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RELAXING OCCUPATIONAL LICENSING IN ITALY: A STAGGERED DIFFERENCE IN DIFFERENCES ANALYSIS USING BALANCE-SHEET DATA OF ITALIAN PHARMACIES

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Relaxing occupational licensing in Italy: a staggered difference in differences analysis using balance-sheet data of Italian pharmacies

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Abstract

This paper examines the effects of a policy implemented in Italy in 2012, deregulating the market of pharmacies, in order to reduce barriers to entry and improve competition.

Drawing municipal-level data from Aida for the following years 2011-2019, we assess the impact of the reform on revenues and net profits of pharmacies located in municipalities where there have been new openings.

In order to properly examine the policy that adopts a staggered implementation we propose an evaluation method that include three different estimation steps, using some recently developed methods to deal with staggered adoption, and an event study to compare our final results.

Our findings show that relaxing occupational licensing decreased both revenues and net profits for treated pharmacies across all different specifications of the dependent variables.

Keywords: occupational licensing; deregulation; staggered difference-in-differences; event-study; csdid; did_imputation; generalized difference-in-differences

JEL Classifications: J01, L43, D45

Introduction

This paper study the effects of a relaxation of the licensing restrictions in the market of Italian pharmacies that have been affected in the last decade by a very important reform that changed the way a pharmacy is opened and broadened competition and thus reduced barriers to entry into the profession.

Occupational licensing is, for some authors, a natural solution to problems of information asymmetry and consumer protection, for many others it is predominantly a way of creating a monopolistic position and rent-seeking that limits competition by raising prices and creating barriers to entry.

This issue is particularly pervasive in Italy and many other countries across the world because of the protective barrier provided by the law for many different professions, including those of lawyers, architects, accountants, pharmacists, physicians, engineers, etc.

Using data from 1998 to 2018, we can examine Italy's OECD Product Market Regulation index. There are two groups of indicators: an economy-wide indicator that provides a broad quantitative assessment of a country's regulatory posture and a set of sector indicators that evaluate the efficacy of regulation at the level of specific network and service sectors. These indicators are put together using a large database that is filled with information about laws and regulations. The score of Italy fell from 2.36 (1998) to 1.32 (2018). However, if we examine the index's development over the past ten years, from 2008 (1.49) to 2018 (1.32), we can see that it has remained rather consistent, showing that despite the reforms made over those years, Italy's laws for many occupations are still strict and restrict competition.

A reform that attempted to change the licensed market in Italy by responding to the problems this country had during a difficult sovereign financial crisis is certainly the deregulation that the Monti government put in place in 2012. This reform lowered the pharmacies per inhabitant ratio to improve competition and decrease the barriers to entry in the market of pharmacies.

Some Italian authors have examined this normative in literature. Mocetti, Roma, Rubolino (2018) studied the intergenerational persistence of professionals, exploiting the Monti reform and a difference-in-differences strategy, and find that the reform reduces the propensity for career following. Mocetti, Rizzica and Roma (2021) analyzed two similar types of deregulations in Italy (Bersani 2006 and Monti 2012) using a difference in differences design and found that the reform promote entry of new competitors and decreased the wage premium for many categories of professionals. The market for pharmacists has also been studied by Mocetti (2016), finding that positional rents, produced by pharmacy inheritance, account for the majority of the difference between children of pharmacists and other children in the propensity to become pharmacists through an analysis of intergenerational persistence. Social fluidity can gain if these barriers to competitiveness are eliminated.

Therefore, this paper is intended to be part of a broad research context that examines policies aimed at changing an established regulatory environment in Italy.

We study the exogenous shock derived from the reform implementing a staggered difference in differences design. Using a longitudinal balance-sheet data from Italian limited liability companies and corporations, provided by Aida, we separate the pharmacies that are situated in municipalities where there have been new openings (treated group) from the pharmacies located in other municipalities (control group), investigating how the reform affected their revenues and net profits during a 9-year period, 2011-2019.

In order to yield valid estimates, three different estimation strategies are adopted. First a TWFE model to give a preliminary result, then a difference in differences with multiple time periods estimator (proposed by Callaway and Sant'Anna, 2021), and another difference in difference model using the imputation approach of Borusyak et al. (2022). To compare both methods and corroborate our findings we implement an event-study using the recent developed method proposed by Borusyak et al. (2022).

Our results suggest that the policy attempt seems to be going in a positive direction because both revenues and net profits have declined because of the reform, hence this could justify that greater pharmaceutical coverage in the territory promotes competition.

In the first part of the paper we present an extensive literature review to focus our attention on the occupational licensing research; then we describe in detail what is the normative background of the policy; in the third part we illustrate our data and how the main dependent variables are constructed; in the fourth part we discuss about the estimation methodology used in this paper and what are the steps that we follow to estimate properly the impact of the reform in the Italian context; then we show our result and provide some graphical evidence; in the final part we discuss our main findings and what are the main implications for the market of pharmacies in Italy.

1. Literature review

1.1. Occupational Licensing: definition and effects on the labor market

Recently, occupational licensing has been extensively researched in the literature of labor economics.

Kleiner (2017) define this phenomenon as the "process by which governments establish qualifications required to practice a trade or profession, so that only licensed practitioners are allowed by law to receive pay for doing work in the occupation". This requirement was first created to reduce the asymmetric information bias (Akerlof 1970) and ensure public health and safety for consumers.

This is known in the literature as the “public interest theory”. The counterpart theory, called “capture theory”, assume that licensing restrict competition increasing the wages of the incumbent professionals, the price of the service and lower its quality. Pagliero (2011) compared these two theories, and the empirical evidence showed that capture theory is the most adequate to explain this phenomenon. In fact, any industry with sufficient political power to influence the government will try to harm the competition through subsidy demands, limiting competitors' entry, price-fixing laws, and controlling firms that provide substitutes or complementary products (Stigler 1971).

Maurizi (1974) said that the greater the likelihood of price and pay increases in that market, the greater the tendency to erect more barriers to entry into a licensed employment, therefore incumbents can impose more difficult entrance requirements and further restrict entry (Kleiner 2000), especially when the elasticity of the demand for services offered by the profession is lower, because the licensing will be more profitable (Stigler 1971).

The debate focuses on the barriers to entry placed in all licensed occupations. Law and Kim (2005) found a justification for this by specifying that the highest entry barriers are those in which consumers directly purchase the good or service and where quality heterogeneity has been caused by knowledge progress, while Gellhorn (1976) stated that the primary effect of licensing is to increase the cost of entering the market and, at the expense of higher costs for the consumer, licensing increases the status of the service provider.

1.2. Wage effects of occupational licensing

It is well-known in the literature that licensing results in a wage premium for incumbents, Timmons and Thornton (2008) assessed the impact of licensing on Radiologic Technologists wages, finding that licensing increases wages by as much as 3.3%.

A wage premium seems to appear also from the papers of Gittleman, Klee and Kleiner (2015), around 23.6 percent on average, and Mocetti, Rizzica and Roma (2021), about 9 percent.

Kleiner, Krueger (2009) studied that own a license increases the hourly earnings of the incumbents by 14 percentage points.

Inspired by Gittleman, Klee and Kleiner (2015), Koumenta and Pagliero (2018) used different data of occupational regulation based on European Union (EU-SOR), and obtained that incumbents earn 9.7 percentage points more than unlicensed workers.

Furthermore, licensing appears to increase earnings more on average for workers in occupations marked by high earnings than for workers with low earnings (Kleiner 2000).

1.3. Job Mobility

Licensing works as a barrier to entry in the market, reducing market fluidity, generating low levels of employment. Pashigian (1979) studied that professionals' interstate movement has been significantly and quantitatively reduced because of occupational licensing. If licensing requirements are different between two geographically neighboring states or between two regions in close proximity to each other, workers may have to repeat investments made to obtain a license when they move. This can depend by state arrangements for instance, that can restrict interstate mobility for some categories of professionals, such as dentists and lawyers (Holen 1965). Another problem arises when there are differences in grading standards for a specific job from one region to another. This generated inefficient mobility of Italian lawyers from poorer to richer districts (Buonanno and Pagliero 2018).

Requirements for language proficiency may prevent foreigners who want to work in a certain position from moving between states or regions (Federman, Harrington and Krynski, 2006). This result confirm what Gellhorn (1976) says in literature are extremely similar, he found that members of ethnic minorities are systematically discouraged from obtaining a license because of extremely strict requirements.

In general, the main problem is the decrease of the job-to-job movement when a higher coverage of licensing is taking place in one of them (Hermansen OECD working papers 2019).

1.4. Prices

As we mentioned before licensing benefits incumbent workers raising their salaries at the expense of consumers. Nonetheless it is interesting also to notice what is the related impact on the price of services if we confront a reduction in the availability of that service.

Shepard (1978) analyse the dental care market and found that if there are huge barriers to entry that discourage the competition, the incumbent tends to raise his fee to gain a rent.

Kleiner and Kudrle (1997), examining data from dental health showed that states that choose to adopt a more stringent license coverage than before do not find an improvement of the service but increase the prices of 14 to 16 percent.

1.5. Quality of the service

According to Leland (1979) consumers lack sufficient knowledge about professionals, so there is an adverse selection problem, and licensing acts as a minimal quality requirement. Shapiro (1986) affirmed that if the marginal cost of quality is lower than the value consumers place on it, licensing may increase welfare. Hovewer, Friedman (1962) already suggested that the decrease in the supply of workers does not rise the quality but force the consumers to "pay more for less satisfactory service". In fact, is challenging to assert that the availability of licenses on the market leads in higher quality because of a lack of data and uncertainty in the findings of some studies. Some evidence about the little impact of licensing on quality can be draw from Angrist and Guryan (2008) that found ambiguity in their results about the effect of a standard test for teachers in some US states on teachers' quality. Carroll and Gaston (1981), examining different markets and occupations found that a more tougher licensing requirement lower received service quality.

Analysing the teacher's occupation Larsen (2013) noticed that if there is an increase of the licensing standards needed for the job the distribution of input quality of a teacher who remain in the occupation for many years tend to raise, while the first year teachers , especially in high income areas, showed a reduction in the upper tail of their input quality.

Farronato, Fradkin, Larsen, Brynjolfsson (2020) did not find an an increase in customer satisfaction linked to a stricter licensing requirement but only less competition and higher pricing.

To solve this problem, Gellhornt (1976) suggested that is crucial to correctly measure the quality of the service without jeopardizing future employment prospects. Therefore, many authors propose to use other methods to protect the consumers and not harm the competition in the market, such as registration and certification. This is confirmed by Kleiner (2000) who found that certification is more effective if having a quality signal is needed, because anyone can work in a profession, the government accredits skills through exams, and clients decide whether to engage certified workers or not.

1.6. Relaxing occupational licensing

It is crucial to understand why a government choose to reduce the licensing requirements in a specific job, because it is what the Italian government did in 2012 to expand the opportunities for new pharmacies to open reducing a very strong barrier to entry imposed by the law many years before.

Kleiner, Marier, Won Park, Wing (2014) studied to what extent wages, employment and prices change when a regulation modifies the structure of a licensed occupation market (registered nurses in this context). They concluded that more restrictive regulation lowers the wage and increases the price of medical services.

An interesting case is reported by Barro (2015). He noted that the app Uber promoted the competition in the taxi labour market and decreased by 23 percent the price of the license to operate as a taxi driver in New York.

Mocetti, Rizzica and Roma (2019) analysed the Monti's reform, using a strategy very close to ours. They studied the impact of the reform on earnings of professionals, finding a sudden fall of professionals' wages affected by this reform.

Genakos, Koutroumpis and Pagliero (2018) investigate the impact of maximum markup regulation on prices. They found that reforming the market significantly decrease the prices of the services.

According to Raitano and Vona's assessment of the 2006 Bersani reform, it lessened the impact of a child's family's legal history on their wages.

2. Normative background

In 2012, Mario Monti, during his technocratic cabinet, formed to save Italy from the eurozone sovereign debt crisis, took a series of measures to promote the country's economic growth and competitiveness.

One of these aimed to liberalize the pharmacy market, which needed a change in the distribution service and the access to ownership of pharmacies, to improve competition and limit the drawbacks of licensing. This reform modified the number of pharmacies that can be opened in a municipality.

Before 2012, one pharmacy for every 5000 residents in municipalities with no more than 25000 residents and one for every 4000 residents in the other municipalities could be opened. Therefore, the regulation reduced the number of residents per pharmacy: one for every 3300 residents. After that, regions have been mandated by the government to carry out an identification process of optimal locations where the additional pharmacies can be opened and a selection process of pharmacists who will be the owners of these new activities.

In 2016, regions that started this process earlier have begun to open of new pharmacies, followed by the others over the next four years. Hence, the particularity of this regulation consists in the different starting date of new openings between regions, which allow us to have a developing treatment group over time. In addition, since this reform acts as an exogenous shock, it helps us to use a difference in differences design to evaluate its impact on revenues and net profits.

3. Data

The main dataset is built merging two different data.

The first is called AIDA and was developed and released by Bureau van Dijk S.p.A. It contains firm-level balance-sheet information from nearly 980000 limited liability companies and corporations, both active and failed (apart from banks, insurance companies, and public entities), updated by the most recent year available and for the previous ten years. The University of Calabria offered AIDA for unrestricted use and distribution online.

Using the 6-digit Ateco code 477310, we gather data about the Italian pharmacies for 9 years, 2011-2019. Since this period includes the five years prior to the official opening of new pharmacies, it enables us to accurately evaluate the reform's effects, because we have enough pre-treatment years. Although the year 2020 was available, it provided information about the Covid-19 Pandemic's first year, which is affected by a surge in pharmacy revenues due to an unusual demand for covid tests and drugs.

This dataset offers crucial data for our research. First, the two dependent variables, net profits and revenues, that will be utilized to analyze the policy outcomes. Second, several factors that are necessary to restrict the sample and identify the pharmacies affected by the reform.

The variables that we extracted from AIDA are described in table 1.

We combined AIDA data with information on new pharmacies' openings to create our dataset. Only 16 Italian regions formally and explicitly give on their website precise information about new openings at municipality level. These data are checked with a dataset downloaded from the Italian Ministry of Health[1] to find the exact date of opening of these pharmacies[2]. This information is then reported in an excel file that also includes the official population for each municipality as well as the number of already existing pharmacies[3].

In table 2 are described the number of openings by region and by year. We can notice that the region with the highest number of openings is Lombardia, and the region with the lowest number is Valle d'Aosta. Only 5 regions began to open in 2016, while the majority of them started in 2018. Moreover, as can be seen from the table, the Campania region never opened any pharmacies during this period, so the observations will be considered as never-treated in our analysis. In order to have a more clear idea of how the national coverage of new openings occurred, in Figure 1 is showed the geographic map of Italy and the sum of openings by province.

After combining the two datasets, we keep only those companies that are still operating, have one or no subsidiaries, and were constituted prior to the opening of new pharmacies in that municipality. Therefore, we have a longitudinal dataset of 1004 pharmacies for 9 years; the larger part is in Lombardia (299) and Campania (236), while Valle d'Aosta has the fewest.

In table 3 are reported the summary statistics for our sub-sample. Revenues and net profits are adjusted for inflation using the consumer price index data from ISTAT[4]. To have a more appropriate

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[1] These data can be freely downloaded from the website of the Italian Ministry of Health: https://www.dati.salute.gov.it/dati/dettaglioDataset.jsp?menu=dati&idPag=5

[2] This dataset also contains information about pharmacies' openings, but it is not possible to distinguish between reform-driven and nonreform-driven openings, so it was used only to cross-reference the opening data provided by the regions with the opening date to determine, for each region and each municipality the timing of policy adoption.

[3] These data can be found on this website: http://www.comuni-italiani.it/farmacie/

[4] Data are provided free of charge by ISTAT , from the following websites: http://dati.istat.it/Index.aspx?QueryId=23095#; http://dati.istat.it/Index.aspx?QueryId=23063#

measure of these balance-sheet data we generate 6 dependent variables using information about population and number of pharmacies. First, we divide the revenues by the population of each municipality, generating the variable per capita; second, we sum the revenues by each municipality and year, and divide the final number by the population, creating the variable per municipality; third we divide the sum of revenues, derived before, by the total number of pharmacies for each municipality and for each year, generating the variable per pharmacy. The same method is used for net profits, to have 6 dependent variables that will be useful to assess properly the impact of the reform in our sub-sample.[5]

4. Estimation strategy

The difference in differences design is the best choice for this research because it compares the outcome of a treatment group and a control group, thereby focusing on the impact of the policy.

The reform exogenously assigns the pharmacies into two groups: those in municipalities where there have been new openings and those that have been constituted in municipalities where there have been no additions. As we possess the exact information about new openings for each year and for each municipality, we create a treatment variable that indicates which municipalities are impacted by the reform and which are not.

The local government has been delegated to decide where open the additional pharmacies, then carry out a special tender and rank the pharmacists in order to assign the additional pharmacies. These procedures have been applied with different levels of speed in the Italian regions, therefore the regions have started to open the additional pharmacies in their municipalities in different years, some in 2016, some in 2017, some in 2018 and others in 2019. Since there are more than two time periods and units are treated at different points in time, we are no longer in a normal difference in differences setting. As a result, a staggered difference in differences model is more appropriate for our sample and might produce accurate estimates.

There is a lot of current work on the topic, and several estimation techniques have been developed very recently. The first method that can be used to estimate the causal effect of the treatment is the two-way fixed effects model (TWFE) which is a more flexible variant of the standard difference-in-differences model and includes fixed effects for both the treatment group and the control group, as well as for each period. This could be a good choice for our setting because we have more than two time periods.

[5] We identify the impact of outliers on the distributions of these variables using boxplots. As it became clear that these values were not justified and might pose a serious problem for the estimation in terms of producing biased results, we decided to use the winsorization method in Stata, replacing the extreme values with the 5% percentile of the right and left tails of the distribution.

The main equation for the first estimation step is:

$$Y_{it} = \alpha + \beta_1 D_i + \beta T_{it} + \gamma + \delta + \varepsilon_{it}$$

Y_{it} is one of the six main outcomes that we consider in this analysis. D_i is a treatment variable which is 1 in the group that receives the treatment (for each period in our dataset, even before treatment started) and 0 for the control group. T_{it} is another treatment variable (called active treatment) which is 1 in the treatment group after treatment begins, 0 in the same group before treatment begins and is 0 in the control group. Then we control for year and firm fixed effects[6].

However, some authors pointed out that the parameters associated with this model are challenging to interpret. Moreover, if our main purpose is to yield static or dynamic treatment effect estimates, when we use such staggered DID estimators, our estimates may suffer from significant bias (Baker, Larcker, Wang 2022).

A valid solution to this issue is to implement the method proposed by Callaway and Sant'Anna (2021) to produce an unbiased DID estimator in a model with multiple time periods[7].

The disaggregated causal parameter, which the authors refer to as "group-time average treatment effect" and which is an average treatment effect for group g at time t, contains information about the unit's first year of treatment, and is the main distinction between this type of estimation and the other.

This command estimates the average treatment effects of the treated for group g at time t.

We may also get estimates of the average treatment effect on the treated units for all groups across all periods, for each group or cohort across all periods, and for each period across all groups or cohorts by using the post estimation commands.

The main problem that could arise using this method is that it only uses the period just prior to the intervention as part of the control. Hence, it would be more appropriate if we could have more than one pre-treatment period in order to generate a more efficient estimator of the average treatment effect on the treated. Therefore, we implement the imputation approach of Borusyak, Jaravel, and Spiess (2022) that use the whole pre-treatment period as the reference period to compute the ATT for our policy evaluation.

The final step is to compare these two estimates using the event study plot developed by Borusyak et al. (2022)[8]. As Kelchen, Ortagus, Rosinger, and Cassell (2021), we run more than one estimation

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[6] We use the command reghdfe in Stata, and the option "absorb" to control for year and firm fixed effects.
[7] Using the CSDID Stata command developed by Rios-Avila, Callaway, and Sant'Anna (2022).
[8]The author developed two useful commands in Stata, the first is did_imputation, that estimates the effects of a binary treatment with staggered rollout allowing for arbitrary heterogeneity and dynamics of causal effects; the second is event_plot that plot the staggered-adoption diff-in-diff estimates using post treatment and pre-trend coefficients along with confidence intervals.

because each of these methods are characterized by different parallel trends assumptions, so it could be more efficient to compare results from more than one method to have a clearer idea of the real effect of the policy.

5. Results

5.1. Preliminary investigation

Figure 2 shows an analysis of the average revenues (and net profits) trends in Italy before and after the first year the reform was implemented. It is evident from a first look at the graphs for variables per capita and per municipality that the gap between treatment and control group increases after the first year of the adoption of the policy. It is less clear but still consistent with our research intuition the tendency of the revenues per pharmacy average, whereas it is less evident in the last graph. In fact, as we will see later, two estimation methods will confirm a non-significant effect of the reform on net profits per pharmacy.

The main suggestion that we catch from this preliminary evidence is that our reasoning justifies a deeper analysis to investigate the significance of this difference between the two groups.

Furthermore, it is interesting to notice that the control group is always placed at the top of the graph. This could indicate that these observations are located in little municipalities in which there are few other competitors. Indeed, if we compare the minimum population of the municipalities in the two groups, we find that the minimum population in the control group is 374 inhabitants, while the minimum value in the treatment group is 5064.

5.2. Estimation results and event study

In table 4 we run a two-way fixed effects model in a generalized difference in differences setting. The policy seems to have a negative effect on the revenues and net profits of the treated pharmacies in our sub-sample. The result is confirmed when we use the dependent variables per municipality. However, when we look to the coefficient of interest generated when we divide the sum of the revenues (or net profits) by the total number of pharmacies in the municipality, we can notice that only the revenues of the treated units are significantly impacted by the reform.

The second step is to calculate the Average Treatment effect on the Treated (ATT) using the method proposed by Callaway and Sant'Anna (2021).

Table 5 summarizes our key findings. It can be noticed that the average impact of the reform on the revenues per capita of the treated pharmacies is negative and statistically significant at the 1% level; the magnitude of the impact is the same given by the generalized DID. We discover a lower effect but less significant than before in the second column when we compared the net profits per capita of the treated groups with the others that had not yet received treatment. The ATT stays negative but with a smaller effect than before in the variables per municipality. In the last two columns, the outcome for all categories and all time periods is still negative for both variables. In this case it is shown a significant average treatment effect on the treated for net profits per pharmacy.

As we mentioned before, these methods use different assumptions for parallel trends. Therefore, it might be a good strategy to use another estimation method to confirm our results as a robustness check.

In table 6 are presented the average treatment effects on the treated according to Borusyak et al. (2022)[9]. In this setting, we can interpret our estimates as a general reduction in the revenues and net profits for treated pharmacies compared to pharmacies that are located in a municipality without any openings. This result seems to be valid both when we analyse the impact of the policy on balance-sheet's variables per capita and when we consider the variables per municipality. If we compare this outcome to the previous ones, we can notice that the magnitude of revenues per capita is smaller than before, while the impact on revenues (and net profits) per municipality is slightly higher in this case. Again, we do not find any significant effect on net profits per pharmacy, whereas the coefficient for the revenues per pharmacy is quite similar to the previous one.

The event-study graphs in Figures 3 plot the estimates and the 95% confidence intervals for the models use before. The event periods are 8 pre-treatment periods and 3 post-treatment years.
In the first two graphs there is a significant decrease of the revenues and Net Profits per capita after the reform, and the result become stronger in the Borusyak et al. (2022) model.
When we consider the variables per municipality there is a significant negative impact of the reform only for the first-year post treatment for revenues, but when we look to the net profits, the Borusyak et al. (2022) method provides a negative and significant coefficient even in 2019 (third period post treatment). Finally, it can be noticed a consistent and statistically significant decline in the revenues per pharmacy estimates, confirmed by both estimation methods. However, only a moderate negative impact is showed on net profits per pharmacy during the first post-treatment period, while other estimates present wide confidence intervals, and this make it difficult to deduce what is the real effect of the policy in this case.

5.3. Discussion

The revenues and net profits per capita estimates illustrate that, controlling for the population of the municipality, the outcome appears to be affected by a variation due to the reform. Hence, even

[9] In order to build our estimation properly, we use the option "allhorizons", to pick all non-negative horizons available in the sample, minn(0) to report all coefficients nevertheless and pretrends(8) to exploit all possible pretrends in our dataset and then perform a test for parallel trends.

considering the different size of the municipalities, this does not affect the final result, which describe a significant impact of the policy on balance-sheet data of the treated pharmacies. The finding is also confirmed by the estimation on Net Profits, meaning that the result is robust regardless of the company's expenses.

Using the variables per municipality as dependent variables, the analysis indicates that even if we sum up all the revenues (or net profit) per municipality, the main outcome is still an overall decrease. Therefore, one possible explanation could be that the new openings has increased the competition and so now there is more choice for consumers, and this could result in a reduction in demand for pharmacies that offer less quality service or higher prices.

Finally, it is useful to note how the result on revenues is not affected by the number of pharmacies that operate in the same municipality. When we control for the number of pharmacies the outcome remains robust and significant. The effect on net profits is more complicated to explain, given its ambiguity in the estimates.

Conclusions

In this paper we introduced a policy analysis that implements several estimation strategies and aims to test the effect of a reform that changed the barriers to entry for a licensed profession.

The results describe a well-known situation studied in literature that prompts us to assert that this law can provide an incentive for the market to foster competition among firms.

Therefore, an increase in competition generates lower revenues for pharmacies that experience reduced demand due to a new opening occurring in the same municipality. This outcome remains consistent if we use different specifications of the dependent variable.

This research is unique and distinct from others for several reasons. First, this is the only paper that exploits the precise and official municipal-level pharmacy's openings provided by 16 Italian regions. Second, we use an estimation strategy that is appropriate to accurately assess the policy, which consists of estimating three different models that deal with staggered treatment timing. Third, thanks to the data provided by Aida we can use longitudinal information for 9 years at municipal level. This is a feature that is very difficult to find because other datasets are at provincial or regional level, and this does not allow for a complete and comprehensive study of the impact of the reform since the actual opening of pharmacies occurs only at municipal level. Moreover, the Aida dataset contains crucial balance-sheet information, as revenues and net profits, but also data such as the number of subsidiaries and the year the company was constituted, in order to be able to identify exactly who may be affected by new openings and who may not. However, as we consider only balance-sheet data from limited liability companies and corporations, a sample representation problem might arise, because many pharmacies in Italy are sole proprietorships, especially in small municipalities.

One of the aspects on which this work can be expanded is to analyze data regarding the income of pharmacies' owners, who have been personally affected by the new openings. This evaluation refers to the most important work done in the occupational licensing literature that aim to assess whether there are significant changes in licensed workers' wages.

Moreover, because the reform is still generating new openings it would be interesting to study the effect the policy as pharmacies continue to open, thus considering a treatment intensity in our analysis.

Finally, it would be more appropriate to study the impact of the reform nationwide, hence, adding in our research also the remaining four regions of Italy to get an overall effect of total openings. However, this does not depend on us, as these four regions should provide precise data about openings due to the reform in their official websites.

This paper thus fits into the strand of literature analyzing the impact of a policy that deregulate a licensed profession and furthermore into the recent debate on the analysis of a difference-in-differences staggered model, since two estimation methods developed over the past three years are used in this research.

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Table 1: Description of variables

Name	Description
Id	CCIAA number (given by the Italian Chambers of Commerce)
Year	year categorical variable (from 2011 to 2019)
Region	region identification code provided by Istat
Province	province identification code provided by Istat
Municipality	municipality identification code provided by Istat
Constitution year	constitution year of the firm
Ateco	classification of economic activity provided by ateco 2007 code
Subsidiaries	number of subsidiaries in the company
Revenues	revenues declared in the financial statements in a given year
Net profits	Net profits declared in the financial statements in a given year
Company status	Status of the pharmacy: active, liquidated, insolvency, bankrupt
Legal status	Legal status of the pharmacy according to the Italian laws
Treatment	dummy variable of treatment by year and by municipality
Population	population in a given municipality (provided by Istat)
Pharmacies	number of pharmacies in a given municipality
Openings	number of new openings after the reform
Revenues per capita	total revenues divided by the population of the municipality
Profits per capita	net profits divided by the population of the municipality
Revenues per municipality	sum of the revenues for every municipality divided by the population
Profits per municipality	sum of the net profits for every municipality divided by the population
Revenues per pharmacy	sum of the revenues divided the number of pharmacies by municipality
Profits per pharmacy	sum of the net profits divided the number of pharmacies by municipality

Table 2: number of new openings by region and by year

Region	Year				
	2016	2017	2018	2019	Total
Abruzzo	0	0	0	18	18
Basilicata	0	0	6	4	10
Campania	0	0	0	0	0
Emilia-Romagna	48	24	35	7	114
Friuli-Venezia Giulia	0	0	19	7	26
Lazio	0	0	102	54	156
Liguria	8	6	3	3	20
Lombardia	0	0	211	48	259
Marche	0	0	0	18	18
Piemonte	55	13	4	1	73
Puglia	100	33	13	7	153
Sardegna	0	0	37	0	37
Trentino-Alto Adige	0	0	13	1	14
Umbria	0	0	0	8	8
Valle d'Aosta	2	0	0	0	2
Veneto	0	0	90	36	126
Total	213	76	533	212	1034

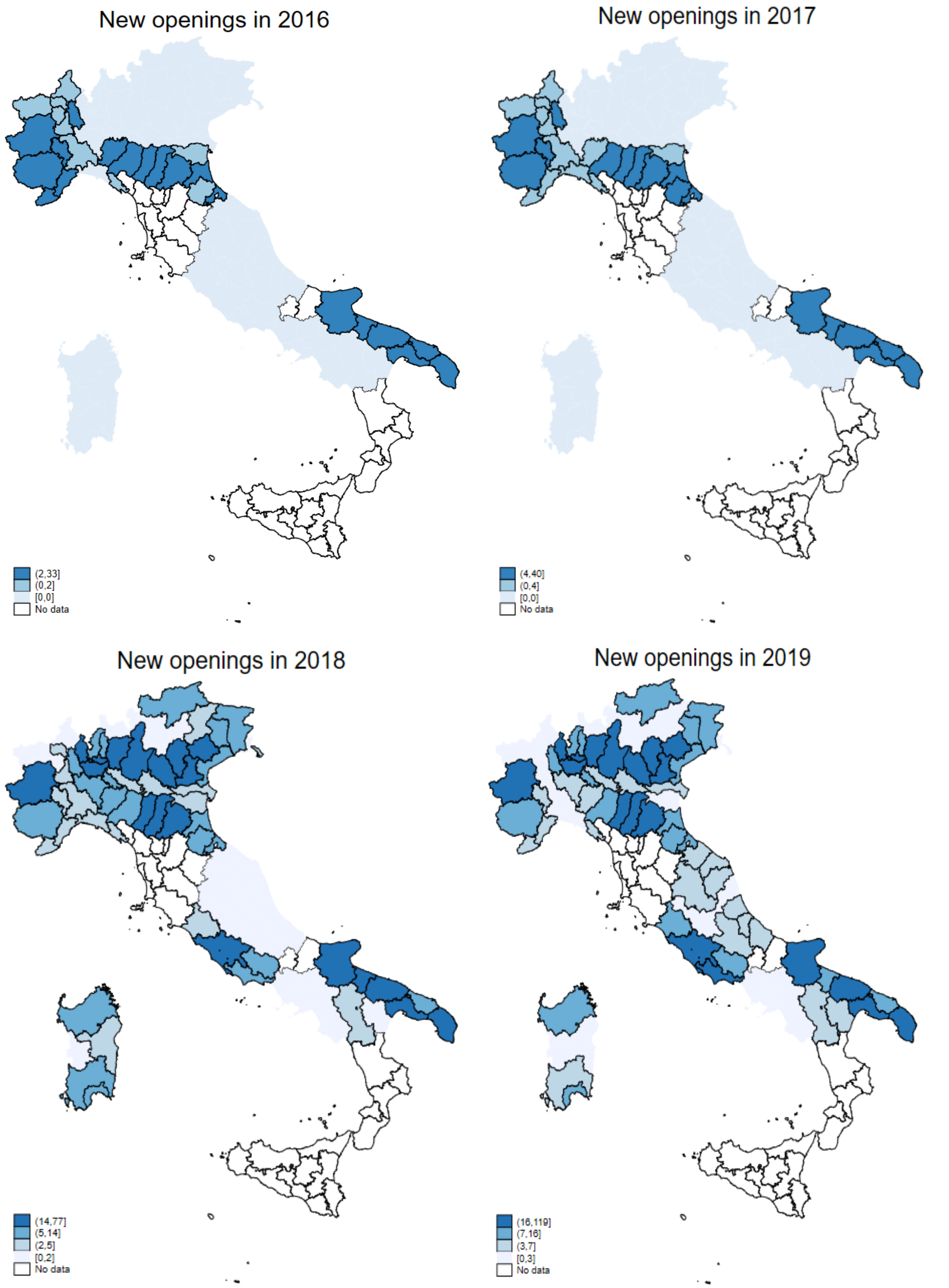
SOURCE: Authors' calculation from the excel file of new openings of pharmacies by municipality extracted by the websites of 16 Italian regions. The reference period is 2011 to 2019.

Table 3: Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Subsidiaries	9036	.12	.324	0	1
Revenues	3372	2788589.8	6830847.5	0	1.246e+08
Net profits	3372	72701.558	433689.58	-4794067	10145054
Treatment	9036	.091	.287	0	1
Population	9036	353313.52	771020.6	374	2761632
Pharmacies	9036	100.007	208.506	1	783
Openings	821	8.161	15.213	0	46
Revenues per capita	3372	110.972	112.073	0	356.469
Net profits per capita	3372	3.034	4.788	-2.956	14.766
Revenues per pharmacy	9036	236551.77	282819.74	0	843988.31
Net profits per pharmacy	9036	5141.571	8859.4	-4035.306	25839.551
Revenues per municipality	9036	133.588	986.413	0	25742.209
Net profits per municipality	9036	3.195	20.849	-191.131	462.231

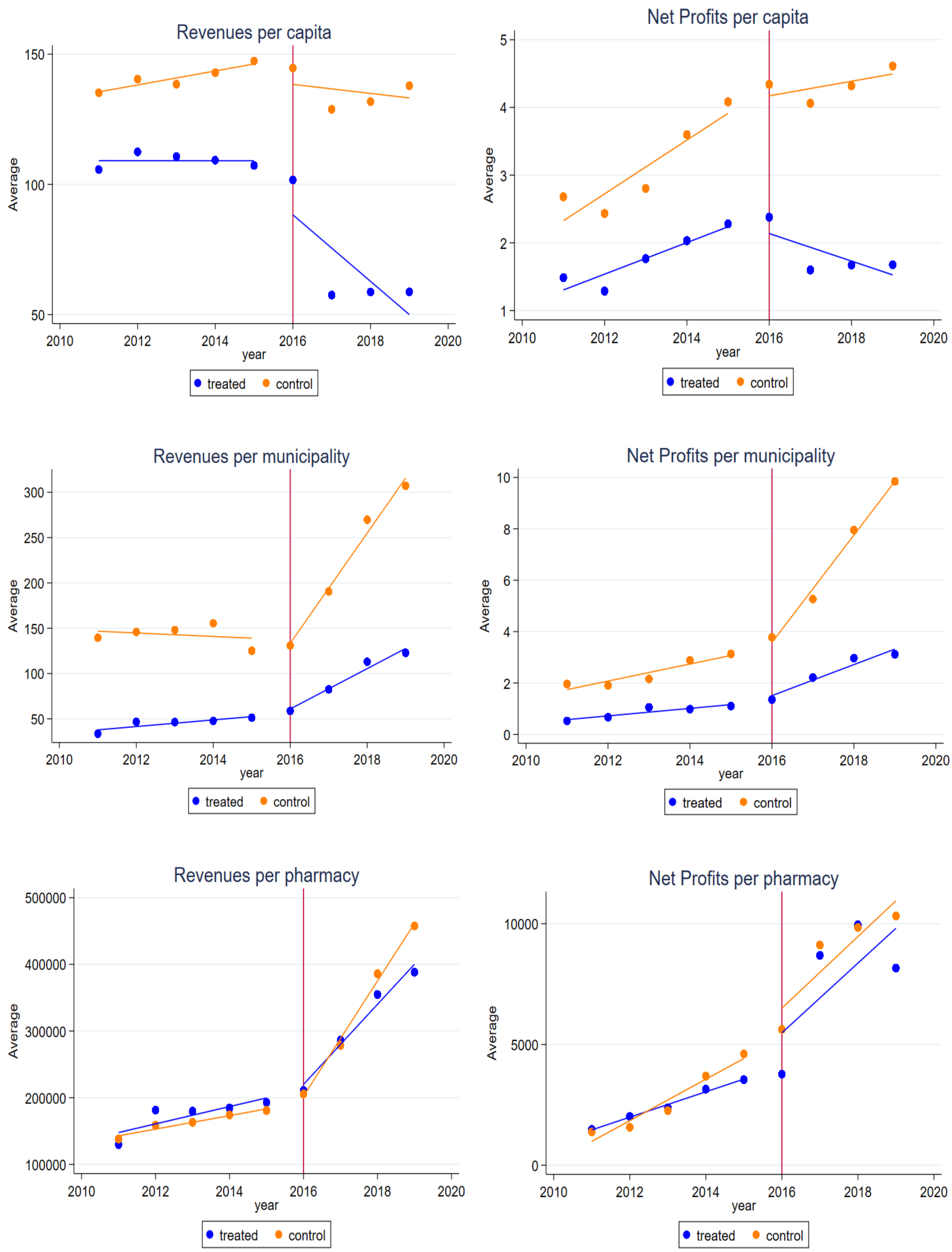
SOURCE: Authors' calculation from the Aida panel merged with the excel file of the new openings by municipality.
The sample includes still active pharmacies that opened before the reform. The reference period is 2011 to 2019. All revenues and net profits variables are adjusted for inflation and are winsorized at 5% to remove the outliers. The openings and the treatment variable are determined using data provided by Italian regions from their websites. Population variable is provided by Istat from the official website.

Figure 1: number of new openings by provinces during the staggered adoption period of the policy



SOURCE: Authors' elaboration from the file that contains the number of new openings, constructed from data provided by 16 Italian regions merged with the shapefile of Italian provinces provided by Istat.

Figure 2: average revenues and average net profits trends in the treatment group and in the control group



SOURCE: Authors' elaboration from the Aida panel merged with the excel file of the new openings by municipality.
The sample includes still active pharmacies that opened before the reform. The variables are adjusted for inflation. The reference period is 2011 to 2019.

Table 4: Generalized Difference in Differences

	(I) Revenues per capita	(II) Profits per capita	(III) Revenues per municipality	(IV) Profits per municipality	(V) Revenues per pharmacy	(VI) Profits per pharmacy
Treatment	-10.362***	-0.678***	-64.971***	-3.311***	-51330.7***	-473.845
	(2.506)	(0.194)	(12.964)	(0.478)	(6742.40)	(299.170)
Observations	3244	3244	9036	9036	9036	9036

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses.

SOURCE: Authors' calculation from the Aida panel merged with the excel file of the new openings by municipality.

The sample includes all still active pharmacies that opened before the reform. The reference period is 2011 to 2019. The dependent variables are adjusted for inflation. The estimates represent the coefficient of the Treatment variable in a Generalized Difference in Differences setting.

Table 5: average treatment effect on treated (according to Callaway and Sant'Anna, 2021)

	(I) Revenues per capita	(II) Profits per capita	(III) Revenues per municipality	(IV) Profits per municipality	(V) Revenues per pharmacy	(VI) Profits per pharmacy
ATT	-10.884***	-0.407*	-57.253***	-2.423***	-54360.9***	-1312.84***
	(2.938)	(0.230)	(13.551)	(0.775)	(11383.32)	(542.802)
Observations	3110	3110	9036	9036	9036	9036

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses.

SOURCE: Authors' calculation from the Aida panel merged with the excel file of the new openings by municipality.

The sample includes all still active pharmacies that opened before the reform. The reference period is 2011 to 2019. The dependent variables are adjusted for inflation. The estimates represent the average treatment effect on the treated given after computing a Difference in Differences with Multiple Periods estimator (Callaway and Sant'Anna, 2021), using the CSDID command, developed by Rios-Avila, Callaway, and Sant'Anna (2022).

Table 6: average treatment effect on treated (according to Borusyak et al., 2021)

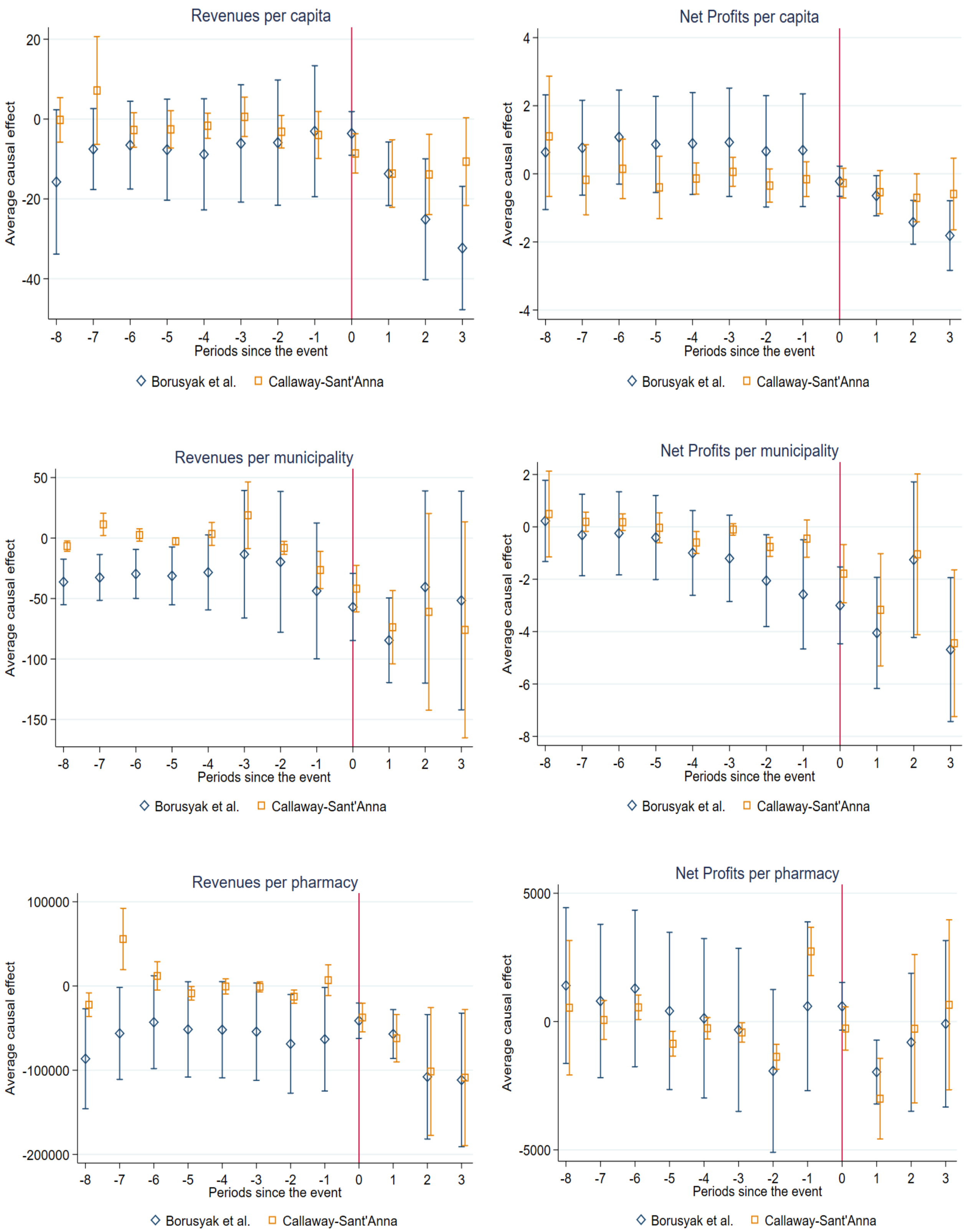
	(I) Revenues per capita	(II) Profits per capita	(III) Revenues per municipality	(IV) Profits per municipality	(V) Revenues per pharmacy	(VI) Profits per pharmacy
ATT	-9.474***	-0.491**	-66.731***	-3.398***	-54770.3***	-536.890
	(3.193)	(0.228)	(16.655)	(0.858)	(12550.81)	(487.143)
Observations	3196	3196	9036	9036	9036	9036

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses.

SOURCE: Authors' calculation from the Aida panel merged with the excel file of the new openings by municipality.

The sample includes all still active pharmacies that opened before the reform. The reference period is 2011 to 2019. The dependent variables are adjusted for inflation. The estimates represent the average treatment effect on the treated given after computing a Difference in Differences design with staggered adoption of treatment, using the imputation approach of Borusyak et al. (2022).

Figure 3: Event study



SOURCE: Authors' calculation from the Aida panel merged with the excel file of the new openings by municipality.
The sample includes all still active pharmacies that opened before the reform. The reference period is 2011 to 2019. The dependent variables are adjusted for inflation. The graphs represent the event study that compares a Difference in Differences with Multiple Periods estimator (Callaway and Sant'Anna, 2021) with the imputation approach of Borusyak et al. (2022).