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Hospital mergers in the Netherlands: influence on healthcare professional retention

Master Thesis Health Economics

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Abstract

This research investigates the impact of horizontal hospital mergers in the Netherlands on employment, focusing on the retention of healthcare professionals as a measure of employment. The primary research question explores the effect of hospital mergers on the probability that healthcare professionals are retained at merging hospitals compared to non-merging hospitals between 2012 and 2021. To estimate the impact of hospital mergers, this study employs a recently developed staggered difference-in-difference design. This method assesses whether there is a significant difference in the probability of retention for healthcare professionals between merging and non-merging hospitals. The findings indicate that, by extending the pre-treatment period hospital-specific trend, healthcare professionals at merging hospitals have a 0.36% higher probability of being retained one year after the merger compared to those at non-merging hospitals. This difference is statistically significant. However, no significant differences are observed for other post-treatment periods. The study reveals that hospital mergers in the Netherlands result in a modest but positive effect on retention of healthcare professionals at merging hospitals one year post-merger. This finding contrasts with previous studies, suggesting that mergers do not necessarily have detrimental effects on healthcare professional retention.

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1 Introduction

Healthcare expenditure is increasing worldwide (Stepovic 2019). Most OECD countries have seen an increase in healthcare expenditure as a percentage of GDP, encompassing both public and private sectors between 2008 and 2014 (Stiglitz, Fitoussi & Durand 2018). This trend is also visible in The Netherlands. The share of the Dutch GDP that can be contributed to the healthcare sector has increased from 7.7% in 2000 to 11.2% in 2021 (CBS 2022). The increasing trend is not likely to stop.

Along with the increase of the healthcare sector's share in countries' GDP, the concentration in the hospital markets also increased. From 1994 to 2015 the U.S. hospital industry has seen more than 1000 mergers (Gaynor et al. 2015). The American Hospital Association (1992) defines a hospital merger as a combination of previously independent hospitals formed by either the dissolution of one hospital and its absorption by another, or the creation of a new hospital from the dissolution of all participating hospitals. Similar to the U.S., The Netherlands also saw a large number in hospital mergers. Roos, Schut & Varkevissier (2018) show that from 1990 to 2017 The Netherlands saw more than 40 hospital mergers and the Authority for Consumers and Markets (ACM) reviewed in their paper *Prijs- en volume-effecten van ziekenhuisfusies* (ACM 2017) 30 proposed hospital mergers between 2004 and 2016.

Studies do not always depict positive effects after a hospital merger. The price effects of mergers are higher for hospitals that were substitutes for patients, were in markets with low insurance concentration, and were less likely to result in efficiencies (Brand, Garmon & Rosenbaum 2023). An example of an efficiency could be lower administrative costs due to the consolidation of services (Ferrier & Valdmanis 2004). Also, chances are that it is possible for hospital mergers to result in or intensify monopsony power in labour markets (Gaynor 2021). A distinction can be made between the effects on the hospital–insurer market, where outcomes measured after a merger are prices, and the effect on the hospital–labour market, where outcomes measured after a merger are wages and employment.

The effect of hospital mergers on the hospital-insurers market has been widely studied. Capps & Dranove (2004) find that consolidations among competing hospitals lead to higher prices. This is confirmed in a case study by Haas-Wilson & Garmon (2011) who found significant post-merger price increase after the merger between Evanston Northwestern and Highland Park hospitals. Brand, Garmon & Rosebaum (2023) also found a price increase looking at 558 hospital mergers.

There is a recent interest in the effects of mergers on the labour market in the general economy. Todd & Heining (2024) examine how acquisitions affect workers. They look at buyers, a firm with a plant, who acquire a target, a firm with a similar plant, in the same local labour market using detailed administrative data. Their conclusion is that there are both winners and losers in the labour market after a merger. The recent interest is also visible in merger control. Berger et al (2023) state that labour market implications of mergers have historically been ignored in antitrust policy and try to help policy focus more on labour market implications.

Somewhat less studied is the effect of mergers on the hospital–labour market. The few studies that were conducted primarily focus on wages. Wages are influenced by consolidations. A wage reduction was observed for two categories of skilled hospital workers when the merger caused a significant increase in market concentration (Prager & Schmitt 2021).

Literature on the effect of mergers on hospital – labour market, with respect to employment, however, is even scarcer. This would be relevant for merger control, because in recent years the number of mergers has increased and the pressure on health care is increasing due to understaffing, without knowing what the impact of mergers is. This research will investigate horizontal hospital mergers in the Netherlands and its effect on employment for healthcare professionals. A horizontal merger happens when two or more independent companies, producing the same or closely related services, come together to form either a single entity or a robust inter-organizational alliance (Conrad & Shortell 1996). To assess the effect of a hospital merger on employment, retention for healthcare professionals is used as measure for employment. Retention is increasingly applied in literature as a measure for employment, as for instance by Todd & Heining (2024) and Dobbelaere et al. (2022). It captures whether a healthcare professional is retained in a given year by a hospital.

The following research question is formulated to investigate the effect of a hospital merger on retention for healthcare professionals:

What is the effect of hospital mergers on the probability that healthcare professionals are retained at merging hospitals compared to non-merging hospitals in The Netherlands between 2012-2021?

This study will contribute to the existing body of literature by applying the newly developed Callaway & Sant'Anna (2021) staggered difference-in-difference estimation method. The staggered difference-in-difference estimates if there is a difference in the probability that a healthcare professional is retained between merging and non-merging hospitals. To the best of my knowledge, the new staggered difference-in-difference design has not been previously applied within the context of hospital mergers and their effect on the retention of healthcare professionals. Providing extra information on the possible outcomes of hospital mergers on employment can provide authorities with an extra tool to assess hospital mergers.

The remainder of the paper will be organized in the following manner. In Section 2 the theoretical framework is explained. The dataset and variables used together with the empirical framework will be discussed in Section 3, after which the results are presented in Section 4. Section 5 and 6 conclude the paper with the discussion and conclusion, respectively.

2 Theoretical framework

2.1 Mergers and general labour markets

Many papers in literature have examined the effect of a merger on the labour market outside of the hospital market. Dobbelaere et al. (2022) looked at firm consolidation in The Netherlands and examine worker retention, various measures of earnings and income and benefit uptake for workers who were present at target and acquirer firms. In the four years after the takeover, they find that workers are 6 percentage points less likely to be retained and work 77.61 fewer hours at the consolidated firm compared to control firms. Over-placed workers and duplicative workers are particularly less likely to be retained at the consolidated firm. While target workers are negatively impacted by the merger, workers at acquirer firms experienced little impact on their employment, wages, or overall income.

Mergers outside the hospital market also influence wages post-merger. Todd & Heining (2024) find differences between target and buyer workers after a merger. They find that acquisitions lead to a reduction in the earnings of target workers by €552 five years post-acquisition, with no significant changes in the earnings of buyer workers. However, retained workers from either the buyer or target see average annual wage increases by €237 and €509, respectively. According to Todd & Heining (2024), the main losers from acquisitions are women over 48 years of age, particularly those employed at target firms in the years prior to an acquisition.

A possible explanation for the previously discussed effects after a merger might be an increase in monopsony power. Mergers may lead to increasing monopsony power and compared to a perfectly competitive labour market, monopsony leads to lower employment and lower wages (Marinescu & Hovenkamp 2018). Monopsony power is expected to be an issue in most of the US labour markets (Azar et al. 2020).

More negative effects can be expected according to Angerhofer & Blair (2021). Altogether, they find that labour markets are susceptible to monopsonistic exploitation, and when labour supply curves are positively sloped, the utilization of monopsony power can result in harmful effects on workers. Monopsony in the labour market reduces employment below the level of employment in a perfectly competitive market, enabling the monopsonist to increase its profits by hiring fewer workers and paying wages below their productivity, thereby capturing the surplus for itself (Marinescu & Hovenkamp 2018). Sæther (2005) indicates a positive physician labour supply curve for physicians in Norway. As a result, hospitals that can exercise monopsony power after a merger might cause harmful effects on its workers.

2.2 Hospital mergers and hospital labour markets

Hospital mergers involve various intentions, take a long time to implement and have several positive and negative effects. Ferrier & Valdmanis (2004) mention multiple reasons why hospitals merge. First, mergers may reduce non-price competition, sometimes called the medical arms race. The medical arms race leads to a duplication of services which improves the financial performance of the hospital but also increases the costs (Trinh, Begun & Luke 2008). Second, an increased patient base could lead to higher utilization rates, increased marginal productivity of labour and enhanced revenue. Third, administrative costs should decrease due to the consolidation of services. All with the purpose of increasing the productivity and efficiency of the hospitals.

Increasing productivity and efficiency are not the only reasons to merge. According to Postma & Roos (2016), the primary reasons for hospital mergers are to enhance healthcare provision and to strengthen market/bargaining power. Increased market power can be used to multiple ends from taking advantage of quantity discounts on large purchases (Finkler 1985) to having more negotiating leverage against managed care organizations or health insurers (Harris, Ozgen & Ozcan 2000).

For hospital mergers in The Netherlands there is often several years between the administrative merger date and the legal merger date, which concludes the merger. Due to the long duration of the merger, healthcare professional might be able to anticipate the merger. Anticipation is explained by Hanglberger & Merz (2015) as expecting a new situation. Because of the gap between the administrative merger date and the legal merger date, healthcare professionals might anticipate future changes due to the announced merger and adjust their actions accordingly.

In theory, hospital mergers yield positive outcomes for society. Unfortunately, in practice, hospital mergers also bring negative effects with them in relation to prices, wages, and employment. Capps & Dranove (2004), Haas-Wilson & Garmon (2011), and Brand, Garmon & Rosebaum (2023) all find price increases after hospital mergers.

Although there is an abundance of literature addressing the impact of hospital mergers on prices, the number of papers looking into wages is scarce. In America, nurses' wages increased by $4.08 less per hour compared to similar workers in other sectors during the same period. This suggests that hospital system consolidation contributes to the suppression of nurses' wages (Allegretto & Graham-Squire 2023). Furthermore, Prager & Schmitt (2021) find that high levels of unionization appear to mitigate the negative wage effect after a hospital merger. The counterpart of unions for physicians in The Netherlands are *maatschappen* and since 2015 also *Medisch Specialistisch Bedrijven* (MSB’s). *Maatschappen* and MSB’s seem to influence wages post-merger and therefore they might also influence physician retention post-merger.

However, when it comes to the effect of hospital mergers on employment literature is even more scarce. There is one paper by Ingelsrud (2017) that explores the effect of hospital mergers on employment. Ingelsrud (2017) found that employment turnover is significantly higher in the second year after the merger compared to the years preceding the merger. Specifically, the turnover destination within the hospital sector is notably higher in the second year of the merger than in the pre-merger years. However, for other destinations such as other sectors or out-of-work, there were no significant effects. Her findings confirmed that turnover is a consequence of mergers, which come with replacement costs, loss of productivity and compromised continuity of care.

2.3 Exploring hospital labour market by difference-in-difference

As previously mentioned, the literature of the effect of hospital mergers on employment is scarce. There is a research gap on the effect of a horizontal hospital merger on healthcare professional retention, particularly in The Netherlands. To help fill the research gap this study will look at all horizontal hospital mergers between 2012-2021. The predominant strategy to study the impact of consummated mergers in the setting of hospital mergers is the difference-in-difference estimation (Gaynor et al. 2015). The simplest form of the difference-in-difference is the Two-Way Fixed Effect regression (TWFE), which uses two groups and two time periods and is robust to treatment effect heterogeneity, under the assumption of parallel trends. Treatment effect heterogeneity refers to the variation in the treatment effect across different groups or individuals within the study. However, the TWFE is not robust to treatment effect heterogeneity if there are more than two time periods and if there is variation in treatment timing (Callaway 2023).

To contribute to the literature a newly considered difference-in-difference approach, proposed by Callaway & Sant'Anna (2021), that accepts the use of multiple time periods and variation of treatment timing, is used. There are three difference-in-difference estimators that can be used for their staggered difference-in-difference approach. Those are the Outcome Regression (OR), from Heckman et al. (1997), the Inverse Probability Weighting (IPW), from Abadie (2005), and the Double Robust (DR), from Sant'Anna & Zhao (2020). The DR method is used as it combines the OR and IPW methods by incorporating models for both the outcome evolution and the propensity score. Also, this technique only needs the accurate specification of one of these models, which is either the outcome evolution for the comparison group or the propensity score model. Therefore, using the DR method makes it more robust to model misspecifications than the OR and IPW methods. The key assumptions of this model are that treatment is irreversible, random sampling, no treatment anticipation, conditional parallel trends based on 'never-treated' and there is overlap. This will be discussed in the Section 3.2.3.

3 Data and Empirical strategy

This section will go over the data and empirical strategy used. First, the source of the data and the selection criteria will be discussed. Then, variables included in the model will be explained. Finally, the empirical strategy employed will be described.

3.1 Data and variables used

3.1.1 Sample selection

The starting dataset used for this analysis comes from Vektis, the Dutch insurance companies' center for information and standardization in health care. This dataset contains information from the AGB-registry and it consists of administrative data from individual healthcare professionals in The Netherlands from 2012 to 2021. Healthcare professionals are for instance physicians, nurses, dieticians. The dataset includes detailed information about healthcare professionals such as date of birth, gender, name of hospital where they are employed.

In The Netherlands, up till 2015 physicians needed an AGB-code to be able to receive their fees, since hospitals paid them separately from non-physicians. From 2016 and onwards, due to *Wet Marktordening Gezondheidszorg*, formal healthcare professionals need an AGB-code to be able to claim for care provided, otherwise they will not get paid. Within the group of formal healthcare professionals, all physicians need an AGB-code, but this requirement does not apply to all non-physicians. Only non-physicians who receive fees separately from the health insurer need an AGB-code. This can, for example, be through an own company or something else. The dataset therefore contains representative number of physicians but not a representative number of non-physicians.

The AGB-registry dataset misses variables that are needed for the analysis such as what type of hospital a healthcare professional is working at or total yearly revenue per hospital. With the aim of complementing the AGB-registry dataset various other datasets are merged with the variables necessary for the analysis. There is an overview of all variables added in Table 3.1. The data sources that are used next to Vektis to complete the dataset are Geodan, a location intelligence company, and CBS, the Dutch Central Bureau for Statistics. After adding the necessary variables, the dataset is called the master dataset. At this point the master dataset consists of cross-sectional data and is expanded to panel data as it is a prerequisite for the analysis.

The master dataset is then restricted. First all years before 2012 and after 2021 are excluded. After that, hospital types Independent Treatment Centers (ITC) and University Hospitals (UH) are deleted from the sample, as these two types are to some extent different from the other hospital types: ITC’s are small for-profit healthcare institutions whereas the other hospital types are large not-for-profit healthcare institutions (Gradus, Koning & Noailly 2007); UH’s are excluded as they conduct scientific research and educate students to become future physicians besides their primary function of patient care. This is the only hospital type authorized to perform that function. The last changes that are made to the sample are restrictions to the treatment and control group, which will be discussed in Section 3.2.1. Figure 3.1 provides a schematic representation of the sample selection.

Table 3.1 All the variables added to the AGB-registry dataset and data sources

Variables added to the AGB-registry dataset	Data sources
Type of hospital	Vektis
Starting and ending date of employment contract	Vektis
Municipality where physician lives	Geodan
Province where hospital is located	CBS
Travel time for physicians	Geodan
Total yearly revenue per hospital	Vektis

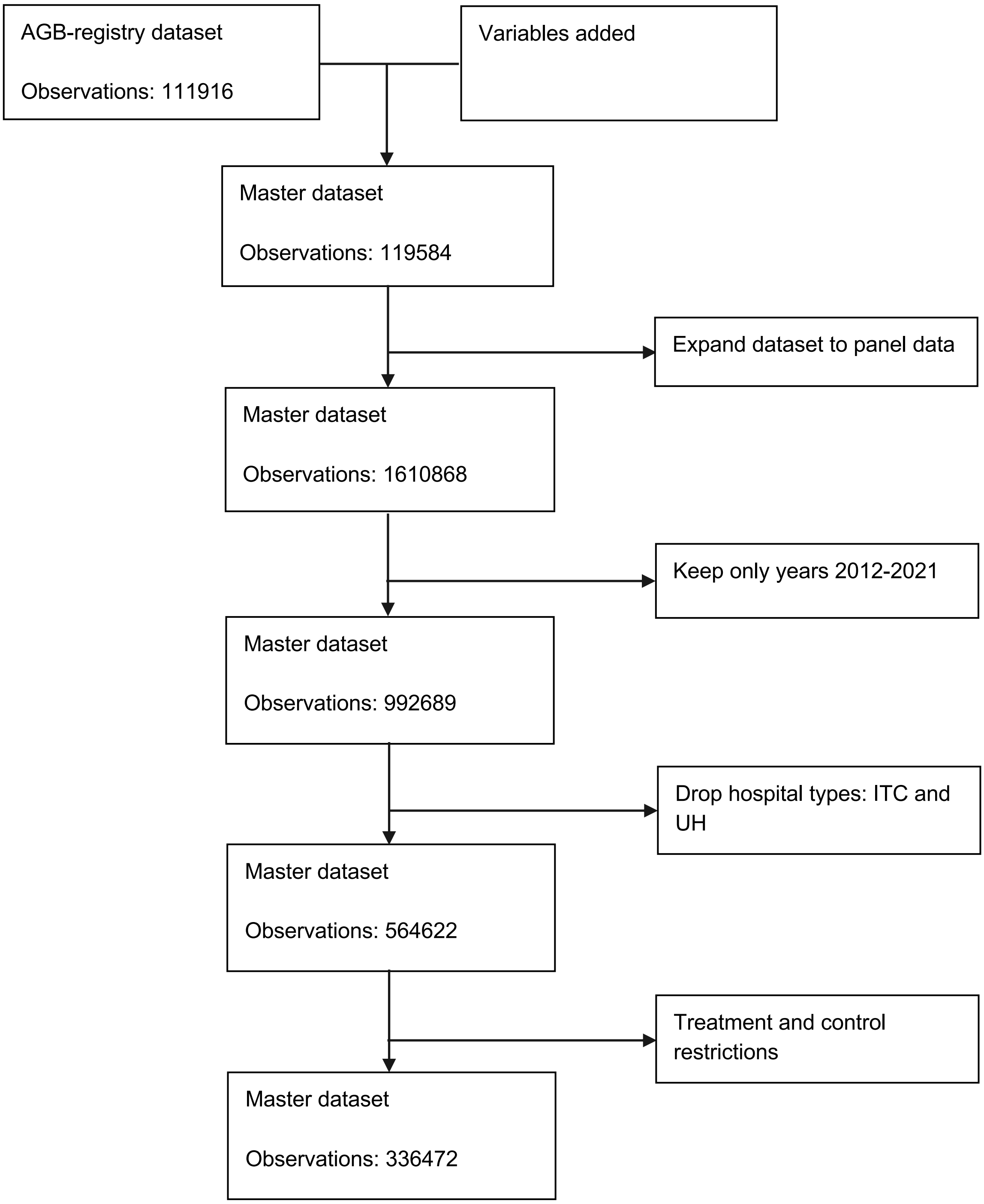


Figure 3.1 schematic representation of the sample selection

3.1.2 Variables used

The main dependent variable of interest is retention. $Retention_{it}$ is a binary variable containing value 1 if healthcare professional i is retained in year t and 0 if healthcare professional i is not retained in year t. Being retained by a hospital means that healthcare professional i needs to be employed up until November 30th in year t. Measuring the difference in retention explains the effect of a merger on employment.

The main independent variable of interest is whether a healthcare professional is in the treatment group or in the control group. $Treatment_{it}$ contains value 1 if healthcare professional i in year t works at a hospital that has merged between 2012-2021, this is the treatment group. It contains value 0 if healthcare professional i in year t works at a hospital that has not merged or has not had any merger activities for five years between 2012-2021, this is the control group. When a healthcare professional has multiple employment contracts, these contracts are separated so that each individual contract is considered as a distinct healthcare professional. This method ensures that a healthcare professional can never simultaneously be part of both the treatment and control group. To be eligible for the treatment group a healthcare professional must be employed at the hospital at the time of the merger and must have worked at the same hospital for at least two years prior to the merger. Until the year of the merger a healthcare professional is 'not-yet treated' and a healthcare professional becomes 'treated' in the year of the merger and stays treated for all periods afterwards. To be eligible for the control group a healthcare professional must have been employed for a minimum of two years at a non-merging hospital or be employed for a minimum of two years at a hospital that has had no merger activities for at least five years. This group can therefore be seen as 'never-treated'. In short, the treatment variable consists out of the treated, the not-yet treated and the never-treated.

Various control variables are included in the model. One control variable that will be used is the type of hospital. It includes the hospital types Teaching hospital, Top-clinical hospital, and General hospital. Goodman (2006) found differences in the percent changes in employment for specific types of hospital during the 1990-2004 period. Another control variable is the type of specialization the healthcare professional practices. It contains 50 different specializations such as surgery and cardiology. Different types of skilled hospital workers experience reduced wage growth if the concentration increase induced by a merger is large (Prager & Schmitt 2021). In a study by ABN AMRO (2019), a Dutch bank, male workers are willing to travel twice as far to work as female workers. Hospital mergers can lead to longer travel times if units are displaced or closed and this will affect female healthcare professionals differently from male healthcare professionals. Therefore, the time in minutes that a healthcare professional needs to travel to the hospital they work at is included as a control variable. Total yearly revenue of the hospital is used as a control variable because it might follow the same trend as retention. Intuitively, if a hospital makes more revenue, then the hospital has more financial room to retain healthcare professionals. Also, demographic covariates such as age, gender, and province where the hospital is located are added to the model.

3.2 Empirical strategy

3.2.1 Treatment vs. control

In the paper *Prijs- en volume-effecten van ziekenhuisfusies* (ACM, 2017) a list of all proposed hospital mergers from 2007 up to and including 2016 is provided. To complement the list of hospital mergers after 2016 an ACM Excel file is used, where all concentration reports are tracked. Combining the information from the paper and Excel file, a list of all hospital mergers during the 2012-2021 period is created. From this list all mergers with UMC's were excluded together with all the mergers that in the end were not implemented. In Table 3.2 all hospitals that, either belong to the treatment or control group, are presented. Healthcare professionals that are employed at the hospitals in the left column are in the treatment group.

A distinction can be made between two groups of healthcare professionals within the control group. These two groups are the never-treated group and the not-yet treated group. The never-treated are healthcare professionals that are employed at hospitals that have not merged or have not had any merger activities for five years during the 2012-2021 period. The not-yet treated consists of healthcare professionals that are employed at hospitals that belong to the treatment group, but till the year of the administrative merger date they belong to the control group. The healthcare professionals that belong to the control group are employed at the hospitals in the right column of Table 3.2, where the never-treated are noted in normal font and the not-yet-treated are in italics. As comparison group the never-treated is used in the difference-in-difference analysis.

Table 3.2 Hospitals that are included in the treatment and control group

Hospital included in treatment group	Hospital included in control group
Bravis Ziekenhuis	Bernhoven B.V.
Dijklander Ziekenhuis	*Bravis Ziekenhuis*
OLVG	*Dijklander Ziekenhuis*
Spaarne Gasthuis	Maasziekenhuis Pantein B.V.
Stichting Alrijne Zorggroep	Meander Medisch Centrum
Stichting Elisabeth-TweeSteden Ziekenhuis	Medisch Centrum Leeuwarden B.V.
Stichting Haaglanden Medisch Centrum	*OLVG*
Stichting Isala Klinieken	Rode Kruis Ziekenhuis B.V.
Stichting Sint Antionius Ziekenhuis	Saxenburgh Medisch Centrum
Stichting Sint Franciscus Vlietland Groep	*Spaarne Gasthuis*
Stichting Treant Ziekenhuiszorg	Stichting Albert Schweitzer Ziekenhuis
Stichting Zuwe Hofpoort Ziekenhuis	*Stichting Alrijne Zorggroep*
Stichting Zuyderland Medisch Centrum	Stichting Amphia
ZorgSaam Ziekenhuis	Stichting BovenIJ
	Stichting Catharina Ziekenhuis
	Stichting Deventer Ziekenhuis
	Stichting Diakonessenhuis
	Stichting Elisabeth-TweeSteden Ziekenhuis
	Stichting Elkerliek Ziekenhuis
	Stichting Flevoziekenhuis
	Stichting Gelre Ziekenhuis
	Stichting Groene Hart Ziekenhuis
	Stichting Haaglanden Medisch Centrum
	Stichting Het van Weel-Bethesda Ziekenhuis
	Stichting IJselland Ziekenhuis
	Stichting Interconfessionele Stichting Gezondheidszorg Rivierenland
	Stichting Isala Klinieken
	Stichting Jeroen Bosch Ziekenhuis
	Stichting Laurentius Ziekenhuis Roermond
	Stichting Maasstad Ziekenhuis
	Stichting Martini Ziekenhuis
	Stichting Medisch Spectrum Twente
	Stichting Nijmeegs Interconfessioneel Ziekenhuis Canisius-Wilhelmina
	Stichting Protestants Christelijk Ziekenhuis Ikazia
	Stichting Rijnstate Ziekenhuis

	Stichting Rivas Zorggroeg
	Stichting Sint Antonius Ziekenhuis
	Stichting Sint Franciscus Vlietland Groep
	Stichting St. Anna Zorggroep
	Stichting Tergooi
	Stichting Treant Ziekenhuiszorg
	Stichting Viecuri, Medisch Centrum voor Noord-Limburg
	Stichting Wilhelmina Ziekenhuis Assen
	Stichting Zaans Medisch Centrum
	Stichting Ziekenhuis Amstelland
	Stichting Ziekenhuis Gelderse Vallei
	Stichting Ziekenhuisgroep Twente
	Stichting Zuwe Hofpoort Ziekenhuis
	Stichting Zuyderland Medisch Centrum
	Stichting voor medische en verpleegkundige zorgverlening st. Jans Gasthuis
	Tjongerschans
	ZorgSaam Ziekenhuis

Note. Hospitals belonging to the not-yet-treated are in italics

3.2.2 Empirical design

To quantify the effect of a hospital merger on healthcare professional retention a difference-in-difference design in used. The reason for this is that the predominant strategy to study the impact of consummated mergers in the setting of hospital mergers is the difference-in-difference estimation (Gaynor et al. 2015). The difference-in-difference approach estimates the Average Treatment Effect for the Treated (ATET) by comparing the average change in outcomes observed in the treated group to those in the control group. This comparison assumes that, in the absence of treatment, the average outcomes for both groups would have followed parallel paths over time. The most general formula for a difference-in-difference can be described by the following formula (Goodman-Bacon 2021):

$$y_{it} = \alpha_i + \alpha_t + \beta^{DiD} D_{it} + \varepsilon_{it}$$

Where α_i is the dummies for time-invariant coefficients, α_t the time periods, D_{it} the treatment dummy and ε_{it} the error term.

The data used in this research has as characteristics that it contains more than two time periods and variation in treatment timing. Therefore, a TWFE regression cannot be used. Callaway (2023) suggests using a new difference-in-difference estimator developed by Callaway & Sant'Anna (2021). They designed a difference-in-difference estimator with staggered treatment adoption setups. This staggered difference-in-difference approach calculates a disaggregated parameter called the group-time average treatment effect. The group time average treatment effect indicates the average treatment effect for group g at time t, where a group is described by the period when units are first treated. It accounts for more than two time periods and variation in treatment timing, while still being robust to treatment effect heterogeneity. From here on, it will be referred to as the staggered difference-in-difference. The staggered difference-in-difference will also be used to run a sub-analysis on two sub-groups, which are only physicians including physician assistants and basic physicians, and only physicians excluding physician assistants and basic physicians.

3.2.3 Assumptions of the staggered difference-in-difference

For their staggered difference-in-difference Callaway & Sant'Anna (2021) Require that seven assumptions need to be satisfied in order to provide robust estimates. When all the assumptions are satisfied, the staggered difference-in-difference provides robust estimates.

Assumption 1 explains that treatment is irreversible. This means that no units are treated at time t=1, and once a unit receives treatment, it will always be treated in the following periods. This assumption holds since, to satisfy this assumption, the treatment group has been structured in such a way that healthcare professionals are always treated after they become treated. Also, the first cohort of hospital mergers is in 2013. So, in 2012 there are no hospital mergers and therefore nobody is treated in 2012.

Assumption 2 describes random sampling. This assumption imposes that each healthcare professional i needs to be randomly picked from a large population of interest. Physicians are representative in the dataset, but non-physicians are not completely representative in the dataset. Even though the non-physician group might not be representative, the total amount of all healthcare professionals is large, and they have no control whether the hospital they are employed at is going to merge. So, they have no influence whether they belong to the treatment or control group. Thus, this assumption likely holds.

Assumption 3 defines that there can be no treatment anticipation. It implies that healthcare professionals working at a hospital that is going to merge do not anticipate the merger that will happen in the future, and for example leave. The administrative merger date, rather than the legal merger date, is used to determine when a hospital is merging to minimize the anticipation effect. Using the legal merger date would violate the assumption as it does not account for healthcare professionals anticipating the merger at the administrative merger date and leaving the hospital before the legal merger date due to this new situation.

Assumption 4 states that there are conditional parallel trends based on the never-treated group. In other words, given the control variables, the average outcomes for the group initially treated in period g and the never-treated would have followed parallel paths if the treatment had not occurred. If this assumption holds, the control group will serve as the perfect counterfactual for the treatment group. To achieve a parallel trend, a hospital-specific trend is included by extending the trend observed in the pre-treatment period into the post-treatment period, following the same intuition as Agguzzoni et al. (2018). Using the hospital-specific trend, the coefficients will be calculated by hand. The reason is that the method by Callway & Sant'Anna (2021) does not have a feature that can plot an alternative parallel trend.

Assumption 5 is the overlap assumption, and it is an extension on the overlap assumption by Sant'Anna & Zhao (2020). They describe overlap as a condition where a small portion of the sample must receive treatment, and for each control variable, there should be a minimal chance that the unit remains untreated. Callaway & Sant'Anna (2021) extend this assumption to multiple time periods and different treatment timing. This assumption holds, because each (control) variable included has healthcare professionals in both the treatment and control group.

Assumption 6 and 7 can be described together. Assumption 6 and 7 are general assumptions required for a linear or nonlinear outcome regression. These assumptions are satisfied since the statistical software program that is used, Stata 18.0, takes care of these requirements.

4 Results

In this section the results of the study are presented. First the descriptive statistics are described and displayed. After that the results of the staggered difference-in-difference are explained and shown.

4.1 Descriptive statistics

The descriptive statistics of the whole sample, the treatment group and the control group are visible in Table 4.1. The whole sample consists of 336,472 observations with a total of 34,991 healthcare professionals and 53 hospitals. The average age for healthcare professionals in the whole sample is 47 and the average time they need to travel to the hospital is around 47 minutes. The treatment group consists of 71,065 observations with a total of 7,539 healthcare professionals and 14 hospitals. The average age of healthcare professionals in the treatment group is nearly 48 years and the average time they need to travel to the hospital is roughly 44 minutes. The control group consists of 265,407 observations with a total of 34,991 healthcare professionals and 53 hospitals. The average age for a healthcare professional in the control group is 46 years and the time they need to travel to the hospital is 47 minutes. At baseline, the number of healthcare professionals and hospitals in the control group are the same as in the whole sample, given that no healthcare professional can be treated at t=1. This is because of the first assumption for the staggered difference-in-difference proposed by Callaway & Sant'Anna (2021).

The distribution of the healthcare professionals in the treatment and control group for the categorical variables type of hospital the healthcare professional works at, province where hospital is located and specialization the healthcare professional practices are visible in Graphs 4.1, 4.2 and 4.3 respectively. The distribution of the type of hospital the healthcare professional works at is similar between the treatment and control group. The only difference is that the control group has a bit more general hospitals and a bit less Top-clinical hospitals in the distribution. The distribution of the provinces in which the hospitals are located is different for the treatment and control group. The control group has all twelve provinces represented in the distribution and treatment group only eight provinces represented in the distribution. The distribution of the specialization the healthcare professional practices appear consistent for both the treatment and control group. There is one specialization in the control group that evidently has a higher share in the distribution than the treatment group and that is the specialization basic physician. The full list of specializations that are used can be found in the appendix.

For control variables gender, age, travel time and revenue a two-sample t-test has been conducted and for the variables type of hospital, province and specialization a chi-squared test of independence has been conducted. The two-sample t-test is used to see if the means of the treatment and control group are significantly different from one another, and when they are, controlling for the variables is justified. The chi-squared test of independence compares the distribution of a categorical variable across the treatment and control groups. When the distributions are significantly different, it justifies the need for controlling for that variable. All t-tests and chi-squared tests of independence reveal that all control variables are significant at the 1% level.

Table 4.1 Descriptive statistics for the whole sample, treatment group and control group

	Groups		
Variables	**Whole sample**	**Treatment group**	**Control group**
Retention	0.9619	0.9454	0.9663
	(0.1915)	(0.2273)	(0.1805)
Treatment	0.2112	1	0
	(0.4082)	(1)	(0)
Gender, 45% male	0.5261	0.4944***	0.5346***
	(0.4993)	(0.5000)	(0.4988)
Age	47.37	51.98***	46.09***
	(12.35)	(11.30)	(12.32)
Type of hospital	2.9533	2.6199***	3.0399***
	(1.7893)	(1.6877)	(1.8048)
Province	7.4136	8.2528***	7.1791***
	(3.0661)	(3.1697)	(2.9949)
Specialization	27.9799	27.2318***	28.1741***
	(13.5104)	(13.4273)	(13.5252)
Travel time	46.51	43.90***	47.21***
	(37.28)	(39.35)	(36.67)
Revenue	2.3×10^8	3.17×10^8***	2.07×10^8***
	(1.01×10^8)	(9.67×10^7)	(8.93×10^7)
Number of healthcare professionals	34,991	7,539	34,991
Number of hospitals	53	14	53
Observations	336,472	71,065	265,407

Note. Standard deviations are in parentheses; *** $p < 0.01$

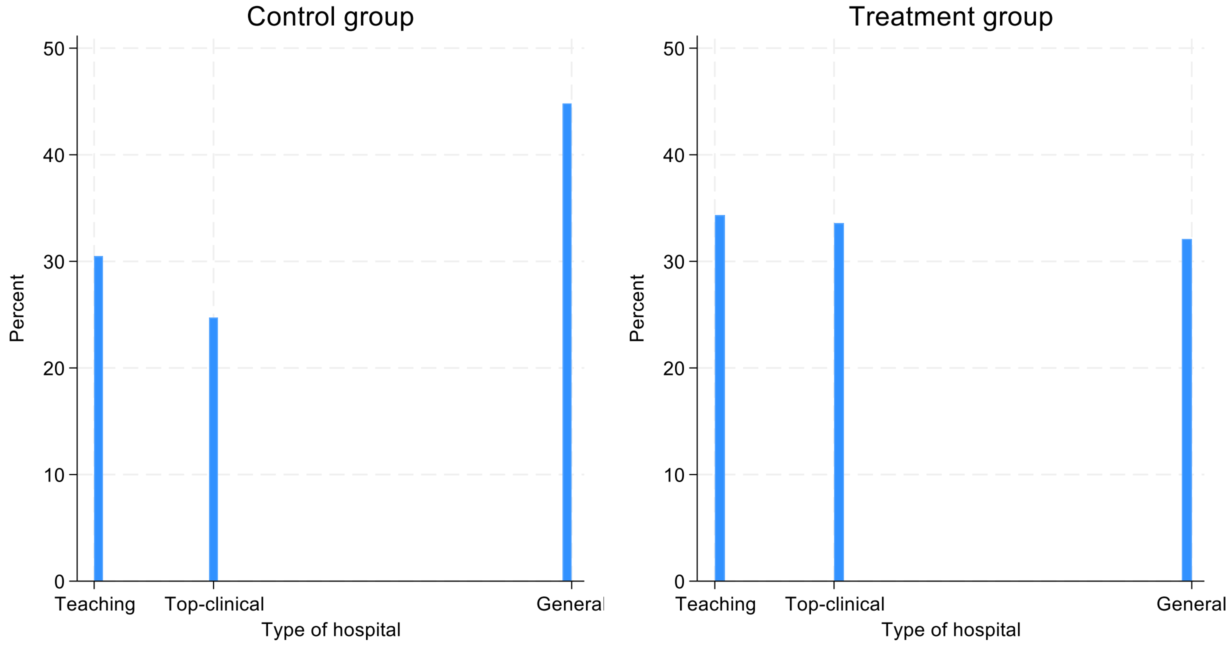


Figure 4.1 Percentages of hospital types present in the distribution for the treatment and control group

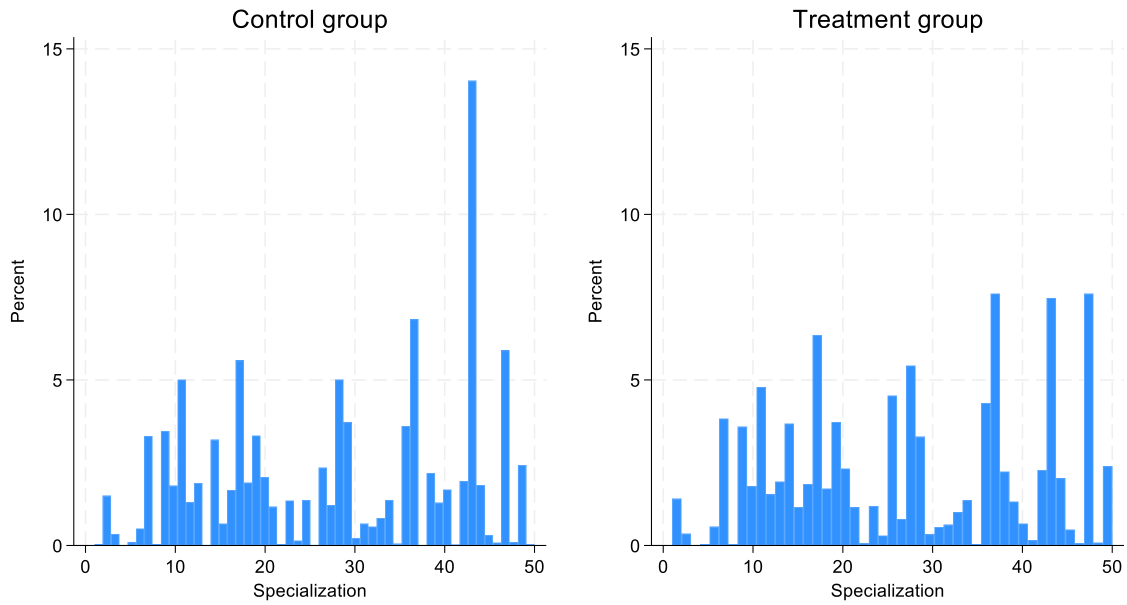


Figure 4.2 Percentage of the specialization the healthcare professional practices present in the distribution for the treatment and control group

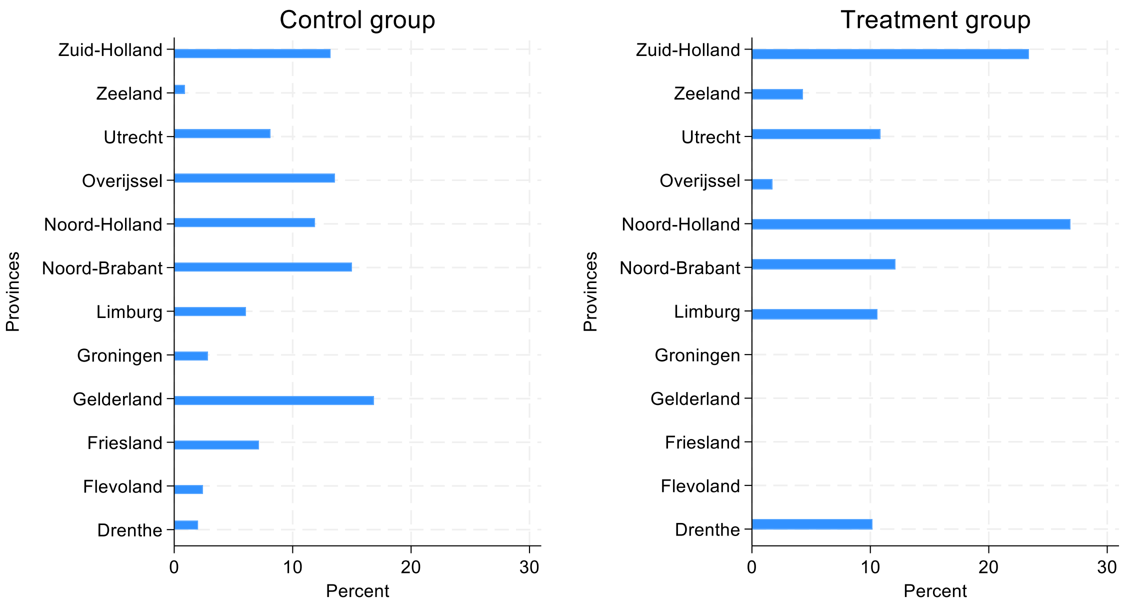


Figure 4.3 Percentage of the provinces present in the distribution for the treatment and control group

4.2 Difference-in-difference

4.2.1 Individual cohorts

The staggered difference-in-difference calculates ATET. This is the difference between the mean change observed in the treatment group with the mean change observed in the control group. In Section 3.2.3 it is argued that the parallel trend assumption holds. Upon investigating Figure 4.4 it is visible that in the cohorts of 2013 and 2014 a parallel trend is present. Though in the cohorts of 2015 and 2016, there appears to be a weaker parallel trend, with a parallel trend evident only in the early pre-treatment years.

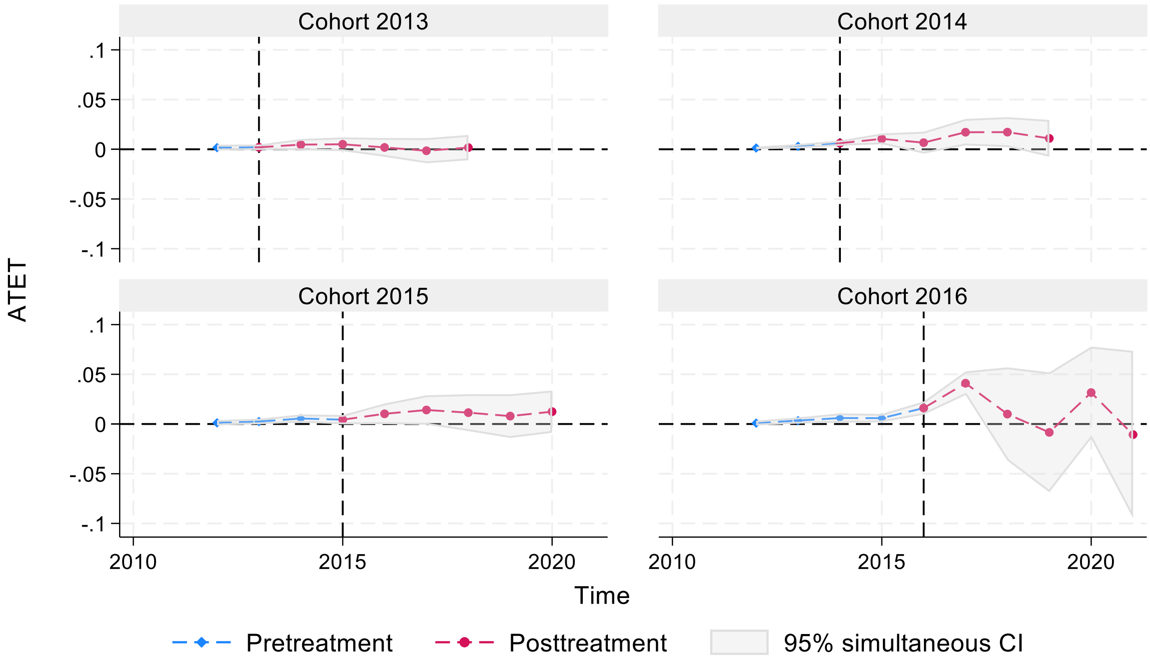
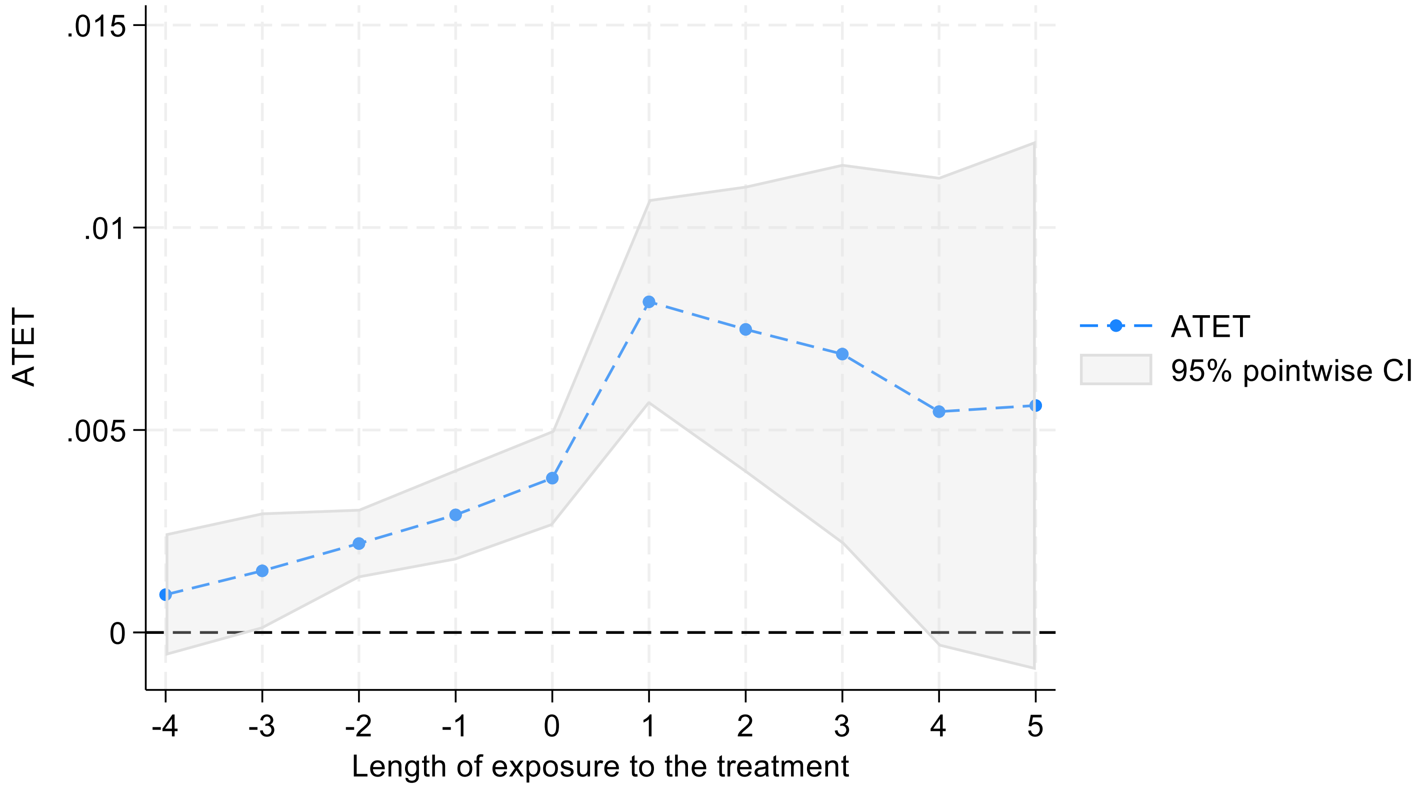


Figure 4.4 Pre- and post-treatment trends for individual cohorts

4.2.2 Aggregated cohorts

The results of the staggered difference-in-difference can be seen in Figure 4.5. In Figure 4.5 all the ATET's are aggregated across the different lengths of treatment exposure. So, at t=1 healthcare professionals that are treated have a 0.82% higher chance of being retained than the never-treated, which is significant at the 1% level, ceteris paribus. However, when looking at Figure 4.5 one thing standing out is that there is no parallel trend in the pre-treatment period. Only at t=-4 there is evidence for a parallel trend, but from there on there is a positive constant linear trend in the pre-treatment period. This is a violation of assumption 4.



Length of exposure	-4	-3	-2	-1	0	1	2	3	4	5
ATET	0.0009	0.0015**	0.0022***	0.0029***	0.003***	0.0082***	0.007485***	0.0069***	0.0055	0.0056
	(0.0008)	(0.0007)	(0.0004)	(0.0006)	(0.0006)	(0.0013)	(0.0018)	(0.0024)	(0.0030)	(0.0033)

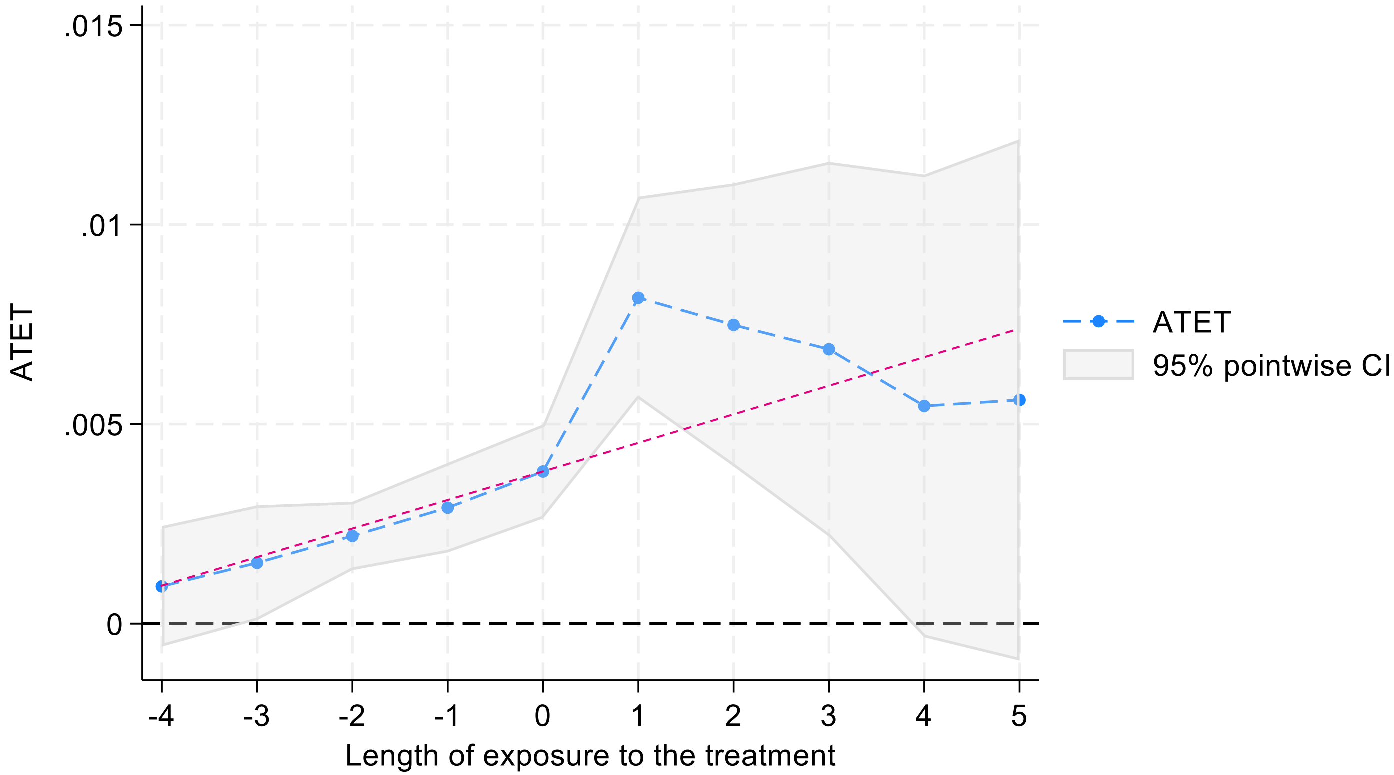
Figure 4.5 Pre- and post-treatment trend aggregated across different lengths of treatment exposure

Note. Standard errors are in parentheses; ** $p < 0.05$, *** $p < 0.01$

4.2.3 Aggregated cohorts with hospital-specific trend

Figure 4.5 shows a positive and increasing linear trend from t=-4 till t=0. This linear trend is conditional on control variables that are justified in the model, since they all have been tested by either a two-sample t-test or a chi-squared test of independence. The linear trend in the pre-treatment period is for this reason precisely measured. Therefore, the hospital-specific trend in the pre-treatment period is extended into the post-treatment period as parallel trend. Figure 4.6 shows the new parallel trend by the dotted red line and the outcomes. There is only one significant outcome and that is at t=1. One year after the merger, healthcare professionals that are treated have 0.36%[1] more chance of being retained than healthcare professionals that are never-treated, and this is significantly different from zero, ceteris paribus. Altogether, with the evidence of a possible parallel trend in Figure 4.4, the precisely measured positive linear trend in the pre-treatment period in Figure 4.5, and the extension of the hospital-specific trend from the pre-treatment period into the post-treatment period, this provides proof of a possible parallel trend.

1 The calculation was done as follows. First, the slope coefficient was calculated for the periods t=-4 to t=0. For the period t=1, the slope coefficient was used to calculate the corresponding coefficient of the hospital-specific trend. Next, the original ATET of t=1 was reduced by the value of the hospital-specific trend of t=1. This process was repeated for all subsequent periods.



Length of exposure	-4	-3	-2	-1	0	1	2	3	4	5
ATET	0	0	0	0	0	0.0036*	0.0022	0.0009	-0.0012	-0.0018

Figure 4.6 Pre- and post-treatment trend aggregated across different lengths of treatment exposure, extending the pre-treatment hospital trend as parallel trend

Note. * Significantly different from zero

4.2.4 Additional findings

Figure 4.7 and Figure 4.8 show additional outcomes from the staggered difference-in-difference. Figure 4.7 shows the average ATET of each cohort within time. In this figure each cohort has a positive ATET and there is an increasing trend in the ATET from 2013 to 2016. Figure 4.8 shows the average ATET within time. Again, all ATET's are positive except for 2021, which could be the result of the Covid-19 pandemic, and there is an increasing trend in the ATET from 2013 to 2020.

The same analysis is also conducted for smaller subgroups within the dataset. The first subgroup is only physicians including physician assistants and basic physicians and the second subgroup is only physicians excluding physician assistants and basic physicians. The results are visible in the appendix. The outcomes of the both the subgroups are similar to that of the whole sample.

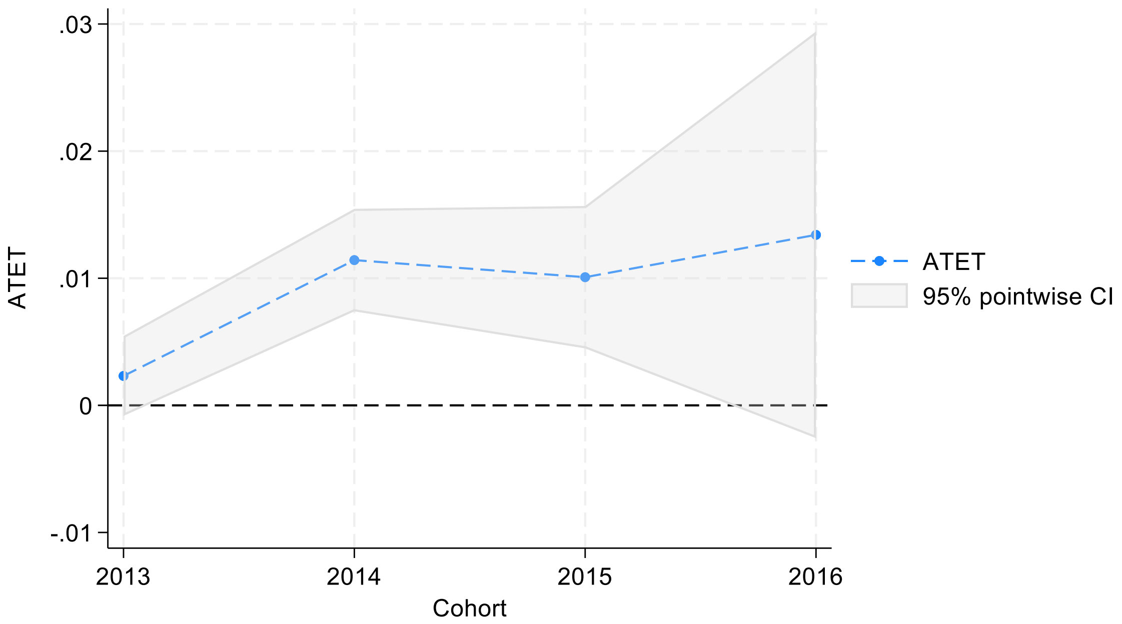


Figure 4.7 The ATET of each cohort over time

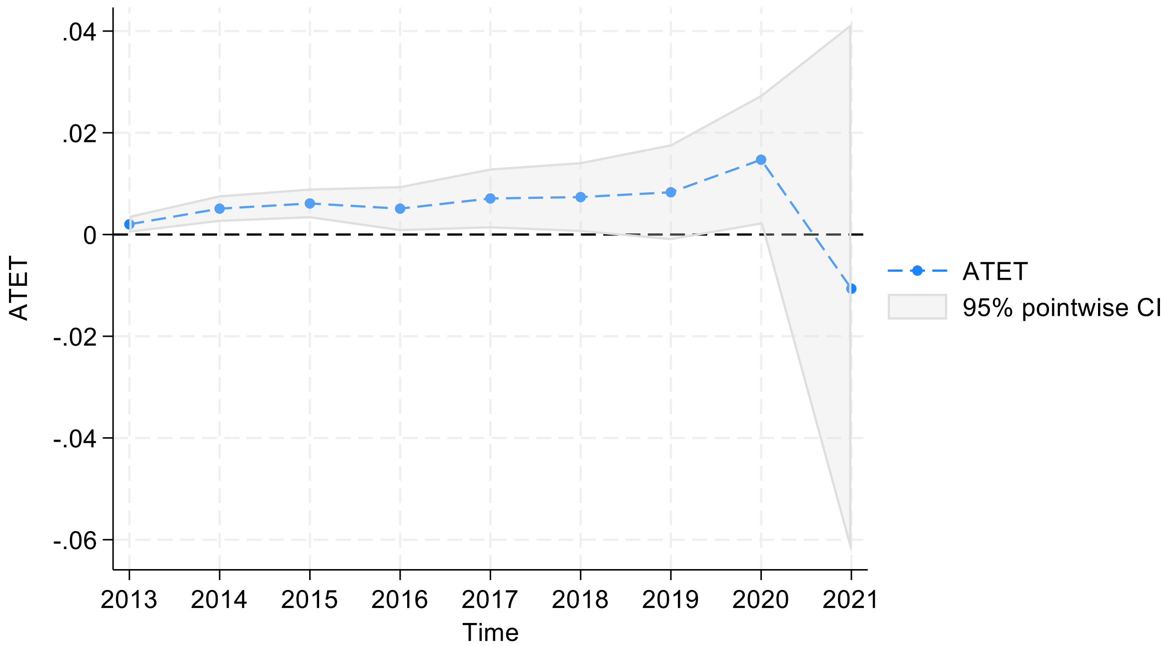


Figure 4.8 The ATET for each year over time

5 Discussion

This study aims to analyze the probability that a healthcare professional employed at a merging hospital is retained at the merging hospital after a merger, compared to a healthcare professional employed at a non-merging hospital during the 2012-2021 period. This section will look at the results found in section 4 in more detail, after which the limitations of this research will be elaborated. Lastly, this section will shed its light on future research and give a recommendation.

5.1 Main findings

By extending the pre-treatment period hospital-specific trend, healthcare professionals at t=1 have a 0.36% higher chance of being retained at a merging hospital than healthcare professionals at a non-merging hospital, and this difference is significantly different from zero, ceteris paribus. For the other post-treatment periods there are no coefficients significantly different from zero.

Ingelsrud (2017) showed that after a hospital merger only in the second year after a merger there is a significant effect compared to the years preceding the merger. Similarly, this study also shows a significant effect but only in the first year after the hospital merger. A hospital merger only seems to influence healthcare professionals in the beginning years after the merger and the influence weakens as the years go by. In contrast to Ingelsrud (2017), who found a positive association between hospital mergers and employment turnover, which can be seen as negative association between hospital mergers and retention. This study finds a positive association between hospital mergers and retention. There is an explanation for this difference. Ingelsrud (2017) found that the increase in turnover within the hospital sector is caused by the turnover between the merged hospitals. After a merger, healthcare professionals employed at the merging hospitals are more likely to switch between those hospitals. This could explain both the significant turnover and retention after a hospital merger.

Another explanation for the increase in the probability that healthcare professionals are retained at the merging hospital might be caused by the anticipation effect. Hospitals that merge might be able to exert an attracting effect on healthcare professionals. They can increase their patient base (Ferrier & Valdmanis 2004), which might lead to more vacancies. Since it takes many years to legally complete a merger, healthcare professionals can anticipate this and move to the merging hospitals. However, efforts have been made to mitigate the anticipation effect as much as possible by using the administrative merger date instead of the legal merger date. Healthcare professionals are only included in the treatment group if they have been employed at the same hospital for at least two years prior to the merger and in the control group if they have been employed at the same hospital for a minimum of two years. Hence, it can be argued that the anticipation effect is not contributing to the increase in the probability that a healthcare professional is retained at the merging hospital.

The positive effect of a hospital merger on retention might also be explained by Prager & Schmitt (2021). They show that unionization can mitigate the negative wage effect after a hospital merger. So, chances are that unionization can also mitigate the negative effect of hospital mergers on employment, which in the context of this study is less layoffs and more retention. To that end, it cannot be ruled out that unions, *maatschappen* or MSB's may also influence employment after a merger. Intuitively this sounds reasonable, since unions, *maatschappen* and MSB's strongly advocate for their employees and take a firm stand against budget cuts and layoffs.

From the data it shows that healthcare professionals after a merger have small but higher chance of being retained. This is in contrast with evidence from mergers outside the hospital sector. Dobbelaere et al. (2022) find that workers are 6 percentage points less likely to be retained at the merged firm in the four years after the merger. The findings of Dobbelaere are in line with a possible rise in monopsony power after a merger.

A possible explanation for this difference in outcome in this study, compared to that of Dobbelaere et al. (2022), is that one reason for hospitals to merge is to reduce their non-price competition, sometimes called the medical arms race (Ferrier & Valdmanis 2004). Martinez-Giralt & Barros (2013) explain that the medical arms race makes hospitals invest in the latest technology to signal their quality to both potential patients and medical personnel, as this real or perceived quality signal is useful to attract market volume and medical personel, being a significant factor for both patients and medical professionals when choosing among hospitals. Trinh, Begun & Luke (2008) also show that the medical arms race leads to a duplication of services. The signal can exert an attractive force on healthcare professionals and due to the duplication of services, a larger workforce is needed. Therefore, healthcare professionals employed at the merging hospital can have a higher chance of being retained.

5.2 Limitations and strengths

This study faces several limitations. First, only eight of the twelve provinces, where the hospitals are located, are present in the treatment group, whereas all provinces are present in the control group. In the treatment group, the other four provinces had no hospital mergers that met the merger criteria during the 2012-2021 period. This might negatively affect the control group as the perfect counterfactual for the treatment group, since the treatment and control group are not the same for this control variable.

The second limitation is that the model cannot control for non-physicians who are union members and physicians that belong to a *maatschap* or MSB. Prager & Schmitt (2021) show that unionization can mitigate the negative wage effect after a hospital merger. It cannot be ruled out that unions, *maatschappen* or MSB's may also influence employment after a hospital merger. If unions, *maatschappen* or MSB's are correlated with employment after a hospital merger, then being a member of a union or belonging to a *maatschap* or MSB will be captured by the error term by not controlling for them, which will make the treatment group exogenous.

Third, the number of physicians in the dataset is representative but the number of non-physicians is not representative. All physicians need an AGB-code, otherwise they do not get paid, but this is not the case for non-physicians. Only non-physicians who receive fees separately from the health insurer need an AGB-code. This comes with a problem for the random sampling assumption. Only a certain subgroup of the non-physicians needs an AGB-code and therefore they might not be random. This is a violation of the random sampling assumption. Even though the non-physician group might not be random, they have no control whether the hospital they are employed at is going to merge. This still makes the allocation whether the physicians and non-physicians belong to the treatment or control group random.

The final limitation is the absence of a parallel trend when the individual cohorts are aggregated, despite evidence of parallel trends within the individual cohorts. This is a violation of the of the parallel trend assumption. However, this is solved by extending the pre-treatment period hospital-specific trend to the post-treatment period. The hospital-specific trend accounts for a valid parallel trend in the post-treatment conditional on the control variables included.

One strength of this study is that it uses a staggered difference-in-difference approach instead of a TWFE regression. Recent research has proved that a TWFE regression is not robust when there are more than two time periods and if there is variation in treatment timing. The dataset used in this study is characterized by the fact that it has more than two time periods and that there is variation in treatment timing. The staggered difference-in-difference approach still provides robust estimates with these characteristics.

The use of the AGB-registry is another strength. The AGB-registry, where the starting dataset is recovered from, is a national dataset with detailed healthcare professional information. Within the coverage of the database, due to the financial implications of the dataset, it is likely to be accurate. Thus, it is the best dataset for this study and accurate enough to trust the findings.

5.3 Future research and recommendation

5.3.1 Future research

Looking at the parallel trends for the individual cohorts in the pre-treatment period the parallel trend is visible. When the cohorts are aggregated, the pre-treatment shows a positive linear trend, which cannot be explained. For that reason, the pre-treatment hospital-specific trend is further extended into the post-treatment period as the parallel trend. It would be valuable to know the reasons for the underlying trend. Understanding the factors behind this trend could provide insights into the baseline characteristics of hospitals before merging, allowing for more accurate evaluations of policy impacts and improving the validity of future studies.

Second, from the dataset the hospital type ITC is dropped. ITC's are not included as they are small for-profit healthcare institutions whereas hospitals are large not-for-profit healthcare institutions (Gradus, Koning & Noailly 2007). By including ITC's in the sample they would have hindered the control group in being a good counterfactual. Studying the effects of mergers at ITC's on employment would be interesting for future research, as they can be compared to the results of this study. Examining mergers in for-profit versus not-for-profit healthcare settings could reveal differences in employment outcomes, contributing to a deeper understanding of how profit motives influence labour dynamics.

Third, the dataset lacks a representative number of non-physicians. This is a problem because the findings in this paper are not entirely generalizable for non-physicians. To better understand the effect on non-physicians, it would be valuable to conduct this analysis on a dataset representative for non-physicians. Investigating the impact on non-physicians would shed a light on the broader effects of mergers on the entire healthcare workforce, not just on physicians. Their inclusion could provide a more comprehensive picture.

5.3.2 Recommendation

Based on the implications in Section 5.1, it is possible that highly skilled healthcare professionals are present during the negotiations between hospitals intending to merge. They can leverage their experience and knowledge to demand, for example, the latest technologies or additional funds for research. When their demands are met, they would be more likely to stay at the merged hospitals. Also, hospitals send out signals to healthcare professionals to stay through the medical arms race (Martinez-Giralt & Barros 2013). Altogether, this may lead to higher retention within merged hospitals while also experiencing higher turnover after a hospital merger, since the higher turnover is caused by the turnover between the merged hospitals (Ingelsrud 2017). A possible consequence might be that different groups of healthcare workers from the merging hospitals can learn from each other. The diffusion of diverse perspectives, knowledge, and technologies can lead to spillover effects, potentially increasing the quality of care for patients. The ACM may incorporate these perspectives when reviewing hospital mergers.

6 Conclusion

This study aimed to analyze the effect of hospital mergers in The Netherlands on the probability that healthcare professionals are retained at the merging hospitals compared to non-merging hospitals during the 2012-2021 period. The main result is that healthcare professionals employed at the merging hospitals have a 0.36% higher chance of being retained then healthcare professionals employed at the non-merging hospitals one year after the merger using a hospital-specific trend. This finding is small in magnitude but in contrast to findings documented in earlier studies. This suggests that hospital mergers do not always cause negative effects on healthcare professional retention.

7 Appendix

Table 7.1 List of all specializations

Nummer	Specialization
1	Huisarts
2	Mondziekte en kaakchirurgie
3	Tandartsen
4	Dentomaxilaire orthopaedie
5	Arts bedrijfsgeneeskunde
6	Apothekers
7	Dietisten
8	Podotherapeuten
9	Oogheelkunde
10	Keel-, Neus-, Oorheelkune
11	Chirurgie (heelkunde)
12	Plastische chirurgie
13	Urologie
14	Obstetrie en gynaecologie
15	Neurochirurgie
16	Dermatologie en Venerologie
17	Interne geneeskunde
18	Gastro-enterologie (MDL)
19	Cardiologie
20	Longziekten
21	Reumatologie
22	Allergologie
23	Revalidatie
24	Cardio-thorocale chirurgie
25	Psychiatrie
26	Neurologie
27	Geriatrie
28	Anesthesiologie

29	Radiologie
30	Radiotherapie
31	Nucleaire geneeskunde
32	Klinische chemie
33	Medische microbiologie
34	Pathologie
35	Klinische genetica
36	Kindergeneeskunde
37	Fysiotherapie
38	Orthopedie
39	Logopedie
40	Physician assistant
41	Oefentherapeuten
42	Verloskundigen
43	Basisarts
44	Ergotherapeuten
45	Echoscopie
46	Vaktherapie
47	Verpleegkundigen
48	Huidtherapie
49	GZ-psychologen
50	Onbekend

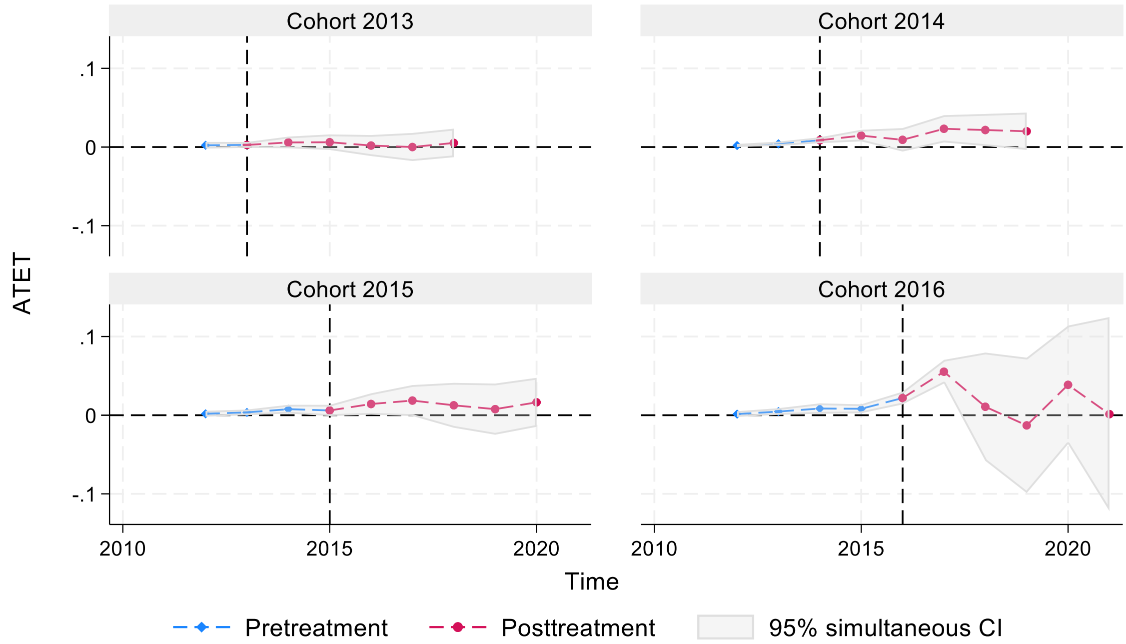


Figure 7.1 Pre- and post-treatment trends for individual cohorts using the subgroup only physicians including physician assistants and basic physicians

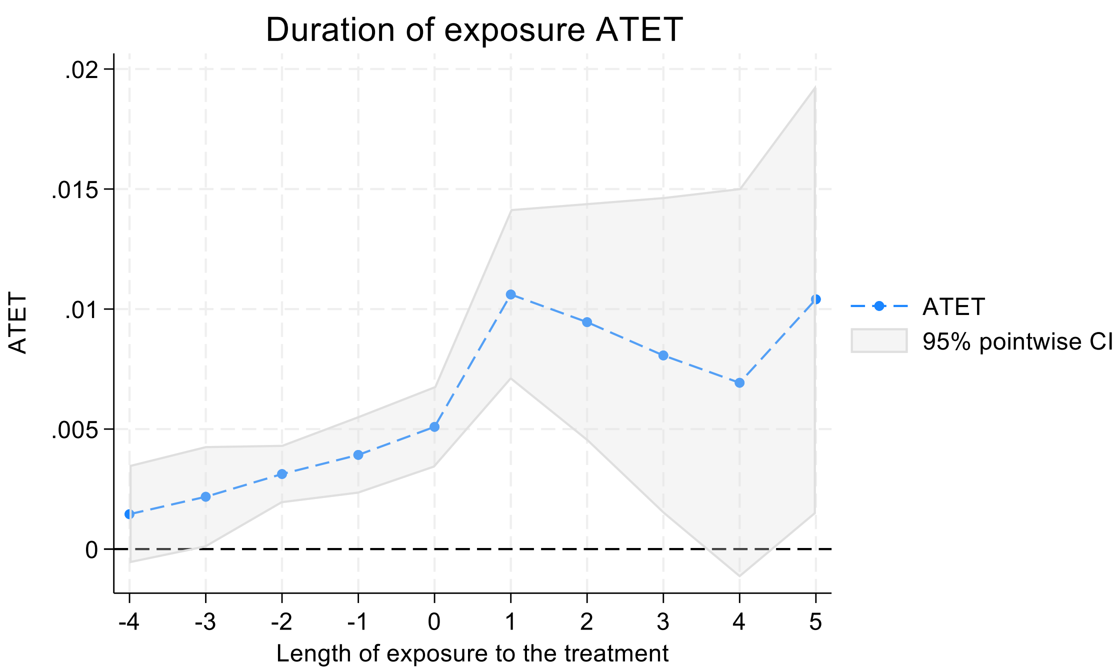


Figure 7.2 Pre- and post-treatment trend aggregated across different lengths of treatment exposure using the subgroup only physicians including physician assistants and basic physicians

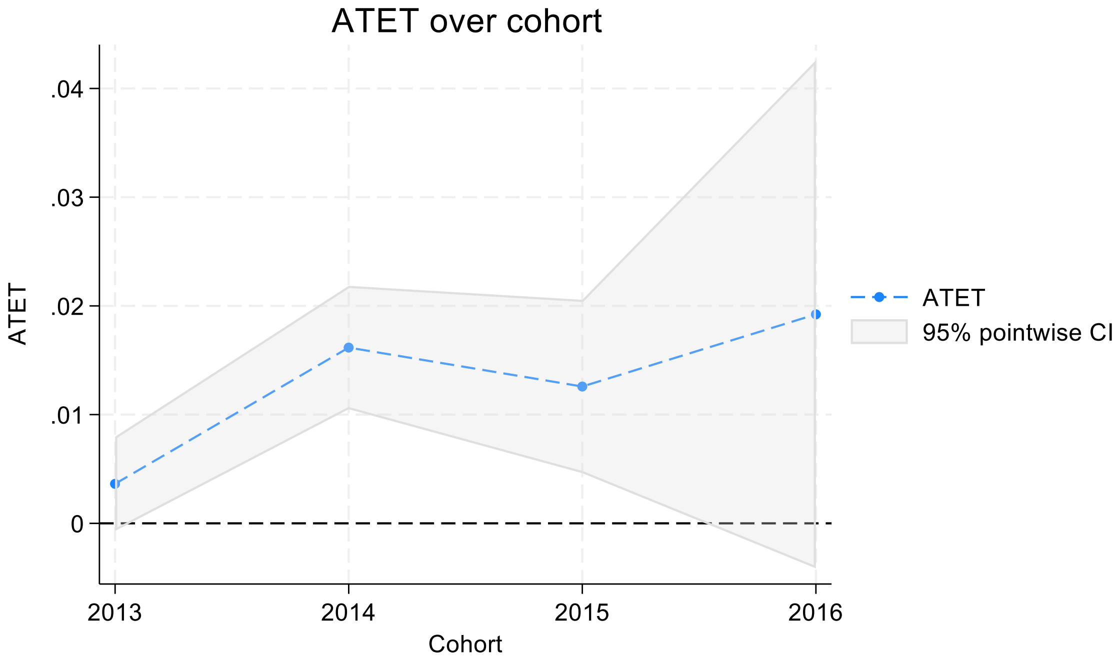


Figure 7.3 The ATET of each cohort over time using subgroup only physicians including physician assistants and basic physicians

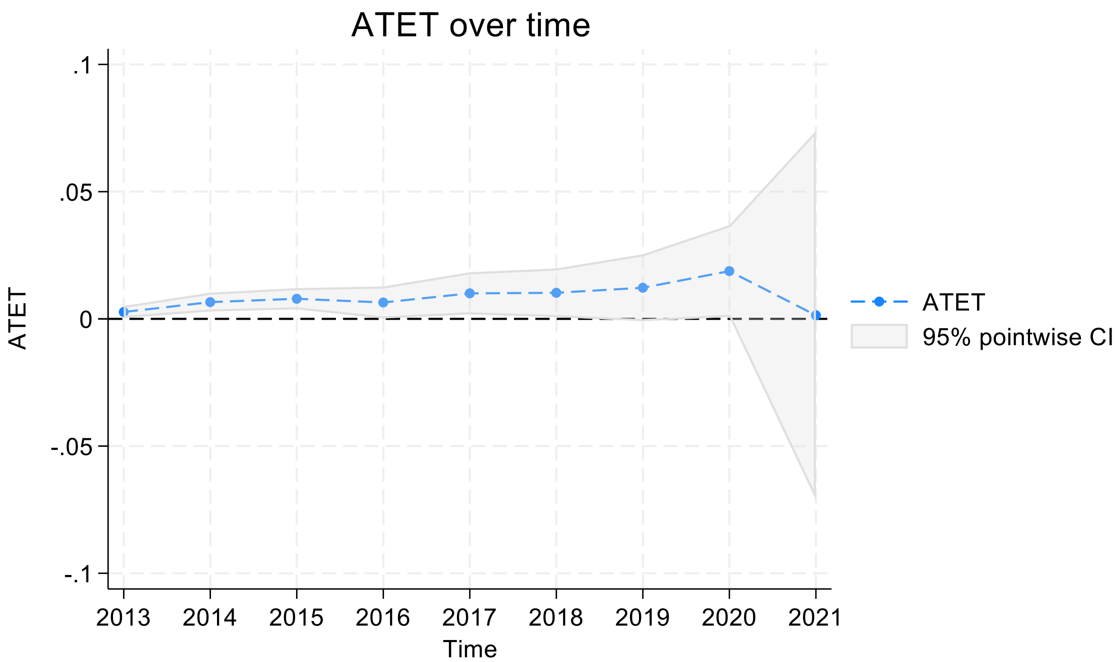


Figure 7.4 The ATET for each year over time using subgroup only physicians including physician assistants and basic physicians

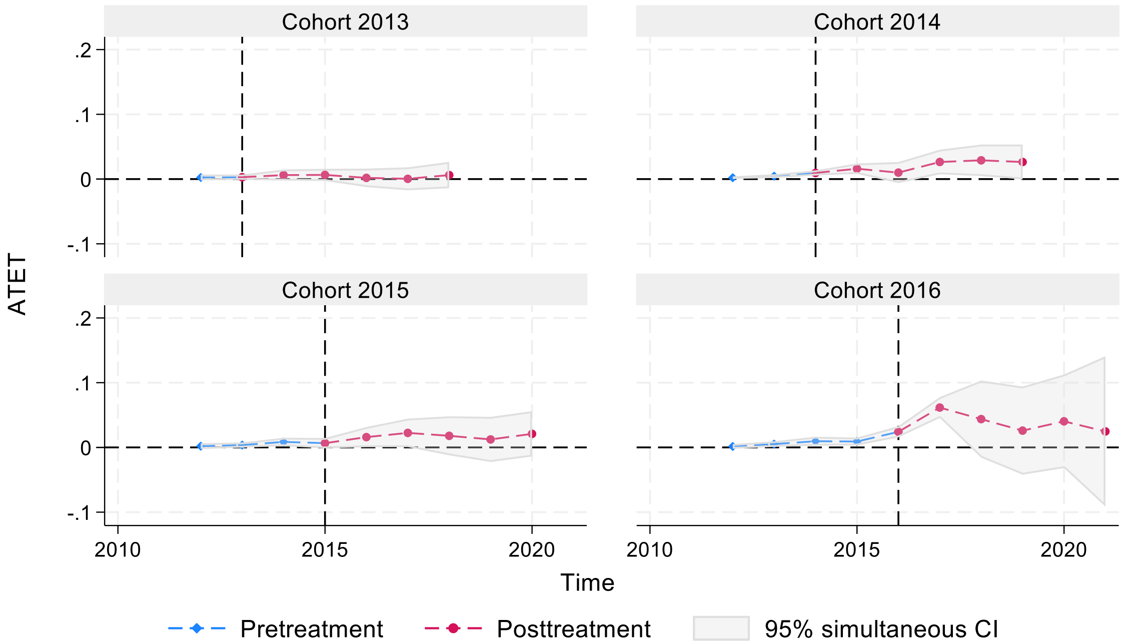


Figure 7.5 Pre- and post-treatment trends for individual cohorts using the subgroup only physicians excluding physician assistants and basic physicians

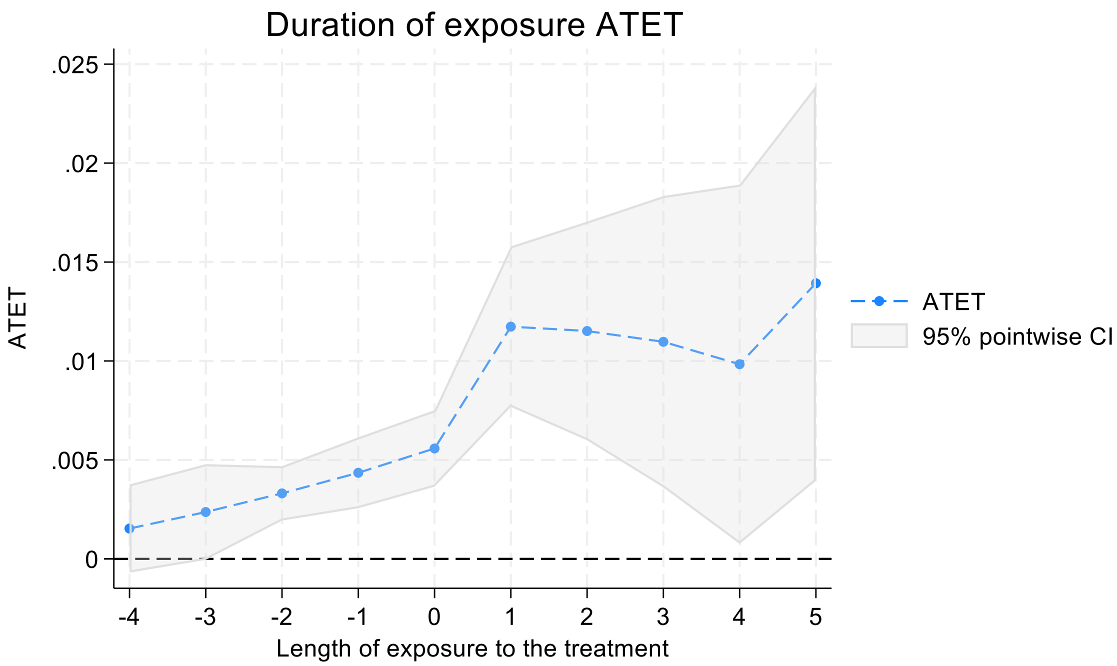


Figure 7.6 Pre- and post-treatment trend aggregated across different lengths of treatment exposure using the subgroup only physicians excluding physician assistants and basic physicians

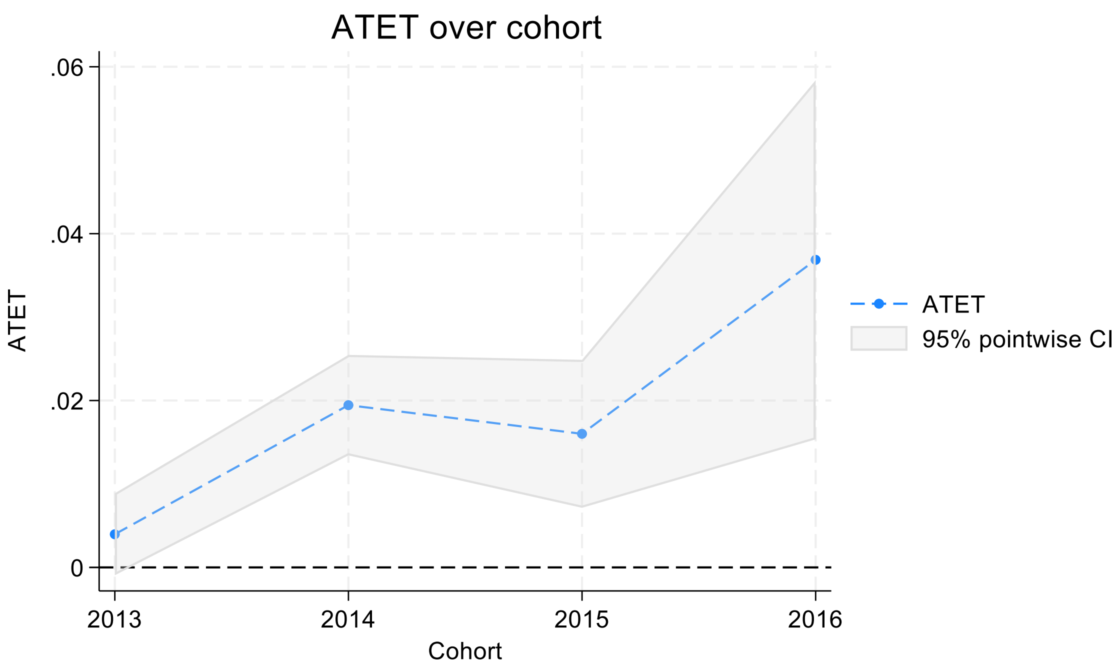


Figure 7.7 The ATET of each cohort over time using subgroup only physicians excluding physician assistants and basic physicians

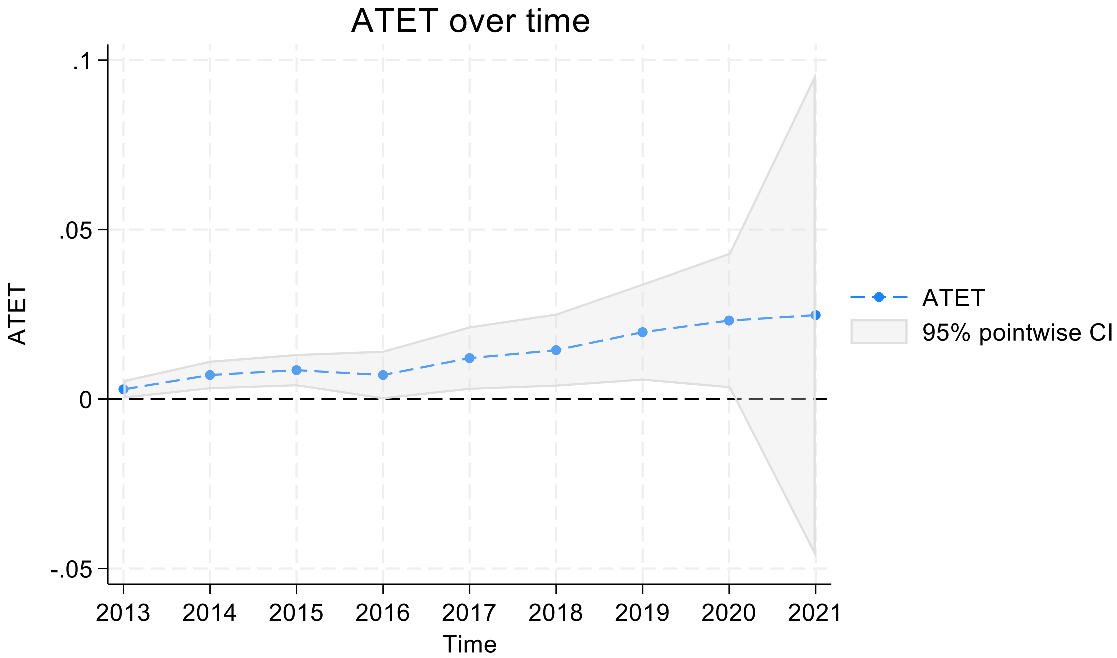


Figure 7.8 Figure 7.4 The ATET for each year over time using subgroup only physicians excluding physician assistants and basic physicians

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