumbent operators, related to mobile plans, not in baskets over 20 gigabytes, and publicly available on the public price list.

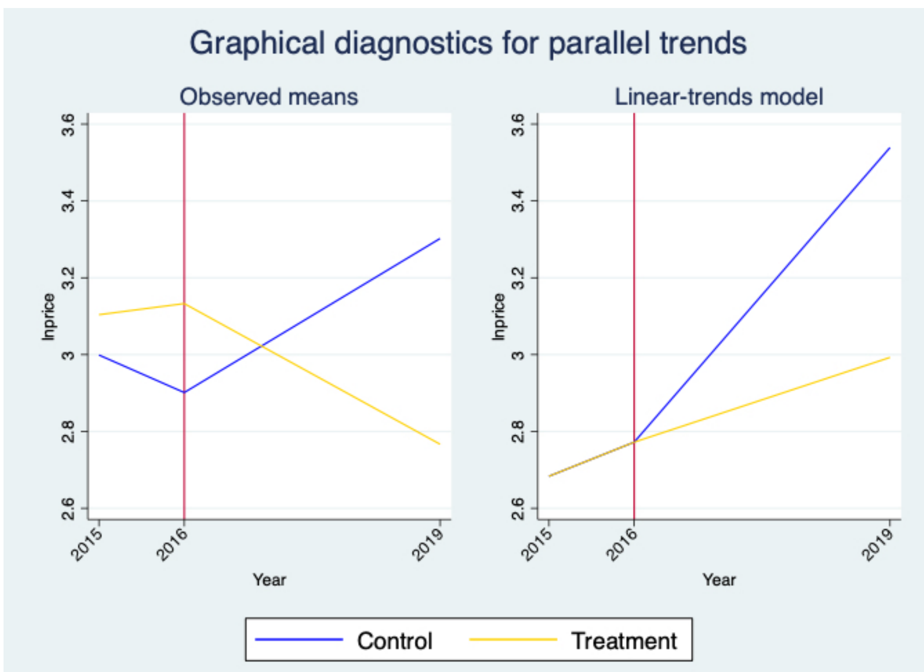

Figure 11. Difference in Differences estimation plot: the United Kingdom as control group country.
The leftmost plot depicts the observed trend in Italy (treatment group country) and the United Kingdom (control group country). The rightmost plot highlight the difference between the expected trend without treatment and the actual trend.

In the second regression output, using Ireland as the control country, and

including only the first 4 baskets, we get the second effect's estimation. This effect is associated with the entry of a new MNO instead of the classical remedies. The estimated reduction in prices due to this treatment is between 62% and 83%. These analytical results are graphically shown in Figure 12.
This estimation is the least robust in terms of assumptions. The most important assumption, common trend, is rejected. This is still the best option we have to estimate this specific effect and we find it useful anyway. Again, the estimated effect is not only statistically significant but also of great effect size. What causes underestimation previously is still present in this case.

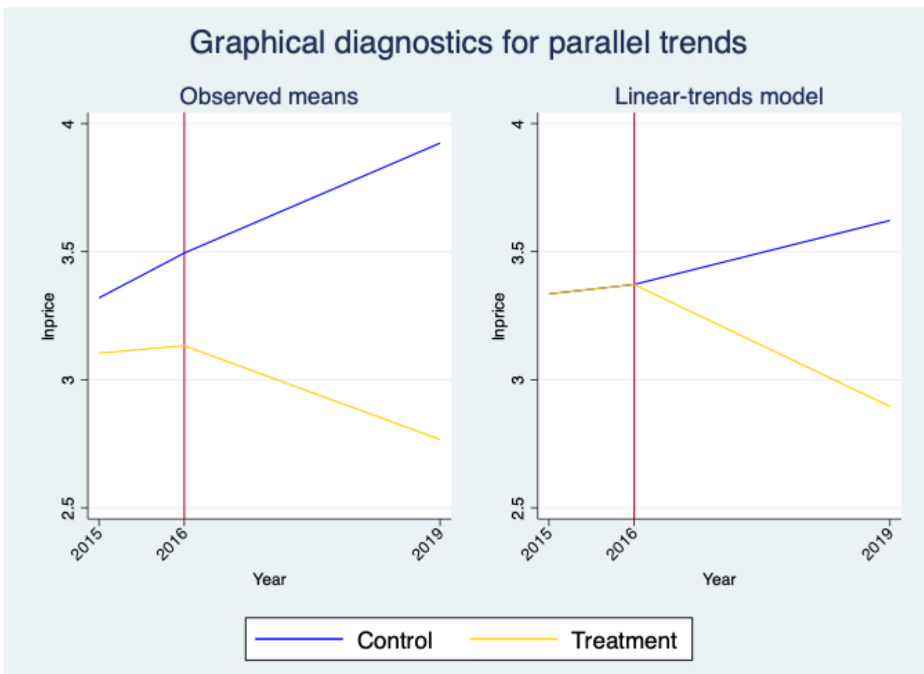

Figure 12. Difference in Differences estimation plot: Ireland as control group country. The leftmost plot depicts the observed trend in Italy (treatment group country) and Ireland (control group country). The rightmost plot highlight the difference between the expected trend without treatment and the actual trend.

The third regression output, using Finland as the control country, and including only the first 4 baskets, is associated with a merger followed by an entry of a new MNO instead of not even asking for a merger. The estimated reduction in prices due to this treatment is between 37% and 53%. These analytical results are graphically shown in Figure 13.
This estimation is robust in terms of assumptions. This is the most commonly used setting for estimating the effect of entries and mergers. However, as dis-

cussed in Section 4.4.2, we are not completely convinced about the independence on idiosyncratic shocks. The estimated effect is still statistically significant and of great effect size. What causes underestimation previously is still present in this case. In addition, we have to remember that here we did not control for the specific $DataVolume$ in each offer because it is not available for Finland.

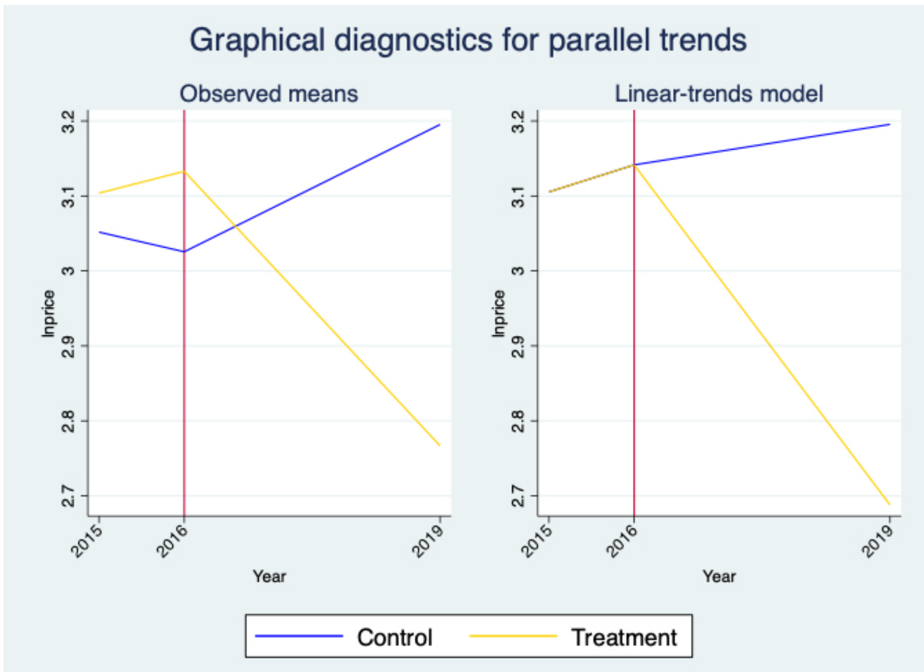

Figure 13. Difference in Differences estimation plot: Finland as control group country. The leftmost plot depicts the observed trend in Italy (treatment group country) and Finland (control group country). The rightmost plot highlight the difference between the expected trend without treatment and the actual trend.

The three different magnitudes estimated are consistent with our expectations. We expected the effect of a merger and an entry to be lower than the effect of the entry alone because mergers tend to increase prices. Indeed, the effect estimated with Ireland is greater than the ones estimated with Finland and the United Kingdom. Furthermore, comparing the UK to Finland, we expected the former to be greater than the latter. Asking for a merger and not obtaining it could have been associated with a price increment: the operators willing to merge may still try to cooperate.

6. Robustness checks

This Section aims to validate the robustness of our estimations checking if including outlier observations, including only one basket each time, moving the treated year, and other types of variations, lead to consistent results. All the Tables discussed in this section are in Section 8.1.

The first robustness check concerns baskets. In Tables 6, 7 and 8 the estimation outputs are presented. In these regressions, we perform the same estimation shown in Section 5 except that we include only one basket each time. Since to be included in a basket only the lower bound of the quantity is required, some regression outputs are identical: they include the same observations because they are the cheapest for both the lower bounds. However, where the observations included are different, the estimated results change very little. The results are all consistent. If higher volume baskets were available we would expect to see greater effect sizes. Looking at Table 6, where the results using the UK as the control country are displayed, we have some clues confirming our expectations. We refer only to this table because here the assumptions are completely met (Section 4.4), and we can see that if we only take into account basket 5 (the highest volume available basket) the effect size considerably increases to between 57% and 88%.

The second robustness check concerns outliers. In Table 9 the estimation outputs are presented. In these regressions, we perform the same estimation shown in Section 5, except that we include also the outlier observations. As we can see the results are pretty consistent with the ones performed excluding them. The estimated causal effect using the UK and Ireland as control countries decreased by around 5%. For what concerns Finland the effect size considerably decrease but we are reasonably convinced that this only happened because we couldn't control for $DataVolume$. Indeed outlier observations are mostly the ones with very high or very low volume.

The third robustness check is performed by including also the observations of 2020. We excluded them in the main DiD estimation because they have been collected differently and only very few observations are present. The results are shown in Table 10. The DiD estimation output is completely consistent with the main estimation: the variations are very little.

The fourth check concern the anticipation of the effect. In Section 4.2.1 we explain that the observation of 2017 and 2018 are excluded because they were measured during the treatment: the merger and the entry were taking place. The observations of 2018 were measured in February while the first Iliad mobile plan was offered in May. However, here, we want to see if there was any anticipatory effect. It is likely that the incumbents, which were already creating their subsidiary fighting brands, were already anticipating the entry also by lowering prices. It is even more obvious if we think that they have already seen how strong is Iliad's competitive behavior when it entered the French market. In Table 11 we show the results of the DiD estimation using 2018 as the first treated year to capture this effect. We can see that the anticipatory effect is comparable to the main effect estimated: the effect is only between 0% and 10% lower.

The last robustness check concerns Data Volume. At different points of this research, we claim that even if observations were collected in baskets, in Italy almost all the observations after the treatment include very high volume, independently from the basket in which they are. To check this claim, we performed the same DiD estimation with the same controls, but instead of price, the dependent variable is $DataVolume$. We can see from Table 12 that it is completely confirmed. The estimated effect on $DataVolume$ of Iliad entry after the merger is an increment between 4,826 gigabytes and 13,995 gigabytes. The estimated effect on $DataVolume$ of Iliad entry instead of classical remedies is an increment between 8,144 gigabytes and 14,537 gigabytes. This increment is huge if we think that 5 gigabytes were considered a good amount before the entry.

7. Conclusions

In this research, we evaluate three specific effects on prices of some developments that occurred in the Italian mobile telecommunication market. These effects are related to a policy applied by the European Commission: the approval of the Wind-Tre merger conditioned on a new and structural remedy, the entry of Iliad. The new reluctant approach developed by the EC, in the assessment of merger requests from 4 to 3 MNOs, created the perfect environment for the Difference in Differences research design. For the first time, the perfect control group for a 4 to 3 merger was available. The United Kingdom, in which 2 MNOs are the same as in Italy (H3G and Vodafone) and share very similar market characteristics, asked for a merger in the same year without having it cleared. Furthermore, we evaluate other two specific effects using Ireland and Finland as control countries. Ireland has been used to evaluate the effect of the new structural remedy compared to the classical ones, while Finland is the classical control group in which nothing happened. The DiD estimations consistently show that the new structural remedy caused a huge price-decreasing effect, thus leading to higher consumer welfare. In particular, we estimate a price reduction effect between 43% and 66% as a result of a merger and the entry of the new disruptive firm. Using the typical counterfactual in which no request for a merger was experienced, we estimate for the same treatment a price reduction effect between 37% and 53%. Finally, a price reduction between 62% and 83% is estimated as the result of the imposition of the new structural remedies instead of the classical ones. All these results seem to be very solid after having performed different robustness checks. However, not all of them have the same internal validity. The estimation performed using the United Kingdom is the most internally valid: all the necessary assumptions seem to be completely met. Nevertheless, these causal effect estimations, are substantial underestimations of the effect on general prices. Due to the composition of our dataset, we were able to estimate only the effect on mobile plan prices publicly available, related to the incumbent MNOs and in the lower market segment. These mobile plan prices are the less affected ones.

In conclusion, it is the opinion of the authors that this new policy implemented by the European Commission has been very effective in pursuing its aims: protect the consumers and preserve competition. Indeed, the treatment is not an increase or reduction in the number of competitors. The treatment is a switch: the MNOs are still 4 as before the treatment. What happened was a shock in the tight oligopoly, a break in collusive behaviors, and a boost in competition. Even if the external validity of this study is limited due to the number of assumptions, we are convinced that the implementation of this remedy in different countries could produce a similar positive outcome. We think that the consistency of our results with the economical theory makes them generalizable. The entry of a new disruptive firm in a mobile telecommunication market, in which a tight oligopoly is established, would decrease mobile plan prices.

For future research, other analyzes could be performed with more comprehensive data. To estimate the general price effect, data including observations on all the active MNOs and MVNOs, with also some representative offers not publicly available, and some higher volume baskets would be more accurate. Including comparable observations collected in 2020, 2021, and 2022 would also allow us to evaluate the medium-run effect. Indeed it is not taken for granted that the behavior of the new entrant would continue to be highly competitive: a collusive setting could reappear after the newcomer has taken substantial market share. A separate examination of the merger effect before the entry would also help in understanding more in-depth what would have been the outcome in the absence of the new policy. In conclusion, even if our results are solid, other tests including different control countries for each one of the estimated effects could be performed.

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8. Appendix

8.1. *Robustness checks tables*

In this Section regression output Tables discussed in Section 6 are displayed.

lnprice	**Basket 1**	**Basket 2**	**Basket 3**	**Basket 4**	**Basket 5**
Causal Effect	**-0.5503***** (0.1318)	**-0.5356***** (0.1199)	**-0.5503***** (0.1318)	**-0.5502***** (0.0928)	**-0.7257***** (0.0807)
Country	0.6229 (0.3850)	0.6323* (0.3685)	0.6229 (0.3850)	0.6229** (0.2711)	0.2358*** (0.0716)
2016	0.0870 (0.1105)	0.0932 (0.1057)	0.0870 (0.1105)	0.0870 (0.0778)	
2019	0.8495* (0.5008)	0.8702* (0.4786)	0.8495* (0.5008)	0.8495** (0.3525)	0.3170*** (0.0519)
GDP Growth	1.7870 (1.4901)	1.8228 (1.4262)	1.7870 (1.4901)	1.7870* (1.0490)	
Data volume	0.0000*** (0.0000)	0.0000*** (0.0000)	0.0000*** (0.0000)	0.0000*** (0.0000)	0.0000*** (0.0000)
Smartphone	0.3752*** (0.0396)	0.4606*** (0.0307)	0.3752*** (0.0396)	0.3752*** (0.0279)	0.5093*** (0.0315)
_cons	1.5822	1.5036	1.5822	1.5822	2.5707

Table 6: DiD regression output coefficients on $lnprice$, with the United Kingdom as control group and Italy as treatment group country.
Each column, which refers to observations belonging to a specific basket, depicts coefficients related to regressions which select observations belonging to the respective basket. Standard errors are indicated in parenthesis.*** p<0.01, ** p<0.05, * p<0.1

lnprice	**Basket 1**	**Basket 2**	**Basket 3**	**Basket 4**	**Basket 5**
Causal Effect	**-0.7361***** (0.1277)	**-0.7013***** (0.1124)	**-0.7361***** (0.1277)	**-0.7361***** (0.0897)	**-0.6955***** (0.0925)
Country	-0.4222*** (0.1460)	-0.4149*** (0.1378)	-0.4222*** (0.1460)	-0.4222*** (0.1026)	-0.3414*** (0.0824)
2016	0.0352 (0.0796)	0.0414 (0.0751)	0.0352 (0.0796)	0.0352 (0.0559)	
2019	0.2879** (0.1443)	0.2830** (0.1324)	0.2879** (0.1443)	0.2879*** (0.1014)	0.2646*** (0.0709)
GDP Growth	-0.0357 (0.0323)	-0.0350 (0.0305)	-0.0357 (0.0323)	-0.0357 (0.0227)	
Data volume	0.0000*** (0.0000)	0.0000*** (0.0000)	0.0000*** (0.0000)	0.0000*** (0.0000)	0.0000*** (0.0000)
Smartphone	0.2777*** (0.0494)	0.3718*** (0.0389)	0.2777*** (0.0494)	0.2777*** (0.0347)	0.4500*** (0.0406)
_cons	3.3416	3.2723	3.3416	3.3416	3.1819

Table 7: DiD regression output coefficients on $lnprice$**, with Ireland as control group and Italy as treatment group country**.
Each column, which refers to observations belonging to a specific basket, depicts coefficients related to regressions which select observations belonging to the respective basket. Standard errors are indicated in parenthesis.*** p<0.01, ** p<0.05, * p<0.1

lnprice	**Basket 1**	**Basket 2**	**Basket 3**	**Basket 4**	**Basket 5**
Causal Effect	**-0.4616*****	**-0.4402*****	**-0.4616*****	**-0.4616*****	**-0.4453*****
	(0.0975)	(0.0791)	(0.0975)	(0.0686)	(0.0920)
Country	-0.0344	-0.0442	-0.0344	-0.0344	0.0773
	(0.2125)	(0.2047)	(0.2125)	(0.1494)	(0.0782)
2016	0.0331	0.0384	0.0331	0.0331	
	(0.0678)	(0.0653)	(0.0678)	(0.0477)	
2019	0.0161	0.0092	0.0161	0.0161	0.1329*
	(0.2991)	(0.2854)	(0.2991)	(0.2102)	(0.0680)
GDP Growth	-0.3956	-0.4046	-0.3956	-0.3956	
	(0.8331)	(0.8024)	(0.8331)	(0.5856)	
Smartphone	0.2361***	0.3322***	0.2361***	0.2361***	0.4161***
	(0.0473)	(0.0383)	(0.0473)	(0.0333)	(0.0406)
_cons	3.1222	3.0712	3.1222	3.1222	2.8023

Table 8: DiD regression output coefficients on $lnprice$**, with Finland as control group and Italy as treatment group country**.
Each column, which refers to observations belonging to a specific basket, depicts coefficients related to regressions which select observations belonging to the respective basket. Standard errors are indicated in parenthesis.*** p<0.01, ** p<0.05, * p<0.1

	United Kingdom		**Ireland**		**Finland**	
lnprice	**1-2-3-4**	All	**1-2-3-4**	All	**1-2-3-4**	All
Causal Effect	**-0.5036***** (0.0662)	-0.4948*** (0.0625)	**-0.6547***** (0.0608)	-0.6328*** (0.0526)	**-0.1431**** (0.0629)	-0.0782 (0.0609)
Country	0.5930*** (0.1954)	0.5981*** (0.1813)	-0.4207*** (0.0712)	-0.4156*** (0.0642)	-0.0749 (0.1408)	-0.1019 (0.1567)
2016	0.0874 (0.0568)	0.0914* (0.0531)	0.0368 (0.0407)	0.0410 (0.0379)	0.0382 (0.0477)	0.0425 (0.0516)
2019	0.7823*** (0.2545)	0.7949*** (0.2379)	0.1935*** (0.0702)	0.1904*** (0.0635)	-0.2695 (0.1965)	-0.3403 (0.2146)
GDP Growth	1.6881** (0.7584)	1.7079** (0.7132)	-0.0357** (0.0161)	-0.0352** (0.0151)	-0.4356 (0.5601)	-0.4973 (0.6079)
Data Volume	0.0000*** (0.0000)	0.0000*** (0.0000)	0.0000*** (0.0000)	0.0000*** (0.0000)		
Smartphone	0.4467*** (0.0190)	0.5035*** (0.0156)	0.3623*** (0.0233)	0.4274*** (0.0193)	0.3415*** (0.0308)	0.4416*** (0.0300)
_cons	1.5981	1.5483	3.2791	3.2311	3.1068	3.0891

Table 9: DiD regression output coefficients on $lnprice$ **and Italy as treatment group country. Outliers are not excluded**.
Each column, which refers to control group's observations belonging to a specific country, depicts coefficients related to two types of regressions: "1-2-3-4" indicates that baskets 5 and 6 are not included; "All" indicates that all baskets are included. Standard errors are indicated in parenthesis.*** p<0.01, ** p<0.05, * p<0.1

	United Kingdom		Ireland		Finland	
lnprice	**1-2-3-4**	All	**1-2-3-4**	All	**1-2-3-4**	All
Causal Effect	**-0.5461*****	-0.5378***	**-0.7267*****	-0.7061***	**-0.4560*****	-0.4431***
	(0.0570)	(0.0532)	(0.0546)	(0.0467)	(0.0408)	(0.0341)
Country	0.6255***	0.6308***	-0.4203***	-0.4160***	-0.0369	-0.0428
	(0.1693)	(0.1556)	(0.0638)	(0.0567)	(0.0934)	(0.0898)
2016	0.0888**	0.0922**	0.0369**	0.0406	0.0345	0.0377
	(0.0486)	(0.0450)	(0.0348)	(0.0320)	(0.0298)	(0.0278)
2019	0.8555***	0.8671***	0.2871***	0.2839***	0.0143	0.0101
	(0.2201)	(0.2037)	(0.0625)	(0.0556)	(0.1311)	(0.1238)
GDP Growth	1.7970***	1.8172***	-0.0355**	-0.0351**	-0.3980	-0.4034
	(0.6551)	(0.6101)	(0.0141)	(0.0130)	(0.3663)	(0.3435)
Data volume	0.0000***	0.0000***	0.0000***	0.0000***		
	(0.0000)	(0.0000)	(0.0000)	(0.0000)		
Smartphone	0.3988***	0.4470***	0.3026***	0.3586***	0.2612***	0.3190***
	(0.0166)	(0.0135)	(0.0207)	(0.0171)	(0.0200)	(0.0167)
_cons	1.5605	1.5161	3.3233	3.2820	3.1089	3.0782

Table 10: DiD regression output coefficients on $lnprice$ and Italy as treatment group country. Observation from 2020 are included.
Each column, which refers to control group's observations belonging to a specific country, depicts coefficients related to two types of regressions: "1-2-3-4" indicates that baskets 5 and 6 are not included; "All" indicates that all baskets are included. Standard errors are indicated in parenthesis.*** p<0.01, ** p<0.05, * p<0.1

	United Kingdom		Ireland		Finland	
lnprice	**1-2-3-4**	All	**1-2-3-4**	All	**1-2-3-4**	All
Causal Effect	**-0.5301*****	**-0.5380*****	**-0.6845*****	**-0.6822*****	**-0.3786*****	**-0.3867*****
	(0.0539)	(0.0510)	(0.0525)	(0.0453)	(0.0362)	(0.0314)
Country	0.5282***	0.5208***	-0.3855***	-0.3801***	0.0801	0.0940
	(0.1584)	(0.1466)	(0.0615)	(0.0550)	(0.0867)	(0.0833)
2016	0.0646	0.0646	0.0506	0.0551*	0.0173	0.0186
	(0.0456)	(0.0426)	(0.0336)	(0.0311)	(0.0284)	(0.0266)
2018	0.8025***	0.7831***	0.5883***	0.5762***	0.5103***	0.5096***
	(0.1233)	(0.1146)	(0.0671)	(0.0597)	(0.0899)	(0.0844)
2019	0.7180***	0.7141***	0.2934***	0.2982***	0.1380	0.1699
	(0.2052)	(0.1914)	(0.0603)	(0.0540)	(0.2338)	(0.1162)
GDP Growth	1.4160**	1.3808**	-0.0271**	-0.0260**	0.0830	0.1434
	(0.6130)	(0.5746)	(0.0136)	(0.0126)	(0.3389)	(0.3178)
Data volume	0.0000***	0.0000***	0.0000***	0.0000***		
	(0.0000)	(0.0000)	(0.0000)	(0.0000)		
Smartphone	0.4016***	0.4494***	0.3181***	0.3720***	0.2657***	0.3230***
	(0.0157)	(0.0129)	(0.0199)	(0.0165)	(0.0191)	(0.0161)
_cons	1.7992	1.7891	3.2700	3.2277	2.8300	2.7594

Table 11: DiD regression output coefficients on $lnprice$ and Italy as treatment group country. Treated observation are from 2018 instead of 2019.
Each column, which refers to control group's observations belonging to a specific country, depicts coefficients related to two types of regressions: "1-2-3-4" indicates that baskets 5 and 6 are not included; "All" indicates that all baskets are included. Standard errors are indicated in parenthesis.*** p<0.01, ** p<0.05, * p<0.1

	United Kingdom		**Ireland**	
Data Volume	**1-2-3-4**	All	**1-2-3-4**	All
Causal Effect	**9411****** (2339)	10407*** (2408)	**11341****** (1631)	12131*** (1559)
Country	-4552 (6863)	-5962 (6974)	3864** (1861)	4384** (1854)
2016	246 (1965)	0 (2016)	859 (1004)	782 (1036)
2019	7035 (8924)	4882 (9135)	9050*** (1801)	8589*** (1801)
GDP Growth	-12001 (26528)	-16128 (27318)	361 (408)	405 (422)
Smartphone	-4343*** (739)	-5798*** (684)	-1110* (632)	-1807*** (598)
lnprice	10897*** (781)	12996*** (721)	6655*** (666)	7971*** (627)
_cons	-20609	-23269	-22431	-26586

Table 12: DiD regression output coefficients on $datavolume$**, with Italy as treatment group country**.
Each column, which refers to control group's observations belonging to a specific country, depicts coefficients related to two types of regressions: "1-2-3-4" indicates that baskets 5 and 6 are not included; "All" indicates that all baskets are included. Finland has not the necessary data to perform this analysis. Standard errors are indicated in parenthesis.*** p<0.01, ** p<0.05, * p<0.1

8.2. *Descriptive statistics*

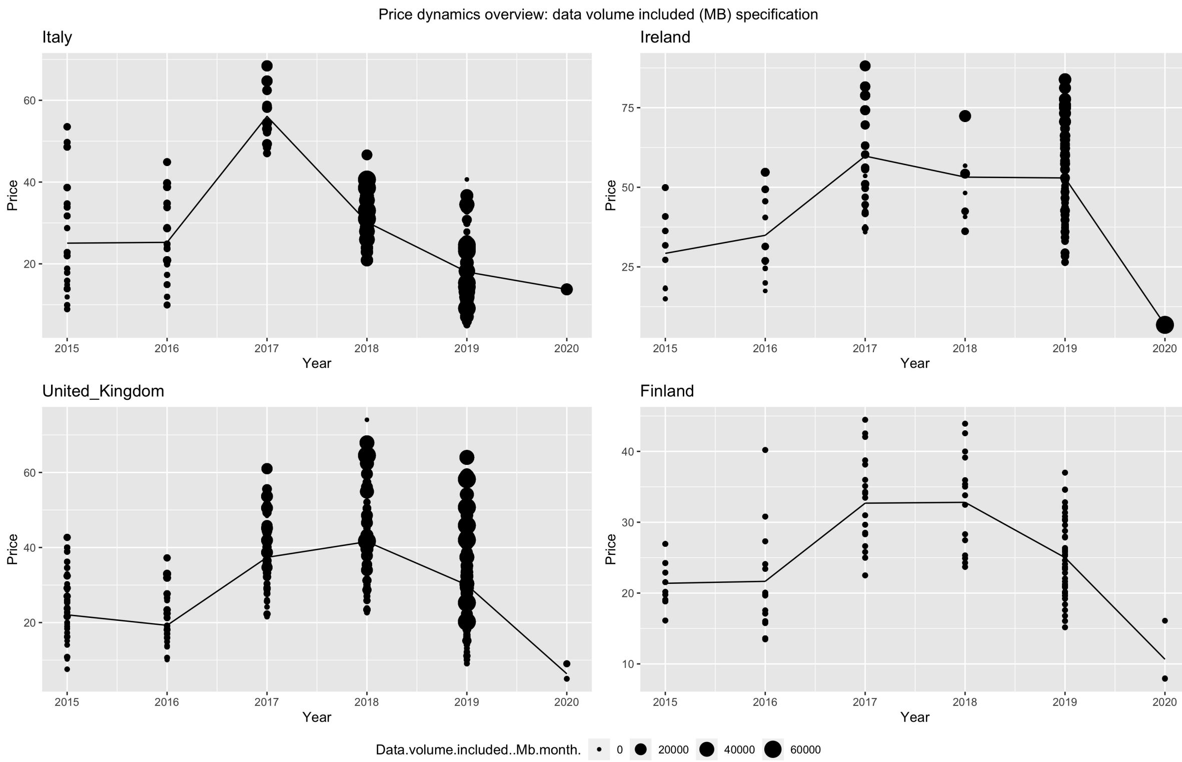

Figure 14. Price dynamics highlighting data volume.
Each point depicts the price related to a specific offer available in a year. The bigger the point, the largest the data volume. Finland has not the necessary data to create the plot, indeed the points have the same size. Be aware that the final part of the graph (2020) is not representative of the real price dynamics, because the set of observations in 2020 is too small and differently chosen.

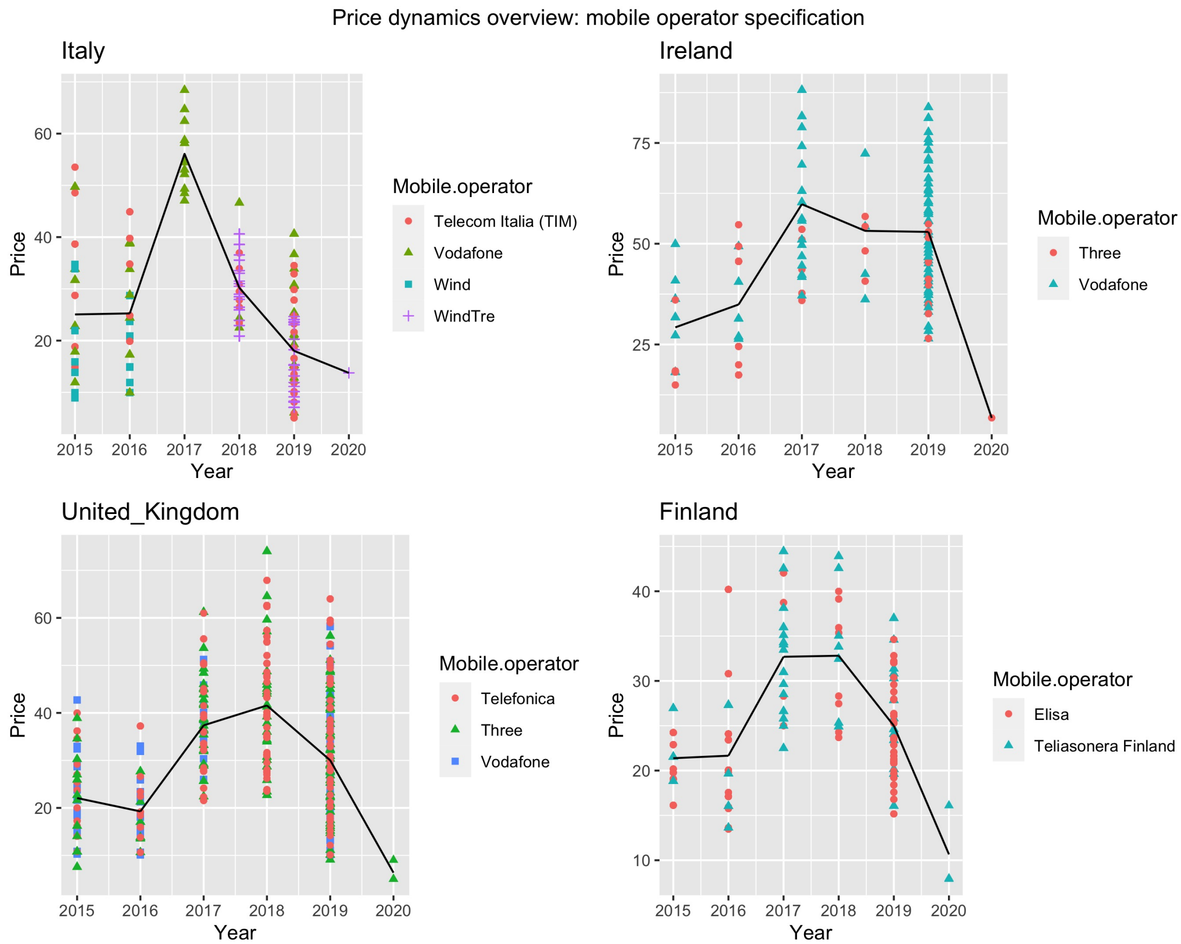

Figure 15. Price dynamics highlighting mobile operator.
Each point depicts the price related to a specific offer available in a year, coloured by the mobile operator which the offer belongs to. Be aware that the final part of the graph (2020) is not representative of the real price dynamics, because the set of observations in 2020 is too small and differently chosen.

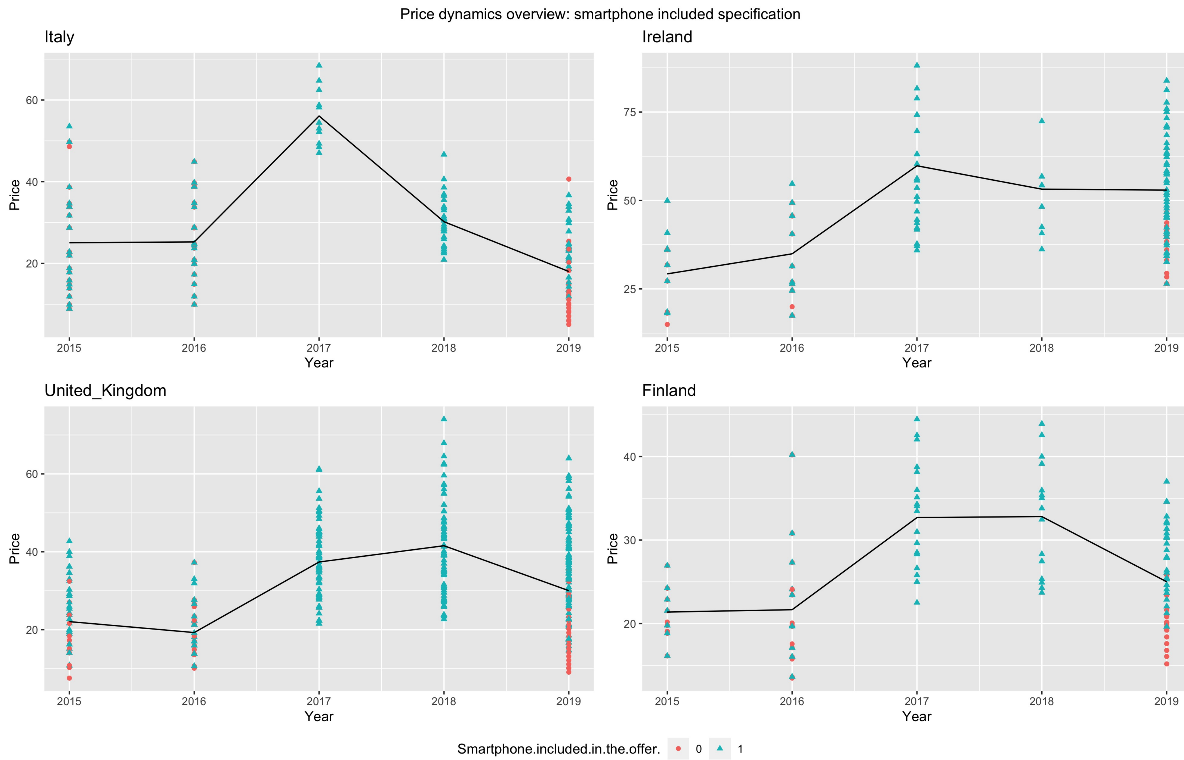

Figure 16. Price dynamics highlighting smartphone included in the offer.
Each point depicts the price related to a specific offer available in a year, and it indicates whether or not the offer includes a smartphone.

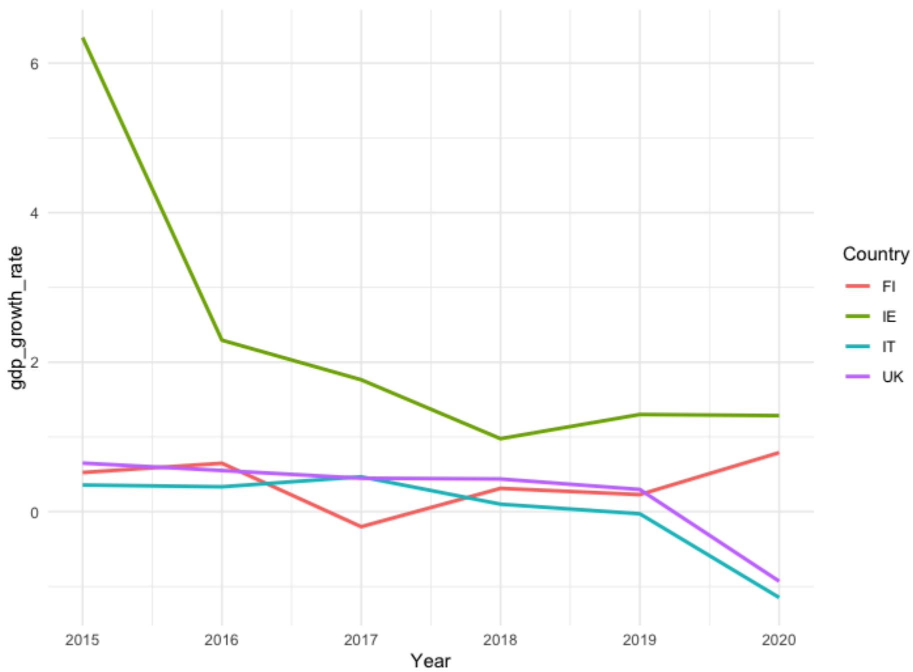

Figure 17. Gross Domestic Product Growth Rate.
Each line depicts GDP growth rate registered from 2015 to 2020 in different countries: Italy (IT), Finland (FI), Ireland (IE) and the United Kingdom (UK).