Empirical analysis on price in Italian mobile telecommunication market: the Iliad effect

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Abstract

This paper aims to analyze the effect of the entry of Iliad in the Italian mobile telecommunication market which was a structural change imposed by the European Commission. This market has always been characterized by the presence of only 4 operators with their own network (MNOs); in 2016 Wind and Tre fusion was conditioned by the European Commission on the entry of another MNO (Iliad) which took place on May 2018. Until the entry of Iliad, there were no structural shocks in this market and the established structure has been defined as "tight oligopoly". This sequence of events gives us a perfect case study for policy evaluation, analyzing how this shock could change the structure of the competition, maybe leading to an effective oligopolistic competition. We found causal relation between the entry of Iliad and price quantity ratio as we expected. The estimated effect resulted in a substantial decrease in the price of gigabytes and call minutes, thus leading to an increase in total social welfare.

1. Introduction

This study provides an in-depth analysis of price/quantity ratio changes in the Italian mobile telecommunication market due to the entry of Iliad. This major event was imposed by the European Commission, which agreed on the merger between two MNOs (Wind and Tre) and designed a structural change to protect consumers' interests. Before this innovation was imposed, the Italian telecommunication market could be defined as "tight oligopoly", which is not beneficial for consumers; the entry of Iliad probably caused the market to change, leading it to become a more effective oligopolistic competition, thus increasing total social welfare. It is important to evaluate the effects caused by this European Commission's policy to understand whether or not it would be beneficial from a social welfare perspective. This is useful to suggest further implementations in similar markets.
To test our hypothesis (price/quantity ratio decreased as Iliad entered the market) we constructed a dataset by collecting many mobile rate plans from both MNOs and MVNOs, before and after the entry of Iliad. We performed web scraping techniques to get the data from *SosTariffe* website, which reports, for each mobile pricing plan, the offer's composition (gigabytes, minutes, and SMSs), its out-of-the-market date, its name and the mobile operator supplying it. Analyzing these data we found evidence of a causal effect driven by the entry of Iliad, which caused the price/quantity ratio to decrease. Using Sharp RDD technique we evaluated the coefficients of many variables, among which the most relevant is the dummy detecting the entry of Iliad in the market (*iliad_entry*, which coefficient captures the causal effect of interest).
The rest of this work is structured as follows: Section 2 illustrates the historical and technical context in which our study operates; Section 3 explains theoretical concepts which are key to understanding the implications of the structural change; in Section 4 we show how we constructed the dataset, designed variables of interest and implemented Sharp RDD in this framework; Section 5 describes econometric results and their interpretation and Section 6 concludes the paper with a concise sum-up. We also integrate all the previous sections with descriptive statistics, robustness, and validation checks in the Appendix (Section 7).

2. Mobile telecommunication market in Italy: context

The Italian telecommunication market has always been characterized by the presence of at most 4 operators provided with a complete infrastructure (meaning, those with their own network: the so-called mobile network operators, MNOs). This market is, indeed, regulated by a mechanism of licenses that entitles the right of using radio frequencies. From 2003, when Tre H3G entered the market, to 2016 there have been the same 4 MNOs (Tim, Vodafone, Wind, and Tre) and a niche of small virtual operators (meaning, those operators which do not owe a network, but they need to find an agreement for the utilization of MNOs networks, the so-called MVNOs).

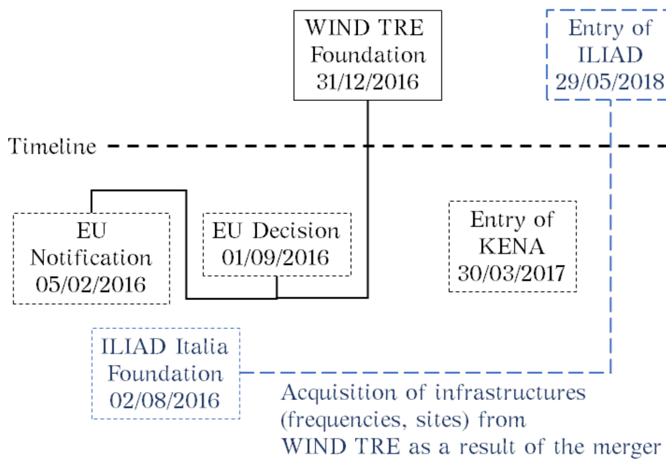

Figure 1. Timeline market dynamics.

In this period no important structural shocks happened to the competitive structure. 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. The merger was conditioned by the Commission on the implementation of corrective structural measures to safeguard competition. 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.

As far as consumers are concerned, this concentration could have led with a high probability, among other things, to (i) a welfare deterioration, (ii) a reduction of the spectrum of choice, (iii) a decrease in the quality of

> mobile services and, finally, to (iv) a (likely) increase in prices, due to the emergence of conditions that would have facilitated strategic coordination among MNOs [2].

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, in 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.

3. Theoretical Framework

Perfect competition with a large number of suppliers and consumers results in prices equal to marginal cost, and 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 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 [3].

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 undertakings individual best reaction to its competitors behavior [3].

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 constraint, low price-elasticity, and low growth of demand. The market scenario established before the entry of Iliad is strongly characterized by all these traits. Our aim is not to say if the market structure established before Iliad entry was collusive tacitly or not (which could also be, but it is not our responsibility), but to show how a structural shock imposed by the European Commission in a tight oligopoly setting (as defined by Ardovino and Delmastro [2]) changed the price/quantity ratio improving or not total welfare for society and maybe leading to effective oligopolistic competition.

4. Study design

In Section 4.1 we describe how the dataset is constructed; in Section 4.2 we list the variables we used and how we built them. In Section 4.3 we describe analytical techniques used to perform econometric analysis and technical tools to achieve the results.

4.1 Dataset

Data recovery of mobile pricing plans could not rely on pre-existing datasets and collections made available by the telecommunication operators themselves: in fact, they do not store any data concerning the past offers they made (or they simply do not allow to access them). We contacted a few sector experts (a few employees from a physical store, a manager from Vodafone, and the director of *mondomobileweb.it*[1] dedicated to news about the telecommunication market), which confirmed that no dataset is available anywhere. The dataset has been constructed by inspecting an Italian price comparison website, *SosTariffe*[2], which has a section dedicated to mobile phone rate plans. This source has been chosen because it has a very useful archive section that contains many past mobile pricing plans. To get the data from the website, we designed a web scraping algorithm (using Python programming language), which is capable of obtaining much information about each mobile rate plan existing in the archive section in *SosTariffe*; for each plan we collected: the mobile phone company name, the mobile rate plan name, the contract length, the quantity of internet data offered, the quantity of minutes and SMSs offered, the contract fee (euros), the plan expiration date in the market (the day after which it is not possible to subscribe the plan anymore). Since the units of measure differ from plan to plan, it has been necessary to convert the data into standardized

[1] https://www.mondomobileweb.it/
[2] https://www.sostariffe.it/

units: gigabytes for internet data, number of minutes for calls, and number of messages for SMSs.

Once we obtained the initial data, we filtered out the observations with no plan expiration date, the ones with no information about internet data, minutes, and SMSs, and the observations which are missing the contract fee. From an initial set containing 888 observations, we ended up with 622 items. Formally, our dataset is observational and the data has been measured at the mobile pricing plan level.

We performed a granular check (consulting *mondomobileweb.it* and other resources) to verify the information collected and to specify many possible contract types, such as business, *winback*[3] (only four observations are present), travel or additional options contracts, and plans including music, movies, or smartphones. We identified which operator is an MVNO and which is not, in order to perform also separate analyses. To conclude the verification of the collected data, we consulted a few sector experts, asking them whether or not the observations are representative and correct.

It would have been nicer to have more observations accounting for the different types of mobile rate plans existing in the market (see Figure 2), in particular, two of them which had played a very important role in replying to Iliad more convenient offers: win-back and renegotiation with actual operators[4].

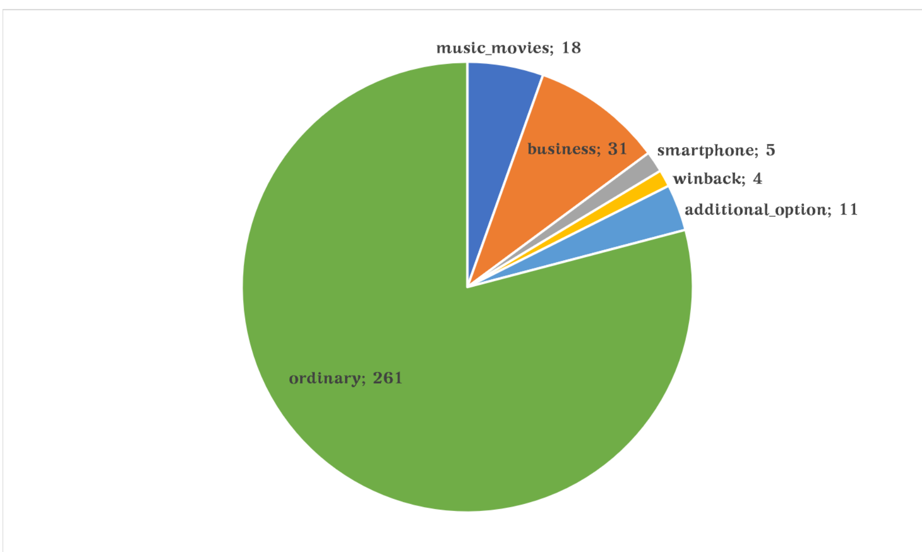

Figure 2. Types of mobile rate plan dataset composition.

[3]Mobile rate plans reserved to past clients who switched to competitors; usually they are more convenient than the regular rates.

[4]Revisited mobile rate plans reserved to actual clients to prevent them from switching to competitors.

However, the dataset is rich enough to perform a reliable analysis knowing that the effect could only be underestimated. Moreover, it would have been nicer to have uniformly time-distributed observations, but this is not possible since new mobile rate plans are put on the market mainly in two periods of the year: in summer and in winter. Another source of impossibility is the reduction of items after the entry of Iliad: it does not make sense to have many differentiated plans because nearly all of them have unlimited quantities offered at a low price.

4.2 Variables

To perform the econometric analysis we constructed the following variables:

- *time_from_iliad_entry* is an integer representing the difference (in days) between a plan's expiration date and Iliad entry's date (which is zero days apart from itself); if the former is before the latter, the integer takes a negative value (and positive otherwise). It is constructed using *out_of_market* date, which represents the moment until the plan is available in the market; furthermore, being an expiration date, it indicates when an operator decides to remove an offer because it does not fulfill the consumer's desires anymore. However, it is important to account for this time lag concerning in-market dates when interpreting econometric results;
- *daily_giga_cost*, *daily_calls_mins_cost* and *daily_sms_cost* represent how many gigabytes, minutes, and SMS one can have in a plan for every euro of cost. It represents the quantity/price (daily measured) ratio of each component (gigabytes, minutes, SMSs). They are computed as follows: $\frac{gigabytes}{contract\_length} * \frac{1}{daily\_cost}$, switching *gigabytes* to either *minutes* or *sms* accordingly;
- *daily_giga_norm*, *daily_calls_mins_norm*, and *daily_sms_norm* represent how many gigabytes, minutes, and SMS are available per day for any plan. These variables are necessary to make the quantities comparable within different components of a plan. They are computed normalizing the following quantity $\frac{gigabytes}{contract\_length}$, switching *gigabytes* to either *minutes* or *sms* accordingly;
- *aggregated_index*, *aggregated_index_cost* are compound variables obtained as follows: the former is computed by adding together *daily_giga_norm*, *daily_calls_mins_norm* and *daily_sms_norm*; the latter is computed in this way $\frac{daily\_cost}{aggregated\_index}$. They capture the price/quantity ratio to make the observations comparable among the three components in a plan and to highlight how they contribute to the general effect we want to study;
- *whatsapp_norm* is computed normalizing the number of researches for the words

"Whatsapp download" in Google search (in Italy). It is a proxy for the Whatsapp penetration rate in Italy;

- *music_movies*, *business*, *smartphone*, *winback*, *additional_option*, *virtual*, *wind_tre_mno*, *vodafone_mno*, *tim_mno* are dummies indicating whether or not a mobile pricing plan contains respectively a subscription for music or movies apps, is a business dedicated plan, includes a smartphone, is a win-back offer, is an additional option, is supplied by an MVNO, belongs to an MVNO using Wind Tre, Vodafone or TIM infrastructures;
- *extra_italy*, $4G$, $5G$, *wind_tre_foundation*, *iliad_entry*, *ho_entry*, *spusu_entry*, *kena_entry*, *very_entry* are dummies indicating time thresholds respectively for the free roaming in EU, the presence of 4G technology, the presence of 5G technology, Wind Tre foundation, Iliad, Ho, Spusu, Kena and Very entry.

4.3 Methodology

The variables *aggregated_index* and *aggregated_index_cost* are computed by adding together *daily_giga_norm*, *daily_calls_mins_norm* and *daily_sms_norm*, as said previously in Section 4.2. To rely on these compound variables we assumed that each normalized (both daily and numerically) component in a mobile rate plan has the same importance, making the weight of the corresponding factors the same. We proved through robustness checks (see Appendix 7.1.3) that this assumption does not interfere with the goodness of our results. However, we noticed that gigabytes and minutes are more important than the number of SMSs in a mobile plan (see Appendix 7.2).
To prepare the data for processing and analyzing steps, we balanced it around Iliad entry date, obtaining a time span from 1000 days before and after the zero time threshold. We then identified outliers in the distribution of *aggregated_index_cost* (being a compound variable it is easier to spot out-of-the-range observations), selecting and dropping items that have a value higher than $3rdquartile + 1.5 * (3rdquartile - 1stquartile)$ (we did not account for extremely lower-the-range values because there are none). The resulting dataset consists of 330 observations. Inspecting those 31 outliers, we found out that their nature is consistent with 4 main categories: travel offers, business offers, additional options, and plans dedicated to consumers who are not interested in having big amounts of gigabytes or who minimize smartphone usage. Elderly people enter the latter category and as reported in [2], they have a very low *churn rate*[5] which could explain a higher price/quantity ratio.

[5] Propensity of switching operator.

In the following, we list the tools we used to obtain the dataset and perform analysis. Web scraping and data collection were performed in Python, using `pandas`, `request`, `BeautifulSoup`, `json`, and `xlsxwriter` libraries. Data management was performed mainly in MS Excel. Data and econometric analysis were performed mainly on Stata and Python (only for correlation functions and plots, with `matplotlib`, `numpy` and `searborn`).
We used a Sharp Regression Discontinuity Design to verify our hypothesis on Iliad entry's causal effect on prices.

> Sharp RDD is used when treatment status is a deterministic and discontinuous function of a covariate, x_i [1].

We are able to work with Sharp RDD because we have many observations in the neighborhood of the threshold: this allows RDD to highlight the mean outcomes of treated and non-treated items at the margin, controlling for confounding factors and extracting the causal effect of interest, which is the mean impact of intervention locally at the threshold. Moreover, there is no value of $iliad\_entry_i$ at which we get to observe both treatment and control observations. The problem is formulated as follows. The treatment status *iliad_entry* is evaluated as

$$iliad\_entry_i = \begin{cases} 1 & \text{if } time\_from\_iliad\_entry_i \geq 0 \\ 0 & \text{if } time\_from\_iliad\_entry_i < 0 \end{cases} \tag{1}$$

where $iliad\_entry_0$ is the Iliad entry cutoff (which is 30th May 2018, the day after the presentation of the first Iliad pricing plan). The model formalizing the RDD idea applied in our case study is characterized by the assignment mechanism (1) and by potential outcomes described by

$$\begin{aligned} E[prices_{0i}|iliad\_entry_i] &= \alpha + \beta * time\_from\_iliad\_entry_i \\ prices_{1i} &= prices_{0i} + \rho \end{aligned} \tag{2}$$

From (1) and (2) we can build the regression

$$prices_i = \alpha + \beta * time\_from\_iliad\_entry_i + \rho * iliad\_entry_i + \varepsilon_i \tag{3}$$

where ρ is the causal effect.
Our main analysis was performed using Stata and its regression tools. We have also approached RDD using ad-hoc packages `rdrobust` and `rdplot`, which are designed onto the theoretical framework illustrated in [4]: these tools served to check on coefficients

resulting from classical regression Stata functions (adjusted on the formal methods described above). We run two other robustness checks (sliding threshold and incremental neighborhood sizes around the threshold), which we will describe in Appendix 7.1.2 and 7.1.1.

5. Econometric results

In the following, we illustrate regression outputs and econometric results interpretation. Figure 3 shows a discontinuity at Iliad entry time threshold in price/quantity ratio distribution (Figure 3 was obtained using `rdplot` Stata command). It not only shows the gap in the dependent variable at the time threshold but also different dynamics before and after the structural shock (marked at *Time from Iliad entry = 0*). We can see that in the previous 1000 days the dependent variable oscillates at higher values without decreasing: this is the perfect representation of previous immobility in the telecommunications market. Immediately after the entry of Iliad it is evident the development of a different trend characterizing market dynamism.

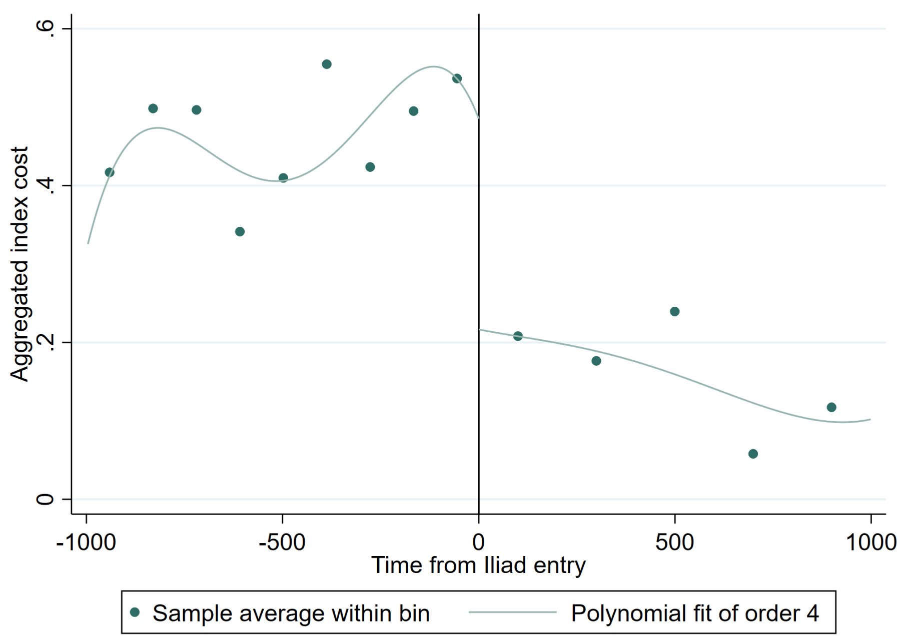

Figure 3. Regression Discontinuity representation. Graphical representation of RD on *aggregated_index_cost* with cutoff set at Iliad entry time threshold using `rdplot` Stata command.

We then implemented the Sharp RD theoretical method described in Section 4.3

using `regress` Stata command, obviously keeping *time_from_iliad_entry* and *iliad_entry*, but adding more and more explanatory variables. Selecting an increasing number of independent variables in the regression framework allows us to spot major changes in the causal effect (*iliad_entry*'s coefficient) and all the other variables.

Regression outputs in Table 1 show that the causal effect captured by *iliad_entry* coefficients are negative and huge compared to constant terms in all six regressions and always significant at 99% confidence level, as expected.

In Appendix 7.1.1 and 7.1.3 we also graphically represent regression (2) iterated at different time thresholds and with different weights in *aggregated_index* (testing our assumption) adding reliability to our analysis.

These effect magnitudes are underestimated because we could not take into account many win-back offers (only 4 observations recognized in the dataset) and no private renegotiation within the same operator (the percentage of users who renegotiate the terms of their commercial relation change from 2% up to around 15% after Iliad entry), which played a massive role in competing with Iliad [2].

Dependent variable : aggregated_index_cost						
	(1)	**(2)**	(3)	(4)	(5)	(6)
time_from_iliad_entry	**0.0000**	**0.0000**	0.0000	0.0000	0.0000	0.0000
	(0.0001)	**(0.0001)**	(0.0001)	(0.0001)	(0.0001)	(0.0001)
iliad_entry	**-0.2966*****	**-0.2919*****	-0.2957***	-0.2968***	-0.3063***	-0.3090***
	(0.0555)	**(0.0538)**	(0.0537)	(0.0539)	(8.0541)	(0.0545)
business	**No**	**0.2848*****	0.2905***	0.2898***	0.2860***	0.2844***
		(0.0600)	(0.0600)	(0.0601)	(0.0600)	(0.0602)
music_movies	**No**	**No**	0.1273	0.1262	0.1219	0.1194
			(0.0790)	(0.0792)	(0.0790)	(0.0793)
smartphone	**No**	**No**	No	-0.0420	-0.0482	-0.0509
				(0.1437)	(0.1434)	(0.1437)
winback	**No**	**No**	No	No	-0.2646	-0.2674
					(0.1601)	(0.1604)
additional_option	**No**	**No**	No	No	No	-0.0415
						(0.0987)
_cons	**0.4753*****	**0.4444*****	0.4406***	0.4417***	0.4502***	0.4530***
	(0.0336)	**(0.0332)**	(0.0332)	(0.0335)	(0.0338)	(0.0345)
Adj R-squared	**0.1525**	**0.2048**	0.2086	0.2064	0.2106	0.2086

Table 1: Regression output coefficients on *aggregated_index_cost*. Each column indicates regression outputs for different sets of independent variables. Standard errors are indicated in parenthesis.*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Adding explanatory variables does not change the magnitude of the coefficient and its significance level. The effect proportion (coefficient/*_const* ratio) computed in regression (2) is -0.65692. Only the *business* dummy variable has a significant coefficient with the expected positive sign (being business plans more expensive because they have more warranties), while the others are not significant. Focusing on the last regression output (6), we can state the following considerations on the remaining variables:

- *time_from_iliad_entry* coefficient (0.000) indicates that the dependent variable is not affected by time passing by. This suggests that without the structural shock the previous setting would probably lead the price/quantity ratio to stay the same;
- *music_movies* coefficient has the expected positive sign (0.1194) and magnitude;
- *smartphone* coefficient does not have the expected positive sign (-0.0509) and it has a very large confidence interval (see Figure 4);

- *winback* coefficient has the expected negative sign (-0.2674) and magnitude;
- *additional_option* coefficient has a negative sign (-0.0415). We expected it to have a positive sign because these types of plans are designed to include lower quantities at higher prices compared to basic plans.

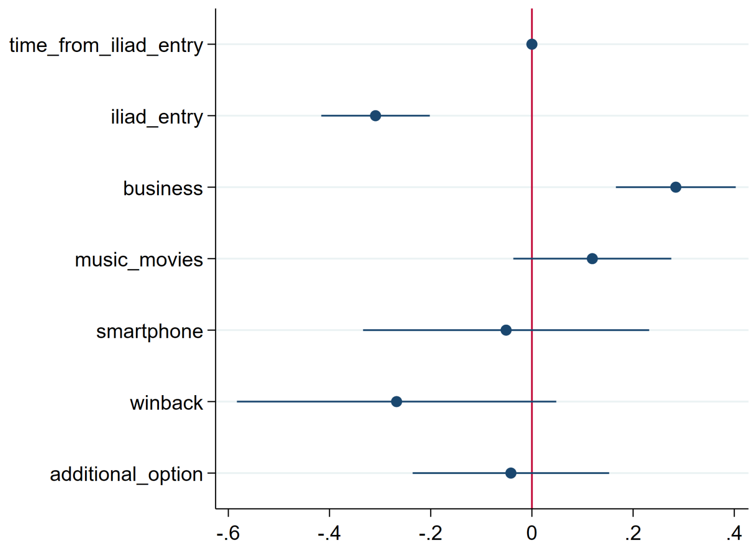

Figure 4. Independent variables coefficient distributions. Graphical representation of independent variables coefficient distributions on *aggregated_index_cost*. Horizontal bars represent 95% confidence intervals.

The coefficient of *music_movies*, *smartphone*, *winback*, and *additional_option* are not statistically significant: this is probably due to the lack of observations of those types (see Figure 2) and inaccurate labeling performed on existing items (these pieces of information are not available for each mobile rate plan). It is important to notice that the Adjusted R-squared value has a substantial increase by adding the *business* dummy variable, but including other variables does not affect it too much.
In Table 2 it is illustrated the regression output given by `rdrobust` Stata command: *aggregated_index_cost* is the dependent variable, while *time_from_iliad_entry* is the independent variable with cutoff specification (0, automatically selected by the algorithm) on *iliad_entry* time threshold. Here we can see that the coefficient of interest capturing the causal effect is perfectly consistent with previous findings in Table 1, giving the study higher reliability.

Sharp RD estimates using local polynomial regression.						
Cutoff c = 0	Left of c	Right of c		**Number of obs**		**330**
Number of obs	195	135		BW type	=	mserd
Eff. Number of obs	97	101		Kernel	=	Triangular
Order est. (p)	1	1		VCE methods	=	NN
Order bias (q)	2	2				
BW est. (h)	390.938	390.938				
BW bias (b)	593.917	593.917				
rho (h/b)	0.658	0.658				

Outcome: *aggregated_index_cost*. **Running variable**: *time_from_iliad_entry*.						
Method	Coef.	Std. Err.	z	Pz	[95% Conf.	Interval]
Conventional	**-0.3004**	**0.07303**	**-41.134**	**0.0000**	**-0.44353**	**-0.15726**
Robust	-	-	-35.100	0.0000	-0.45208	-0.1281

Table 2: `rdrobust` Stata regression output on *aggregated_index_cost*. Regression Discontinuity output on *aggregated_index_cost* using `rdrobust` Stata command with cutoff set at Iliad entry time threshold.

In Appendix 7.1.2 are also reported the coefficient results of the standard regression framework and their confidence intervals at different neighborhood sizes adding reliability to our analysis. In Table 3 we illustrate the regression output on non-aggregated dependent variables using the standard Stata regression command. In these regressions, we only added the business regressor because it resulted to be the only relevant one. We can see that the coefficient of our variable of interest (*iliad_entry*) is positive in every regression, meaning that the entry of Iliad increased the quantity per euro spent. Only in the last regression (on *daily_sms_cost*) the *iliad_entry* coefficient is small and completely not significant, meaning that the structural shock did not affect the quantity/price ratio with respect to SMSs. SMSs are the least relevant part of a mobile plan and this is possibly due to the fact that almost everyone uses online instant messaging applications (i.e. Whatsapp). It is reasonable to assume that Iliad entry did not affect this part of plans because it was not relevant and because the quantity/price ratio increased together with the online instant messaging services downloads (which are free substitutes). We tried to spot this correlation, but we did not manage to do so because our proxy variable (*whatsapp_norm*) for online instant messaging services downloads was not representative.

Regarding *daily_giga_cost* and *daily_calls_mins_cost* regressions, we can say that the Iliad entry effect results in an increase of 1.302 gigabytes and 204.223 minutes per euro paid in a mobile plan.

	(1) *daily_giga_cost*	(2) *daily_calls_mins_cost*	(3) *daily_sms_cost*
time_from_iliad_entry	0.0019***	0.2334***	0.0696
	(0.0003)	(0.0549)	(0.0342)
iliad_entry	**1.3018*** **	**204.2225*** **	**16.3182**
	(0.2828)	**(51.2270)**	**(31.9410)**
business	-1.0648***	-196.9931***	-73.8113
	(0.3156)	(57.1703)	(35.6468)
_cons	1.3247***	253.6591***	102.7095***
	(0.1745)	(31.6121)	(19.7107)

Table 3: Regression output coefficients on non-aggregated variables. Each column indicates regression outputs for different non-aggregated dependent variables. Standard errors are indicated in parenthesis.*** p<0.01, ** p<0.05, * p<0.1

Starting from a constant of 1.325 gigabytes and 253.659 minutes we can say that gigabytes and minutes per euro nearly doubled. It is also important to keep in mind that this is probably an underestimate of the real effect for the reasons previously cited.

6. Conclusions

In this paper, we examined the effect of a structural change imposed by the European Commission on the Italian telecommunication market. We do this by analyzing mobile plan prices in a 2000 days period around the Iliad entry time threshold using Sharp Regression Discontinuity Design.

Econometric analysis shows that this shock produced a huge effect on the price/quantity ratio, thus reducing the price of a really necessary service. This event led the average daily price from 0.57 euros for 0.2 gigabytes, 77 call minutes, and 32 SMSs (in the previous 1000 days) to 0.40 euros for 1.1 gigabytes, 170 call minutes, and 42 SMSs (in the following 1000 days). There was not only a price reduction but also an improvement both in quality and in variety of the supply as said in [2]. This produced a substantial increment in both consumers and social welfare, especially for the less wealthy cohorts of the population (which has a higher *churn rate* [2]). It is important to remark that this happened while keeping constant the number of competitors (four MNOs), but changing their kind: this for sure led from a tight oligopoly to a more efficient type of competition (maybe an effective oligopolistic competition). It is the opinion of the authors that the implementation of similar policies in similar markets would for sure be beneficial. For future research, it would be interesting to see whether this competitive setting will persist keeping on its beneficial effects or not (new establishment of a tight oligopoly). Another possible future research would be to analyze prices in other European markets where no such a change happened to compare them.

7. Appendix

7.1 Validation and robustness checks

7.1.1 Threshold robustness check

In order to check when the greater effect took place and whether or not other relevant events happened in our timeline, we performed iterated regressions (of the form of regression (2) in Table 1), taking into account different time thresholds for the dummy variable *iliad_entry* (which in this framework actually represents *iliad_entry* near to 0 and different events when distancing from it). In Figure 5 we graphically represent the different coefficients and their 95% confidence intervals of this variable at every monthly change in time threshold temporal location. It is easy to see that the most relevant and statistically significant event took place exactly around the Iliad entry time threshold thus providing strong reliability to our causal finding. It is also important to remember that no relevant event different from the Iliad entry took place near that moment: we are sure that the spotted effect could only be associated with it. In the 2000 days taken into account, we can also see that there are no other relevant significant coefficients with only one exception. Between month -19 and month -12 there are few positive and significant coefficients, that are exactly centered around the date of WindTre foundation (31st December 2016), meaning that probably this event produced an increase in price/quantity ratio as expected from economical literature on the number of competitors (decrease in the number of competitors facilitates coordination, probably leading to an increase in price). It is also important to take into account two different lag effects: one provided by the time lag from mobile plans in-market and out-of-the-market date (which would probably provide a slight posticipation of the effect in the graph) and the other is the one provided by expectations of competitors (which would probably lead to slight anticipation of the effect). It is reasonable to think that the two effects compensate each other, thus hiding the anticipation effect and making the higher effect perfectly correspond to the

Iliad entry time threshold.

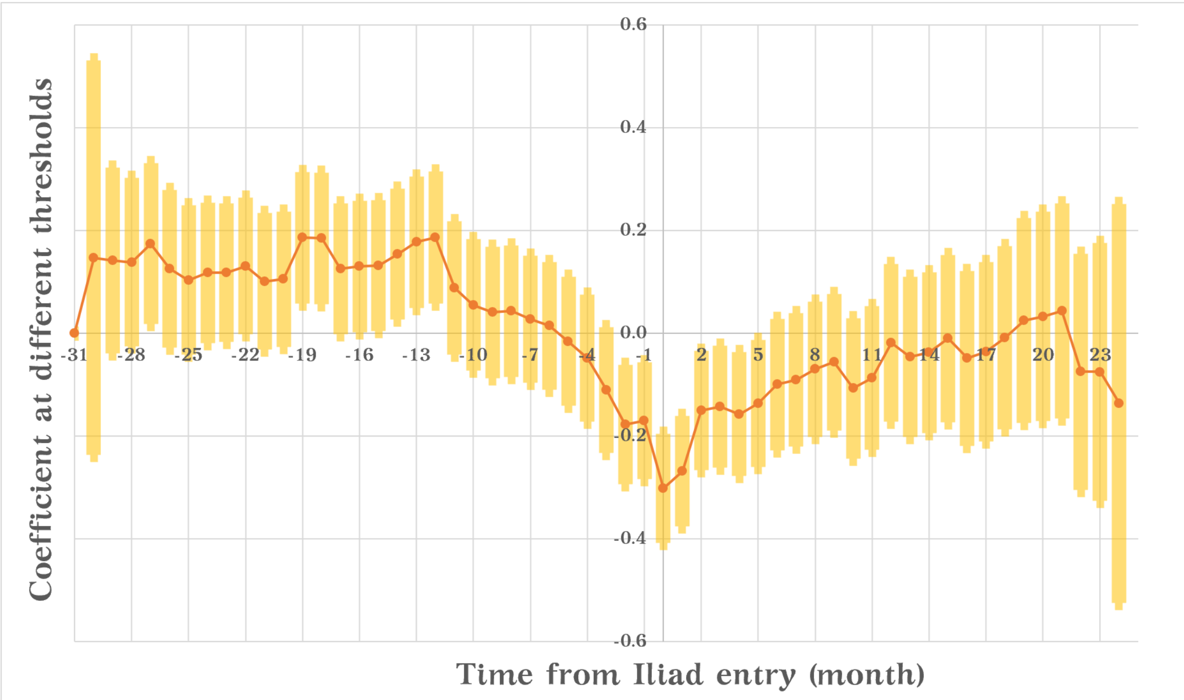

Figure 5. Thresholds robustness check. Graphical representation of regression output coefficients on *aggregated_index_cost* for several threshold variables (monthly time leads and lags). It captures the effects of possible events at different moments on the dependent variable. Vertical bars represent 95% confidence intervals. The timeline is centered at zero, when Iliad entered the market.

In the following, we also show the same graphical representation for the two different types of operators (MNOs and MVNOs), to spot any difference in the two market responses. We expected to see a slight anticipation in the MVNOs graph because it is known that Vodafone and Tim used their associated MVNOs (HO MOBILE and Kena MOBILE) to strongly compete with Iliad, but we didn't find any relevant difference (possibly due to lack of MVNOs observations, only 105, see Figure 2).

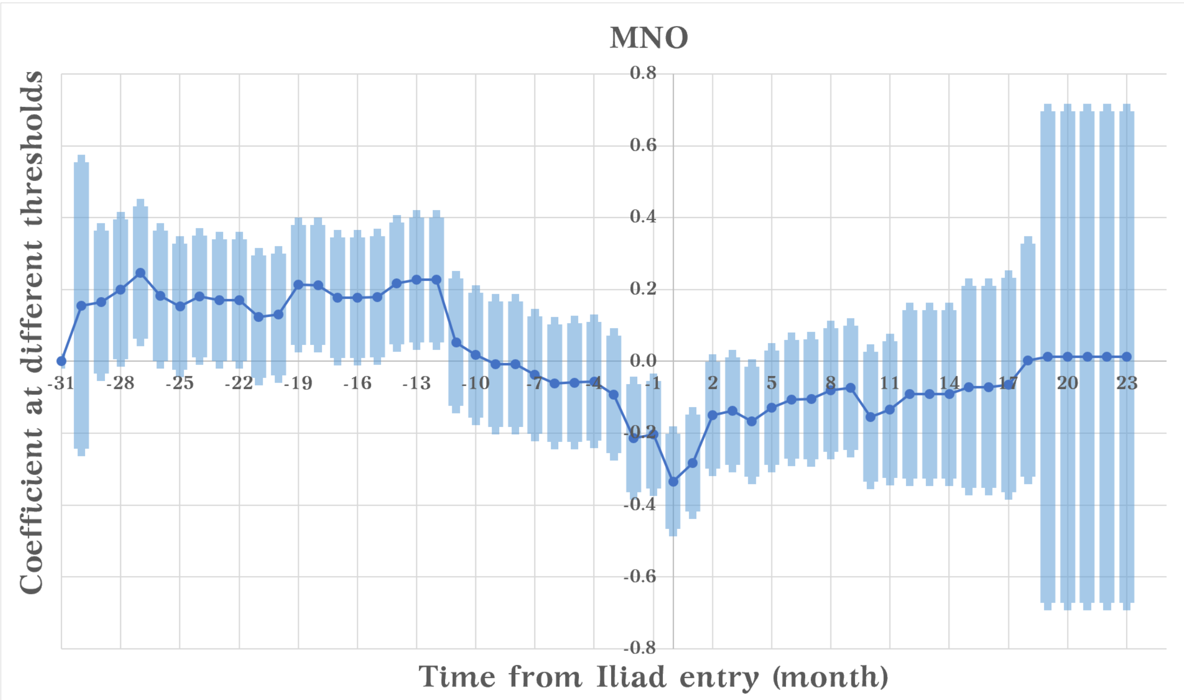

Figure 6. MNO thresholds robustness check. Graphical representation of regression output coefficients on *aggregated_index_cost* for several threshold variables (monthly time leads and lags). It only accounts for MNO mobile pricing plans. It captures the effects of possible events at different moments on the dependent variable. Vertical bars represent 95% confidence intervals. The timeline is centered at zero, when Iliad entered the market.

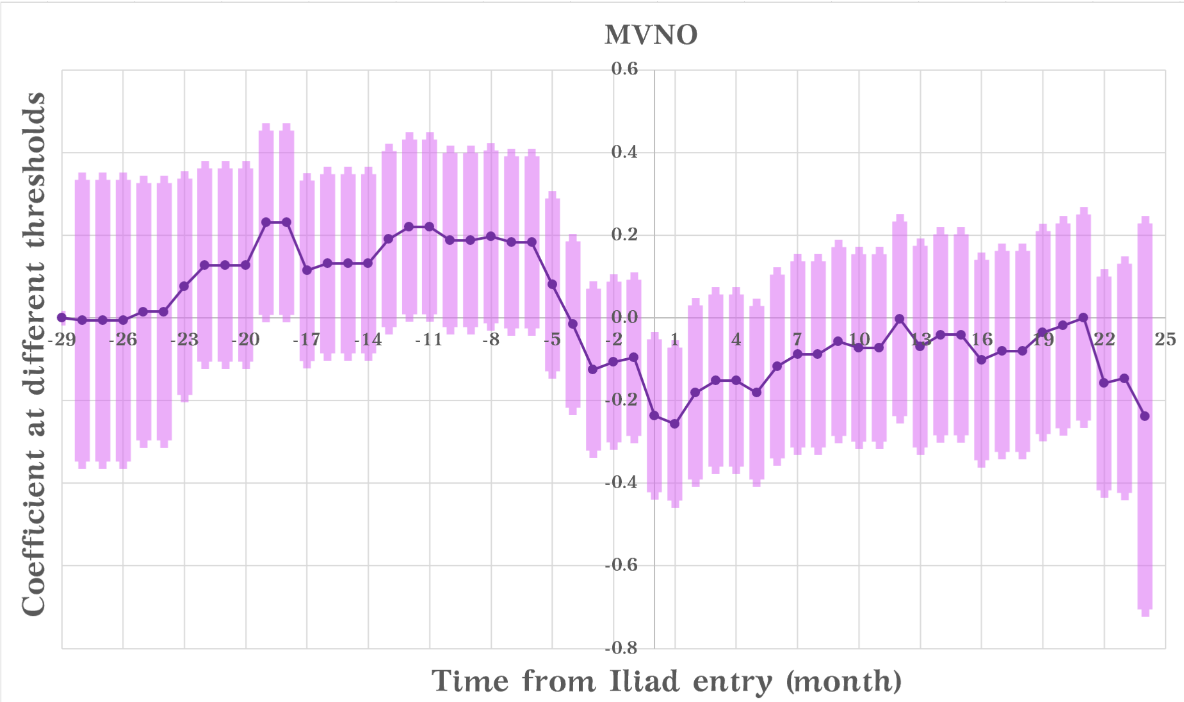

Figure 7. MVNO thresholds robustness check. Graphical representation of regression output coefficients on *aggregated_index_cost* for several threshold variables (monthly time leads and lags). It only accounts for MVNO mobile pricing plans. It captures the effects of possible events at different moments on the dependent variable. Vertical bars represent 95% confidence intervals. The timeline is centered at zero, when Iliad entered the market.

7.1.2 Neighborhood sizes robustness check

In this section, we analyze how the neighborhood size around the time threshold affects the econometric results. In particular, we focus on the causal effect, thus on *iliad_entry* coefficient estimates. Given different monthly ranges (6 months around zero time threshold, 12, 18, ...), we selected subsets according to how many months around the Iliad entry we wanted to include in our regressions: doing so, we were able to evaluate both the magnitude of the resulting coefficients and their statistical significance. We applied this methodology to the entire dataset and onto two distinct subsets (one including only MNOs observations and the other including only MVNOs items).

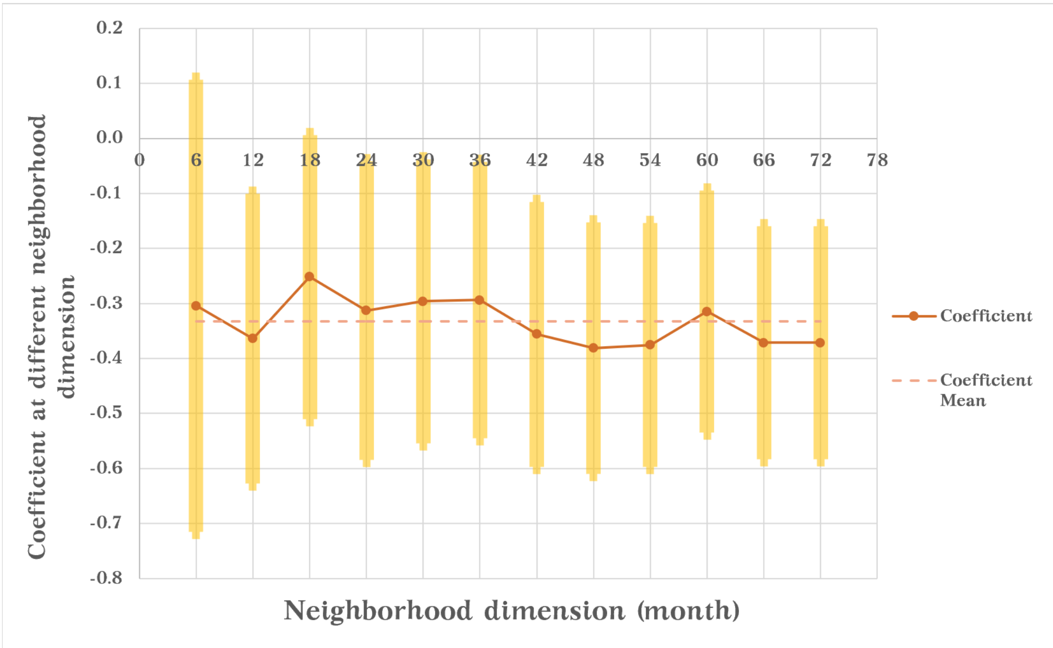

Figure 8. Neighborhood sizes robustness check. Graphical representation of regression output coefficients on *aggregated_index_cost* for several neighborhood sizes around the Iliad entry time threshold (monthly time leads and lags). Vertical bars represent 95% confidence intervals and the dashed line indicates the coefficients' distribution means.

Figure 8 illustrates results using the entire dataset: this picture proves that no matter what the neighborhood size is, the causal effect of interest has always approximately the same magnitude; statistical significance improves as size increases, however, it is worth to notice that after including 42 months it does not change and it becomes stable.

Figure 9 shows that the coefficient magnitude does not change drastically when including more and more observations; this picture is quite different from Figure 8 since the statistical significance is stronger even when we include fewer months in the regression.

Figure 10 illustrates that the coefficient distribution behaves like in Figures 8 and 9, but it is difficult to reach a strong statistical significance: this could be because the cardinality of this subset is not high enough to estimate a strong and significant coefficient.

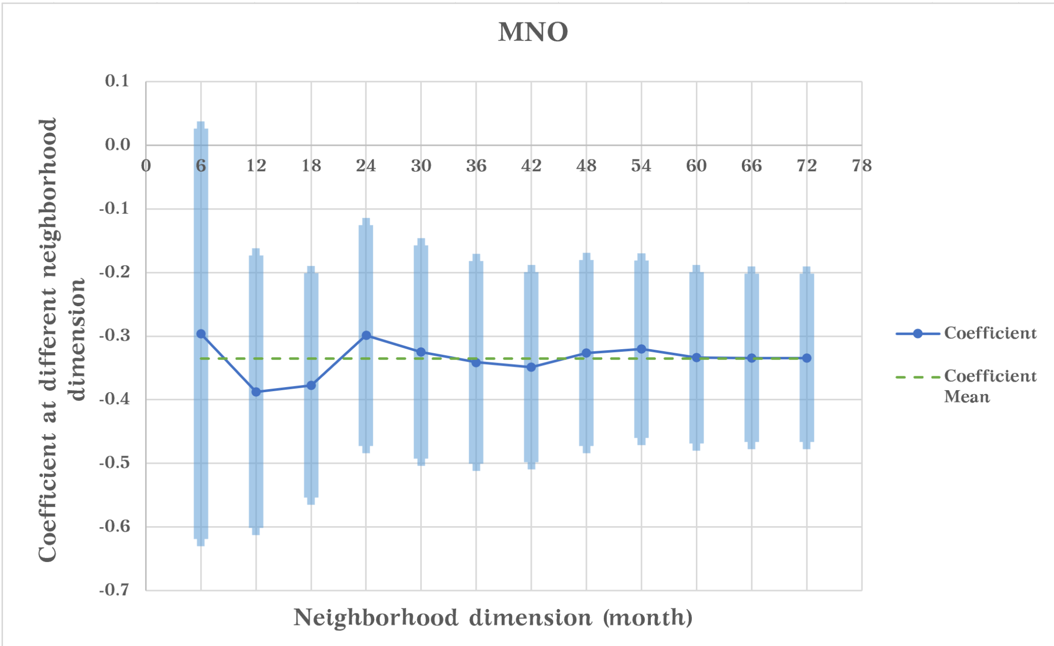

Figure 9. MNO neighborhood sizes robustness check. Graphical representation of regression output coefficients on *aggregated_index_cost* for several neighborhood sizes around the Iliad entry time threshold (monthly time leads and lags). It only accounts for MNO mobile pricing plans. Vertical bars represent 95% confidence intervals and the dashed line indicates the coefficients' distribution means.

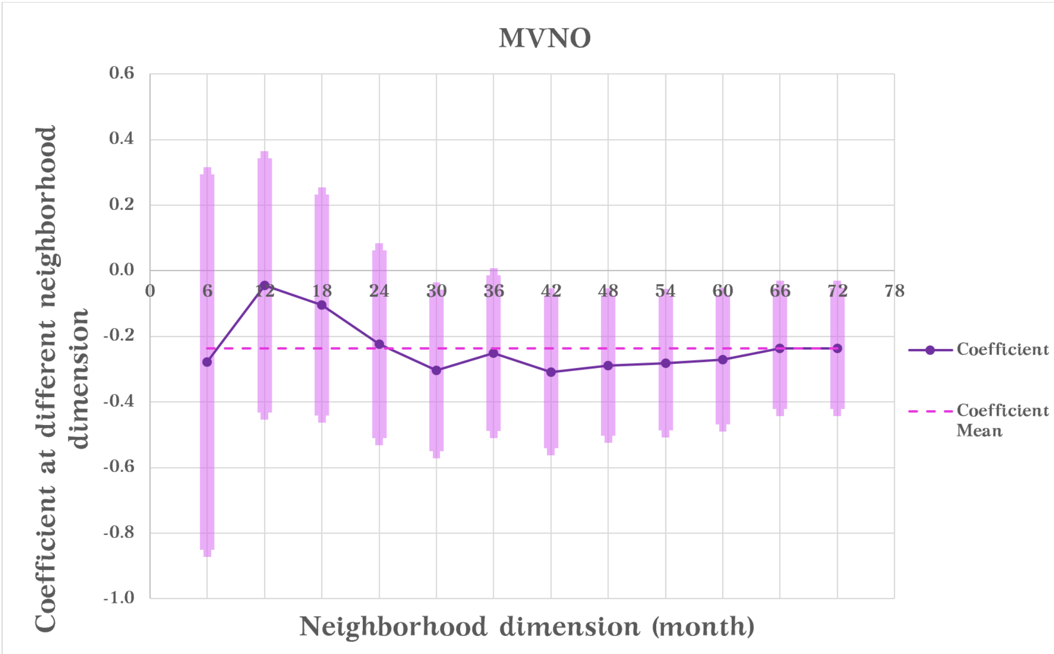

Figure 10. MVNO neighborhood sizes robustness check. Graphical representation of regression output coefficients on *aggregated_index_cost* for several neighborhood sizes around the Iliad entry time threshold (monthly time leads and lags). It only accounts for MVNO mobile pricing plans. Vertical bars represent 95% confidence intervals and the dashed line indicates the coefficients' distribution means.

7.1.3 aggregated_index_cost weight assumption test

Our main assumption relies on the fact that all three components in a plan (gigabytes, minutes, and SMSs) weigh the same: this is a strong assumption because we know that SMSs are less important than the other two components. We want to see if different assumptions would have led to different estimated results. To do so, we produced three different aggregated measures with different weights: *a_i_c_g2_c2_s1* with gigabytes and call minutes having 2 as weighting multiplier, *a_i_c_g4_c4_s1* with gigabytes and call minutes having 4 as weighting multiplier and *a_i_c_g1_c1_s2* with SMSs having 2 as weighting multiplier. Using these new measures we estimated three new regression outputs and we computed the effect proportion of *iliad_entry* coefficient with respect to the constant term (coefficient/*_cons*).

In Table 4 we can see that, as expected when we weigh the first two components

	(1) *aggregated_index_cost*	(2) *a_i_c_g2_c2_s1*	(3) *a_i_c_g4_c4_s1*	(4) *a_i_c_g1_c1_s2*
time_from_iliad_entry	0.0000	0.0000	0.0000	0.0000
	(0.0001)	(0.0000)	(0.0000)	(0.0000)
iliad_entry	-0.2919***	-0.1845***	-0.1085***	-0.2179***
	(0.0538)	(0.0331)	(0.0202)	(0.0459)
business	0.2848***	0.2004***	0.1242***	0.1754***
	(0.0600)	(0.0369)	(0.0226)	(0.0512)
_cons	0.4444***	0.2714***	0.1577***	0.3513***
	(0.0332)	(0.0204)	(0.0125)	(0.0283)
Effect proportion	**-0.65692**	**-0.679703**	**-0.688216**	**-0.620188**

Table 4: *aggregated_index_cost* **weight assumption test**. Each column indicates regression outputs for different weight settings in *aggregated_index_cost* construction. Effect proportion shows *iliad_entry* coefficient / *_cons* ratio. Standard errors are indicated in parenthesis.*** $p<0.01$, ** $p<0.05$, * $p<0.1$

more, the effect proportion increases, while when doing the opposite the effect proportion decreases. However, it is important to say that the proportion only slightly changes and it would mean that our main estimation is slightly underestimated.

7.1.4 Explanatory variables correlation

Working with regressions, it is important to check for multicollinearity in the selected set of explanatory variables: to account for this possible problem, we performed correlation tests on every regressor pair. Results are depicted in Figure 11: this graphical representation shows that no variable is correlated with the others.

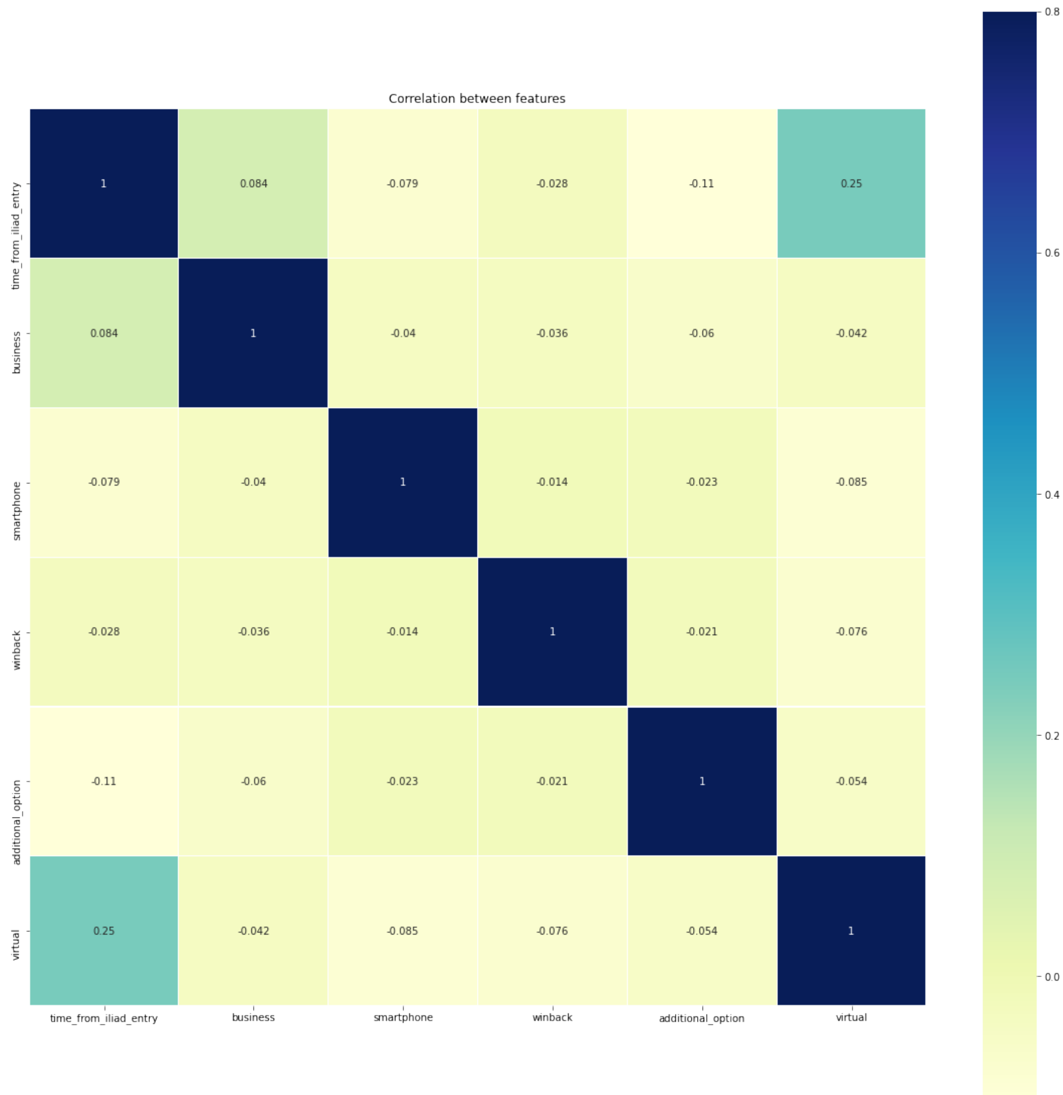

Figure 11. Independent variables correlation matrix. Graphical representation of Pearson's correlation indexes between independent variables.

7.2 Descriptive statistics

In this Section, we provide a graphical representation of the three component (gigabytes, minutes, and SMSs) distributions, to focus on what happens around the Iliad entry time threshold. Figures 12, 13 and 14 illustrate how quantity/price ratios (expressed by *daily_giga_cost*, *daily_call_mins_cost* and *daily_sms_cost*) increase substantially in the first two distributions, but not in the last, consistently with our findings (see Section 5). Figure 15 illustrates an overall picture of the previous three graphics, but it represents the price/quantity ratio instead (being the pictured variable *aggregated_index_cost*).

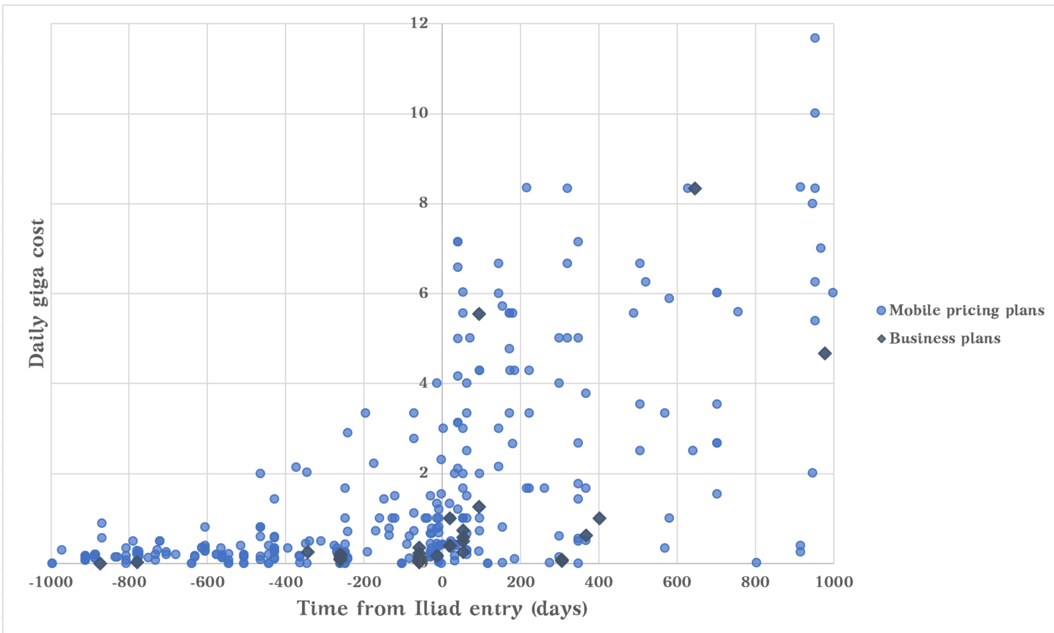

Figure 12. ***daily_giga_cost*** **distribution.** Graphical representation of *giga* quantity per euros of fee (daily).

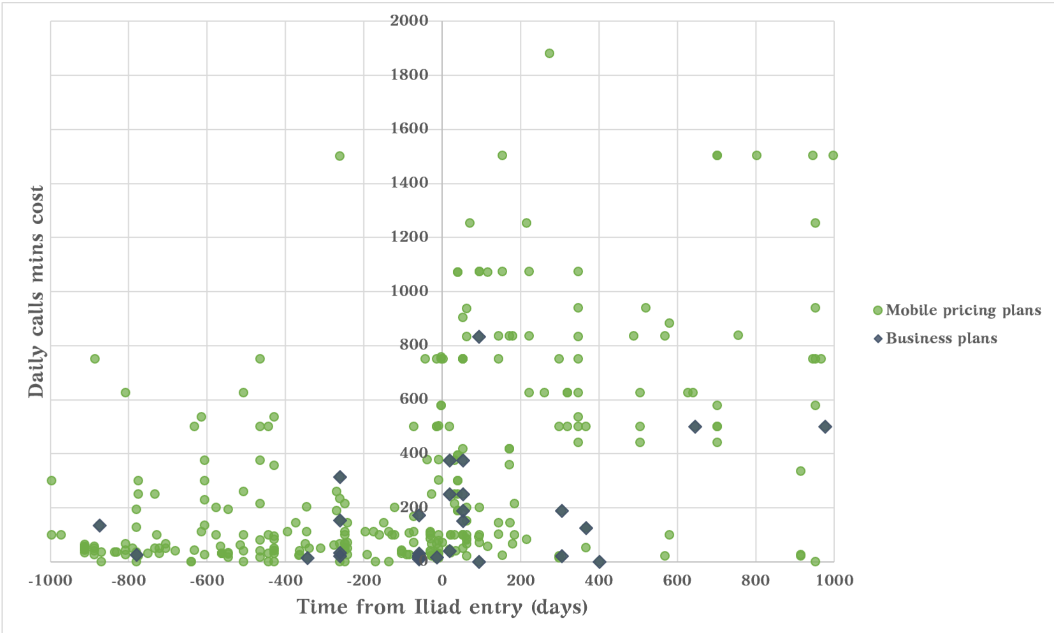

Figure 13. *daily_calls_mins_cost* **distribution.** Graphical representation of *calls_mins* quantity per euros of fee (daily).

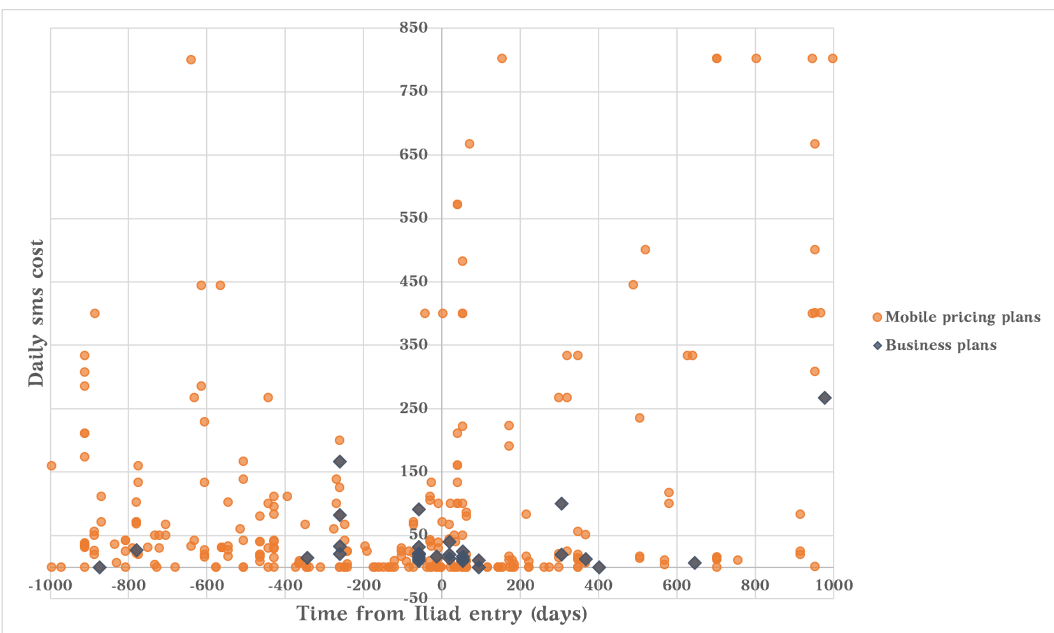

Figure 14. *daily_sms_cost* **distribution.** Graphical representation of *sms* quantity per euros of fee (daily).

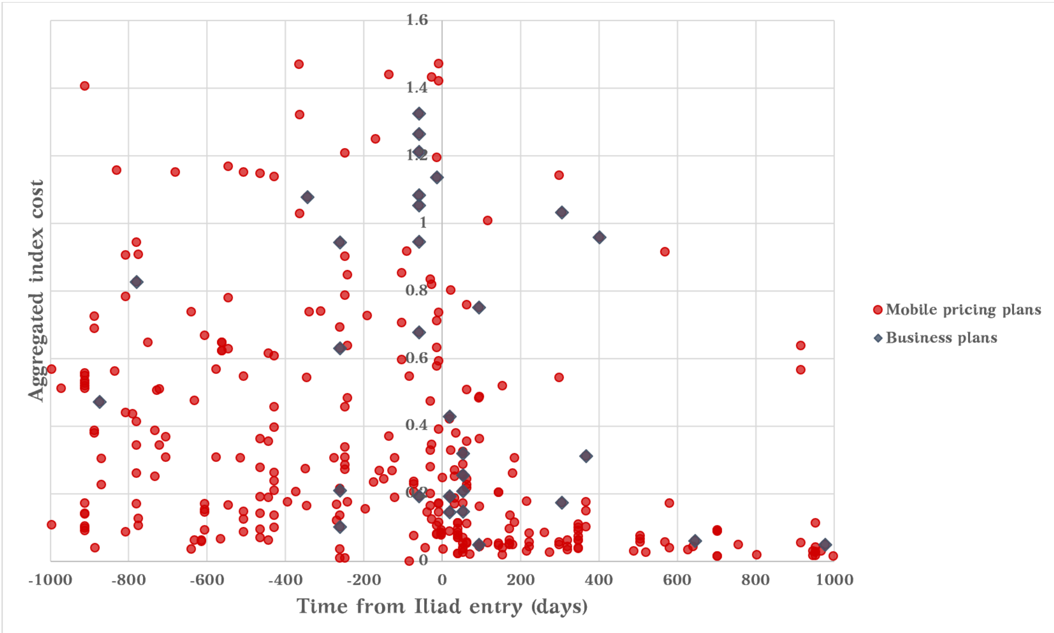

Figure 15. *aggregated_index_cost* **distribution.** Graphical representation of price per unit of *aggregated_index*.

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