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Institute of Economic Studies

MASTER'S THESIS

Estimating the Effect of Teaching Assistant Support on Pupils' Educational Outcomes

Author: **Jakub Komárek BSc.**

Study program: **Economics and Finance**

Supervisor: **PhDr. Václav Korbel Ph.D.**

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Declaration of Authorship

The author hereby declares that he compiled this thesis independently; using only the listed resources and literature, and the thesis has not been used to obtain a different or the same degree.

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Prague, 1st March 2023 Jakub Komárek BSc.

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Abstract

The thesis provides an analytical-quantitative approach towards estimation of the effect of teaching assistant support on educational outcomes. We used nation-wide data of the Czech school system and three types of econometric models, including quasi-experimental *propensity score matching* and *instrumental variable regression*, to explore (i) what determined the provision of teaching assistant support and (ii) whether there has been any statistically significant effect of teaching assistant support on educational outcomes of pupils. We found that primarily a share of socially disadvantaged pupils and having a religious or private founder had a statically significant positive effect on teaching assistant provision. In contrast, we found no statistically significant effect of teaching assistant support on educational outcomes.

JEL Classification	I21, C26
Keywords	Teaching Assistant, Inclusive Schooling, Special Educational Needs
Title	Estimating the Effect of Teaching Assistant Support on Educational Outcomes

Abstrakt

Diplomová práce obsahuje analyticko-kvantitativní pohled na odhad efektu podpory asistenta pedagoga na vzdělávací výstupy. Použili jsme celonárodní data českého školského systému a tři druhy ekonometrických modelů, včetně kvazi-experimentálních *propensity score matching* a *instrumental variable regression*, abychom zkoumali (i) co ovlivňovalo provizi podpory asistenta pedagoga a (ii) zda můžeme dokumentovat jakýkoli statisticky signifikantní efekt podpory asistenta pedagoga na vzdělávací výstupy žáků. Zjistili jsme, že především podíl sociálně znevýhodněných žáků a církevní či soukromý zřizovatel měli statisticky signifikantní pozitivní efekt na provizi asistenta pedagoga. Naopak jsme nenašli žádný statisticky signifikantní efekt podpory asistenta pedagoga na vzdělávací výstupy.

Klasifikace	I21, C26
Klíčová slova	asistent pedagoga, inkluzivní školství, speciální vzdělávací potřeby
Název práce	Odhadování efektu podpory asistenta pedagoga na vzdělávací výstupy

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Acronyms

2SLS Two-Stage Least Squares

EAF Educational Advisory Facility

EU European Union

MŠMT Ministry of Education, Youth, and Sports of the Czech Republic

NERV National Economic Council of the Government

OLS Ordinary Least Squares

PPA Pedagogical-Psychological Agency

PSM Propensity Score Matching

SEN Special Educational Needs

SPC Special Pedagogical Centre

TA Teaching Assistant

UNESCO United Nations Educational, Scientific and Cultural Organization

(…) our future lies in our education. Today's world is such that there is no problem, be it a problem of daily life or a global problem, which could be solved by uneducated people with just some instinct. Education is in fact a key to a happy, peaceful life, to a life which has some ***meaning.***

Václav Havel, 1997

1 Introduction

The modern Czech state inherited a system of special schools for pupils with special educational needs which was responsible for the care for and education of pupils who had difficulties in mainstream schools. As a consequence, mainstream elementary schools did not usually have a significant motivation to include students whose education required the use of non-standard procedures (NPI, 2009). However, since the last decades of the 20th century, there have been a global trend in social policy to promote integration and participation and to combat exclusion. The call for inclusive and integrative was rephrased in The Salamanca Statement and Framework for Action on Special Needs Education (UNESCO, 1994) into a motto ‘Education for All’, alternatively ‘School for All’.

The Czech Republic committed to the principles stated in the Salamanca Statement and more than 20 years later, a significant change has been implemented in the schooling of pupils with special needs, talented pupils, and exceptionally talented pupils in the Czech Republic (ČŠI, 2017). According to Felcmanová (2015, pp. 7), ‘the basic principle of inclusive schooling is to allow all children to reach their educational maximum while respecting their educational needs.’ In practice, the introduction of inclusive schooling meant the legislative embedding of the taxonomy and financing of supporting measures, "necessary adjustments in schooling and school services reflecting the health condition, cultural background, and other life conditions of a child, pupil, or a student" (Michalík, 2015, pp.17). One of the most common forms of supporting measures is the provision of teaching assistants (TAs) support. Consequently, although even before the introduction of inclusive schooling, the number of TAs in the Czech educational system had been constantly rising (Langer, 2015), the number of TAs in Czech elementary schools has almost tripled since 2016.

The introduction of inclusive education has received generous media attention. While the introduction of 'inclusive schooling' has been accompanied by a lively public debate, often framed in the atmosphere of fear of the decay of the Czech educational system or of an 'irresponsible experiment on children' (Feřtek, 2016; 2017), currently, there is an ongoing debate about a change in the system of the provision of TA support (MŠMT, 2022).

Therefore, the primary objective of this thesis is to evaluate the current system, provide an insight into individual trends and parameters, provide policy recommendations, and enrich existing literature studying of TAs' effects. The purpose of this thesis is not to advocate for or against inclusive schooling but to provide evidence for evidence-informed school policymaking. As such, we aim to estimate the effect of more intensive TA support on educational outcomes in the Czech Republic in comparison to the effect of schooling with less intensive TA support. Additionally, we explore what factors determine the provision of TA support in the current system.

The effects of TAs on the educational outcomes of pupils have been studied mostly abroad, particularly in the UK, the US, and Denmark. In 2010, Farrell and others (2010) conducted a systematic review of literature and concluded that 'where properly trained and supported, TAs can have a positive impact on primary-aged pupils' academic progress' (pp. 445). However, to the author's best knowledge, there has not been any robust (experimental or quasi-experimental) estimation of the effect of TA support on the educational outcomes of pupils in the Czech Republic.

To fill the gap in the evidence, we use nation-wide school data recorded in the school reports of the Ministry of Education, Youth, and Sports of the Czech Republic (MŠMT) supplemented by recent estimations of the share of socially disadvantaged pupils in individual schools. The estimated data about the share of socially disadvantaged pupils allow us to control for confounding effect of the school compositions.

The nature of the data is observational and, accordingly, we apply a set of quasi-experimental methods to investigate our research questions. For explorative purposes, we begin with standard OLS regressions. OLS regression is not suitable in our case as the relationship between TA support and educational outcomes is not unidirectional.

To address robustly the problem of endogeneity, we continue with propensity score matching and instrumental variable estimation. In the IVM models, we make us of a *beeline distance of a school from the nearest educational advisory facility (EAF)* as an instrument. We expect the distance from the nearest EAF to have negative effect on the provision of TA support.

The results of propensity score models reveal no statistically significant effect of a relative number of TAs on the pupils' educational outcomes. The first stage of two stage least squares (2SLS) regression provides results contradictory to our expectations. Due to this results, our design of IVM is not suitable for estimating the effects of TA support on educational outcomes. Nonetheless, the first stage of the 2SLS regressions delivers a valuable insight into what factors affects the provision of TA support.

The first stage of our two-stage least squares regression provides evidence to what extent private and religious elementary schools were more competent at the provision of TAs that public schools. We proceed with a detailed examination of the factor which posed severe limitations to our analyses.

Hence, the thesis enriches existing literature primarily by providing additional piece of evidence for the estimation of the effect of TA support. The contribution is beneficial for (i) it is the first quantitative estimation of the effects of TA support in the Czech Republic, former Eastern bloc country, (ii) novel research designs that have not been applied, and (iii) the size of the sample which is nation-wide.

The rest of the thesis is organized as follows. First, we introduce the concept of inclusive schooling and 'supporting measures,' with a particular focus on TAs in the Czech educational system. Second, we present our review of literature concerning the evaluation of effects of TAs at primary and secondary school on educational outcomes. Third, we describe the data we used in the subsequent analysis. Fourth, we formulate the theory underlying our research and state our research questions. Fifth, we acquaint the reader with the data used in our analyses. Sixth, we describe methodology applied to answer the research questions. Seventh, we present the results. Lastly, provide discussion of the results, policy recommendations, and conclusion.

2 Inclusive Schooling & Teaching Assistants

This section aims to provide a concise overview of the philosophy and origins of inclusive schooling, outline the support system for students with special educational needs (SEN), and introduce the pedagogical role of a teaching assistant (TA).

2.1 Inclusive Schooling & Supporting Measures

The concept of inclusive education was developed in response to the segregation and exclusion of students with disabilities from mainstream schools. Inclusive education aims to provide all students, regardless of their abilities or disabilities, with equal opportunities to learn and participate in the classroom. It is based on the principles of respect for diversity, individual differences, and social justice (Hájková & Strnadová 2010).

The system of inclusive education in the Czech Republic is underpinned by a range of "supporting measures," which constitute a critical element of the support provided to pupils with special educational needs (SEN) (Michalík, 2015, pp. 15). By providing additional support to pupils with SEN, inclusive education aims to ensure that the maximum number of pupils can thrive in mainstream schooling. In an inclusive approach to education, pupils' differing abilities are not regarded as a disruptive factor but rather as individual conditions that determine their engagement in the learning process. Every pupil can attain the maximum of their development, provided that the teacher views the achievement of every pupil's educational potential as the primary objective of their professional practice (Hájková & Strnadová, 2010).

The Czech Republic committed to inclusive education after the UNESCO Conference in 1994 in The Salamanca Statement and Framework for Action on Special Needs Education. This document summarizes the principles of a "School for All," which includes a commitment to enable all children, regardless of disability or any other handicap, to attend regular schools (Felcmanová, 2015). In 2009, the Czech Republic ratified the UN Convention on the Rights of Persons with Disabilities, further solidifying its commitment to inclusive education (Michalík et al., 2015, Chapter 1). The philosophy of inclusive schools is supported by evidence, as studies have found no statistical correlation between the presence of pupils with SEN in a class and the educational outcomes of all pupils in the class (Farrell et al., 2007; Sharpe, et al., 1994). Moreover, students with SEN tend to achieve better academic results in regular schools than in special schools (Mitchell, 2014, Chapter 27).

The amendment to the Education Act (No. 561/2004) in 2014 introduced a classification of supporting measures (Parliament of the Czech Republic, 2004). The overarching philosophy of this amendment was to move away from a horizontal model, which classified pupils into categories of health disability, health handicap, and social handicap, and towards a vertical model, which determines the depth of SEN and the appropriate supporting measures. In other words, the determination of the right supportive measures supersedes the diagnosis in terms of its significance (Michalík et al., 2015, Chapter 2).

2.2 Teaching Assistant

One of the major effects of supporting measures was considered to be a more frequent provision of teaching assistance. The main responsibilities of a teaching assistant, teacher's aide, or paraeducator include assisting:

i. pupils with SEN in learning and preparation for learning, adapting to the school environment, and, in the case of pupils with physical handicaps, also with self-service and movement,

ii. teachers in conducting lessons,

iii. and facilitating communication between teachers, classmates, pupils with SEN, and legal guardians (Friend & Cook, 2016, Chapter 10; Kendíková, 2017).

It is important to note that a TA is a different position than a personal assistant or a school assistant. A personal assistant is a social service provided by the Ministry of Labour and Social Affairs for people with reduced autonomy. A school assistant in the Czech educational system is typically funded by so-called "templates," simplified projects funded by the EU funds. A main difference between a TA and a school assistant is the fact that a school assistant is not a pedagogical worker, and their support is not oriented towards a single individual (Kendíková, 2017).

The pedagogical position of a TA was formerly established in the Czech Republic in 2005. Since then, a director could establish a position of a TA with the consent of the regional office. The regional office had decision-making powers regarding the allocation of TA support and its financing. However, as the practices of individual regions differed, there were significant inequalities in the likelihood of receiving TA support, and therefore, this system was evaluated as inadequate (Morávková-Vejrochová et al, 2015; Felcmanová et al., 2015).

There also used to be difficulties related to the absence of clear definition of the position of TA, her system of qualifications, and her responsibilities. The significant improvement occurred only with the creation of materials to support inclusive education within the project 'Systemic Support of Inclusive Education in the Czech Republic'. (Felcmanová et al., 2015). The key material for anchoring the position of TA is the document *'Teaching Assistant Work Standard'* which specifies the basic tasks of a TA in supporting pupils (Morávková-Vejrochová et al, 2015).

According to this standard, there are several types of TA tasks:

i. individual or group support of pupils with SEN within classroom teaching;
ii. individual or group support pupils with SEN outside classroom;
iii. helping teacher with teaching of pupils without SEN while a teacher devotes her attention to pupils with SEN;
iv. assistance with self-care and accompaniment during movement during teaching;
v. joint preparation with a teacher;
vi. tutoring of students;
vii. communicating with parents of pupils;
viii. and consulting with school advisory and EAF staff (Morávková-Vejrochová et al, 2015).

The job description of a TA is closely related to the requirements for her qualifications. The *TA Work Standard* distinguishes 3 levels of TAs according to the extent of responsibility in the educational process.

Level I requires secondary education with a vocational certificate supplemented by a qualification course for TAs. The job description of TAs in this level includes assistance in educational support activities aimed at improving and consolidating social behaviour, and developing basic work, hygiene, and other habits of children, students, or pupils. TAs help with promoting physical activity of children, students, or pupils and ensure the classroom environment, tools, and smooth course of teaching.

Level II requires a secondary education with a graduation diploma supplemented by a qualification course for teaching assistants, up to a university education. The job description of TAs in this level includes explanation of the text, or teaching materials, and individual work with children, students, or pupils according to established educational programs and instructions. TAs participate in the evaluation and sharing of information about a student or group of students, monitor progress and behaviour, and cooperate with the teacher in creating an inclusive learning environment.

Level III requires education in the field of pedagogy, ranging from vocational secondary education with a high school leaving certificate to a university degree, supplemented by a specialized course for TAs. The job description of TAs in this level include independent educational, upbringing, or special educational activities carried out in accordance with the established Individualised Education Plan of a pupil or group of pupils, based on the framework guidelines of the EAF and in accordance with the teacher's instructions (Morávková-Vejrochová et al, 2015).

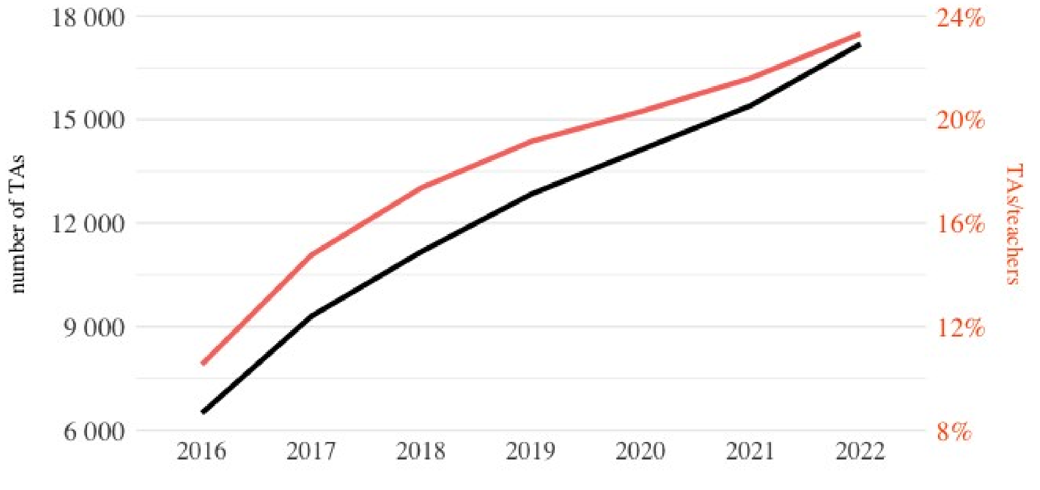
2.3 Provision of a Teaching Assistant

After the passing of the amendment, a student with SEN is theoretically supposed to receive a TA, or any other appropriate supporting measures, by following a three-step process. Firstly, the school recommends that the legal guardian(s) have the pupil diagnosed by an Educational Advisory Facility (EAF), which could be either a Pedagogical-Psychological Agency (PPA) or a Special Pedagogical Centre (SPC). Secondly, the pupil accompanied by her legal guardian(s) visits the EAF, where the type and degree of SEN is determined, and appropriate supporting measure(s) are recommended. Lastly, provided that parent(s) agree(s), the school follows the recommendation of the EAF and provides the recommended supporting measure(s)

(Michalík, 2015; Michalík et al., 2015, Chapter 6). In this model, the provision of a TA is linked to the pupil who has been diagnosed with SEN.

The number of TAs in Czech elementary schools nearly tripled between 2016 and 2022. In 2016, there were 6,496 full-time equivalent TAs, and in 2022, the number rose to 17,190 full-time equivalent TAs. Using a relative metric and relating the number of TAs at elementary schools to the number of teachers at elementary schools, there was an increase from 10.5% to 23.3%. In other words, in 2022, for almost every four teachers at an elementary school, there was one TA.

Figure 2.1: Number of TAs at Czech elementary schools



source: report about the directorate of schools (R13) 2016-2022, MŠMT

However, a study conducted by the Faculty of Education at Palacký University Olomouc (2013, pp. 56) found that the probability of a pupil with similar SEN obtaining a TA as a supporting measure varies significantly among administrative regions of the Czech Republic. The probability can be as much as six times higher in one administrative region than in another. Furthermore, recent study of Hoření and others (2023) found stark differences in practices of individual EAFs within the same administrative region.

Recently, the Ministry of Education, Youth, and Sports of the Czech Republic (MŠMT) (2022) has proposed a change in the system of provision of TAs. In the proposed system, the provision of TA support would no longer be dependent on a particular pupil with SEN but would rather be conditional on set school parameters, including the share of pupils with SEN. Each school would have an assigned maximum limit of TA support per week, calculated based on a number of mainstream classes, their average capacity utilization, a number of classes of 1st – 3rd grade, the share of pupils with the 3rd degree of SEN, and the share of classes with at least one pupil with the 4th or 5th degree of SEN.

3 Literature Review

The purpose of this section is to present a scholarly review of the research studies that investigate the research question of assessing the impact of teaching assistants on academic achievement. We allocate greater emphasis on evidence that is primarily based on quantitative methods and is large-scale, in line with the methodology of this thesis.

One of the earliest and most frequently cited studies examining the impact of teaching assistants is Gerber, Finn, Achilles, and Boyd-Zacharias' (2001) research, which utilized data from the Tennessee Student Teacher Achievement Ratio (STAR) project. The findings of this study showed no beneficial effect on student attainment from having a teaching assistant in the classroom. However, it is essential to note that during this time, most teaching assistants were 'uneducated assistants who spent most of their time on practical tasks, such as paperwork, grading, and lunch duty.' (Andersen et al., 2020, p. 471). This is quite different from today's teaching assistants, who are professionals and paraprofessionals that share instructional responsibilities.

3.1 Farrell, Alborz, Howes, & Pearson's review

In 2010, Farrell, Alborz, and Howes provided the literature review investigating the effect of TAs on pupils' academic achievement in mainstream schools. The selected studies in this review were, subsequently, divided into two categories (i) targeted intervention studies, focused on a small, specified group of pupils with an identified problem in learning and (ii) non-targeted intervention studies, in which the mere presence of a TA in the classroom was linked to the measured academic achievements of all children in a class, school or group of schools. The key research question of the non-targeted studies 'was whether the pupils' attainments in classes, schools, or local authorities containing large numbers of TAs, would be higher than they would be in similar settings with fewer or no TAs, and when other potential confounding variables have been taken into account (Farrell et al., 2010, p. 444).

To begin, we introduce selected non-targeted studies and their methodology as their design is more aligned to our thesis than the design of targeted-interventions studies. Then, we provide a brief summary of the findings of targeted studies.

The authors' selection of non-targeted studies consists of four studies. Two of reviewed non-targeted studies (Blatchford et al., 2001; Gerber et al., 2001) were large scale and included a control group. These studies focused on the impact of TAs on the academic attainments, test scores, of all children in a number of primary schools. Although the main aim of the aforementioned studies was 'to investigate the relationship between class size and pupil attainment, a secondary finding from both studies was that the presence of TAs in a classroom had **no clear and consistent effect on the pupils' average attainments** when other variables were taken into account.' It is important to add the caveat of these studies that the precise nature of the TA support was not described in these studies. (Farrell et al., 2010, p. 444).

The other two selected non-targeted studies are from the 1970s. The research design was applied to small sample as the experiments took place in two separate schools. The study of Loos, Williams, and Bailey (1977) included a control group, an earlier study conducted by Frelow, Charry, and Freilich (1974) did not. The findings of both studies indicated that the presence of the TA had positive effect on the pupils' abilities in literacy and numeracy. Both studied did not focus non only on whether TAs have an impact on pupils‘ academic attainment, but also on which form of TA support is most effective. For instance, Loos, Williams, and Bailey (1977) revealed that the presence of a TA had a positive impact particularly when the TA was assigned a 'helping' rather than simply a 'discipline' role. Therefore, Farrell et al. (2010, pp. 445) state that 'despite some methodological weaknesses in both studies (unacknowledged observer effects and the lack of a control group), the overall findings suggest that locally based non-targeted intervention studies might yield more positive findings in relation to the impact of TAs than do larger studies of the type reported by Gerber et al. (2001) and Blatchford et al. (2001).'

Furthermore, in 2009, Blatchford et al. published a major research report on the deployment and impact of support staff in English schools. Although the study controlled for other explanatory variables that might influence pupil attainment (incl. SEN status, gender, eligibility for free school meals, income deprivation, ethnic group, pupil age, English as an additional language), there was found a negative relationship between the amount of support a pupil received and the progress they made in core national curriculum subjects. In essence '**the more support pupils received, the less progress they made'** (Farrell et al., 2010, p. 435).

Blatchford and others (2009, p. 131-132) suggest possible explanations. 'The most obvious explanation', pupil explanation, stresses the possibility that the reverse causality might be stronger that the explored causality. In other word, although the more support might actually help students, 'pupils are likely to receive support because they are performing less well or have a particular learning or behavioural problem'. However, the authors add that 'it is unlikely that this explanation fully accounts for the relationship between support and pupil attainment because the pupil characteristics that are likely to be the basis for the provision of extra support were included in the statistical analysis'.

Nonetheless, there might be other information on pupils available to a teacher and not captured numerically, which might be related to academic progress, and which might therefore bias the results. 'Teachers experience a pupil on an everyday basis and gain a more rounded picture of a pupil beyond the eight variables cited above. These extra factor could include pupil behaviour and attitudes, parental support or attitudes, or family cohesion.' Still, the authors consider the endogenous characteristics of pupils as unlikely explanation of the negative relationship between support and educational progress (Blatchford et al., 2009).

The authors, therefore, discuss other possible explanation: the varying levels of experience and qualifications of support staff; communication between teachers and TAs[1]; training of teachers for working with TAs; support staff pedagogical and subject knowledge; deployment in terms of pupil separation from teachers and the curriculum, or practice of support staff in terms of face-to-face interactions with pupils.

The selection of targeted intervention studies consists of 9 studies. All of them employ fairly similar methodology: (i) the measurement of the attainments of pupils before and after TA support, (ii) the comparison of pupils' progress with a carefully selected comparison or control groups with no TA support, (iii) pupils had an identified

[1] see, for instance, Jardí, Webster, Petreñas, & Puigdellívol (2022) or Blatchford, Russell, & Webster (2012)

problem in basic attainments, (iv) TAs received training how to deliver support, and (v) fidelity checks that TAs carried out the intervention in a correct way. 'The overwhelming conclusion from all but one of them is that trained and supported TAs, …, **helped primary aged children** with literacy and language problems to make statistically significant gains in learning when compared to similar children who did not receive TA support' (Farrell et al, 2010, p. 439).

The interventions of selected targeted studies ranged from speech and language therapy by speech therapists, various forms of support in reading, literacy, and mathematical skills to rime and phoneme-based teaching. The overwhelming conclusion from all but one of them (Muijs and Reynolds 2003) is that trained and supported TAs, had statistically significant positive effects on gains in learning for children with literacy and language problems.

3.2 Evidence after 2010

More recently, Andersen, Beuchert, Nielsen, and Thomsen (2020) used randomised experiment to challenge, rather, sceptical, previous evidence. The experiment included 105 Danish school with 249 sixth grade classrooms (more than 5,200 students) divided into 3 groups. The first group of 35 schools was treated by support of TA support with a teaching degree, the second group was treated by support of TA support without a teaching degree but with more hours of support, and the third group was a control group (without TA support).

Overall, the study **found significant positive average effects** on reading scores and no statistically significant effect on math scores. The results hold for TA support in the form of both TAs with a teaching degree and TAs without a degree. The authors state that high time intensity support is as important as formal qualifications. Yet the potential mechanisms behind their effects were likely to be different. The TA support with a teaching degree proved to be particularly effective when used as a flexible sort of class-size reduction, whereas the TA without a degree seemed to be particularly effective in classrooms with behavioural problems (Andersen et al., 2020).

There could be explanations why there were larger effects on reading than math. First, there tend to be a higher priority on language arts than math in school, which is scaled-up by the experiment (aides only participated in 3 math lessons per week compared to 4.5 lessons in language arts). Second, the math qualifications of the co-teachers and teaching assistants are relatively low. Third, the reading skills can be exercised more easily by the help of another person than math skills which are more developed by instruction-led teaching (Andersen et al., 2020).

Additionally, Hemelt et al. (2021) utilised variability among districts in how they allocate state-funded positions in North Carolina to assess the influence of TAs and other personnel on outcomes for elementary school students. Nort Carolina allocate slots to districts and not to schools. While some districts allocate slots on a strict *per-pupil* basis, others use various allocation schemes that target slots across schools to give disadvantaged schools more resources. The funding cutbacks after 2010 provided the authors with an instrument for changes in staffing at the district level. The large reduction in state funding for TAs, combined with district and year fixed effects, time-varying demographic characteristics and measures of teacher quality, and county-level economic controls, allowed the two-stage approach to 'generates plausibly causal estimates' (p. 299). The result was '**positive effects on student test scores** in reading and math, with the largest, consistent, and most robust effect in reading' (p. 299). In addition, the effects were larger for students of colour and, suggestively, also for students in high-poverty districts than in other types of districts.

To summarise, there have been a mixed evidence on the effects of TA support on pupils' academic attainments. While earlies studies tended to be rather sceptical, newer studies, with a more robust design, proved a positive effect, more consistently for reading skills. There could be methodological as well qualitative explanations for these disparities. The effect of TA support is reliant on many variables which affects the final outcome, such as the pedagogical and subject knowledge of a TA, the status and form of SEN, or the teacher-TA compatibility and relationship.

3.3 Having a Pupil with SEN as a Classmate

There exists also a distinct field of literature studying the effect on having a student with SEN on her classmates (without SEN).

While there have been documented statistically significant effects on classmates of pupils with **specific** SEN, such potentially disruptive and emotionally sensitive children (Fletcher, 2009; Kristoffersen et al., 2015), when studying effects on classmate of **general** SEN pupils, results were statistically insignificant (Friesen et al., 2010; Ruijs, 2017).

The subcategory of this literature explores an effect of a rapid increase of SEN pupils in mainstream school after the introduction of more comprehensive inclusive schooling.

Recent study from Denmark (Rangvid, 2019) investigated whether being exposed to returning SEN pupils affects the academic achievement of other students in the school-grade cohort. As well as in the Czech Republic, there was a reform in a Danish school system which increased a number of SEN pupils at mainstream schools at the expense of special schools. The authors made use of administrative microdata which track successive cohorts of students as they progress through school and contain extensive and reliable information on test scores and students' family background, as well as school and grade-level identifiers. The main finding was that being exposed to returning SEN pupils during the reform period has a negative effect on test score gains of moderate size, corresponding to half a month of learning gains per year. An investigation into the mechanisms showed stronger effects in schools with little or no recent experience with accommodating returners, in particular if these schools had to accommodate several new returners at the same time. The effect in reform years is **not** significantly stronger than in nonreform years, indicating that no additional harm is caused by the larger return flows in reform years.

4 Theory

The theoretical section provides the formulation of our research questions. We also draw on the literature review and add theoretical framework to our analysis.

4.1 TAs' impact

The literature review provides a mixed evidence whether TA support improves academic attainments. Yet the more recent literature describe mechanisms by which higher TA support may have positive effect on pupils' academic attainments.

Particularly in the position of co-teacher, a TA can play a role of a (flexibly implemented) class-size reduction (Andersen et al., 2020). Peter Blatchford and Anthony Russell (2020) state in their study dedicated to class size that as the class size decreases, there is an overall tendency to an on-task behaviour from pupils and more individual attention from a teacher.

Primarily, low-attaining pupils are those who suffer more in larger classes in terms of more off-task behaviour and teachers' critical comments. With a large class, teachers can struggle to provide the degree of differentiation and individual attention needed to deal with different levels of attainment within the class. 'If there are pupils with special needs in the class, this is likely to add to the differentiation required' (pp. 233).

Consequently, TA's impact in the form of class size reduction can be understood as decreasing the range of pupils' attainments which results in more differentiated teaching, more individual teacher's attention, and more on-task behaviour of pupils.

Another challenge for teachers may have a form of a pupil(s) with behavioural problems. The class composition affects social dynamics between children and therefore classroom management. If a teacher has to devote most of her attention to one pupil with behavioural problems, overall class management becomes much more difficult. In these situations, TA can provide necessary attention for a pupil with behavioural problems and a teacher does not have to reduce her attention for the other students. The management of a pupil with a behaviour problems does not generally require intensive qualification.

Hence, the higher relative number of TAs should enable more frequent class size reduction or provide an additional adult managing a pupil(s) with behaviour problems. thereby making education more effective and, in result, improving pupils' educational outcomes. We state our first hypothesis as follows:

Hypothesis #1

The relative number of TAs have positive impact on primary school pupils' educational outcomes.

4.2 Provision of Teaching Assistants

The current system of the provision of TA is contingent upon the recognition of specific pupil's with SEN entitlement to TA support. The evidence suggests that there are significant differences in the likelihood of the provision of TA support among individual student with SEN (FE PUO, 2013; Hoření et al, 2023). We formulate the hypothesis that the distance of a school from the nearest EAF may constitute an obstacle in the process of TA provision. Most commonly, it is parents who accompany their children to EAF. There is an expectation that, mostly in case of parent(s) from lower socio-economic background or a single parent in rural areas, a journey to EAF can be a threshold obstacle.

A recent study conducted as part of a project of Technology Agency of the Czech Republic for the MŠMT (Hoření et al, 2023) highlights also the significance of the relationship between a school and EAF in the process of providing TA support .

There are also other factors which may consequently influence the provision of TA support such as:

i. specific features of the EAF network in the administrative region where the school is located;
ii. the size of a school;
iii. the type of a school founder;
iv. school-EAF relationship;
v. a share of socially disadvantaged pupils;

vi. and others.

Accordingly, formulation of our second hypothesis follows:

Hypothesis #2

The different characteristics of a school have an impact on the provision of TA support.

In the instrumental variable models, we employ a beeline distance of school from the nearest EAF as our quasi-random instrumental variable. It is our conviction that a distance from the EAF may pose a significant obstacle for many pupils and their families, especially in the rural areas where transport accessibility is limited. Consequently, we expect that a distance of rural school from the nearest EAF could have a negative effect on the TA support provision. Hence, for the purpose of our 2SLS models, we state our instrumental hypothesis as:

Instrumental Hypothesis

The beeline distance of school from the nearest EAF have negative effect on TA support provision.

5 Data

In this section, we present the data which we use for our analysis. The data sources are either reports of the Ministry of Education of Education, Youth, and Sports of the Czech Republic or a dataset of a modelled share of socially disadvantaged pupils at schools constructed by Daniel Prokop and Tomáš Hovorka for the MŠMT (2021).

5.1 Ministry of Education of Education, Youth, and Sports

The MŠMT stores the data about the schooling systems in standardised reports[2]. For the purposes of our analysis, we need information about the number of TAs in individual schools, number of students at elementary schools and their academic attainments, and the addresses of advisory agencies (Pedagogical-Psychological Advisories + Special Pedagogical Centres) and their subsidiaries. Hence, we retrieve data from the following reports for years 2016-2022:

- **report R13:** a report about directorate of schools
  - providing data about the of TAs in directorate of schools
- **report M03:** a report about elementary school
  - providing data about educational outcomes and other school characteristics
- **report Z23:** a report about Pedagogical-Psychological Advisory
  - providing data about the addresses of Pedagogical-Psychological Advisories and their subsidiaries
- **report Z33:** a report about Special Pedagogical Centre

[2] You can find the list of reports stored by the MŠMT at https://www.msmt.cz/vzdelavani/skolstvi-v-cr/statistika-skolstvi/vzory-formularu-vykazu-pro-rok-2022.

- providing data about the addresses of Special Pedagogical Centred and their subsidiaries

The M03 report in year 2022 stores information about 4,815 elementary schools. Pupils in the Czech Republic attend elementary school between age 6 and 15. We decided to include only ‘ordinary’ elementary schools in our analysis and, therefore, excluded schools which provided education in ‘special classes’ at least in one of the reports 2016-2022. We kept only schools which were present in 2022 report. Since we need variables about pupils’ attainments, we included only schools which had at least one pupil in the 9th grade of an ‘ordinary’ class in all reports 2016-2022. As a result, we get a dataset of elementary schools with 854,747 students in a school year 2021/2022 (out of total of 978,324 pupils at elementary schools).

The R13 report in year 2022 stores information about 2,305 directorates of schools which fulfil the afore-mentioned conditions. The ‘directorate of school’ is an administrative unit which can include multiple school and school facilities. Most frequently, one directorate of school includes school of different levels, for example kindergarten and elementary school or elementary school and secondary school. However, it is also a case when one directorate of schools includes more than one elementary school. Since only R13 report stores information about the number of TAs, we have to work with the directorate of schools as the unit of our analysis[3]. Fortunately R13 report provides information whether TA works in pre-school, elementary school, or secondary school. As a result, we have 2,305 units for our analysis.

Since we cannot approximate the analysis to the level of individual classes, we define the number of TAs in a school as a full-time equivalent TAs. Although, the number of physically employed TAs may have an impact on our outcomes, we believe that the treatment consists primarily of the contact hours provided by a TA. Nonetheless, there is a surely a case for a study whether the impact of one full-time TA is comparable to the impact of two half-time TAs.

[3] In the following parts, we use ‘directorate of schools’ and ‘school’ interchangeably if not otherwise specified.

The Z23 report in year 2022 stores information about 46 Pedagogical-Psychological Advisories. However, one PPA often has more than one branch. Consequently, there are 121 unique addresses of PPAs.

The Z33 report in year 2022 stores information about 110 Special Pedagogical Centres. However, again one SPC often has more than one branch. Consequently, there are 159 unique addresses of SPCs. Considering that there are 14 administrative regions in the Czech Republic, we have on average 20 PPAs and SPCs per region.

From the datasets, we use a set of two accessible outcome variables as proxies for pupils' academic attainments. The first is a *grade repetition rate* which is simply number of pupils retaining a grade divided by the total number of pupils at a school. The second is a *non-completion rate* capturing the number of pupils who leave elementary school before finishing the 9th grade. In the Czech Republic, pupils are required to attend school for at least 9 years but not to finish the 9th grade. For instance, if a pupil repeats once one grade, she can leave the school after finishing the 8th grade. While report for year 2022 captures the data about a number of pupils repeating a grade in a school year 2022/2023, in case of a number of pupils which did not complete the 9th grade data are about a school year 2021/2022.

However, primarily years 2020 and 2021 were significantly affected by the Covid pandemic and related government measures. Unfortunately, these measures had indirect and direct impact on our educational outcomes. The statistics about a number of pupils repeating a grade shows an anomaly in the report for a calendar year 2020 and school year 2020/2021. The number of pupils which were repeating a grade is clearly lower than in other years. By contrast, this number is the highest in the subsequent report 2021. After the first school lockdown in spring 2020, MŠMT (2020) ordered schools to have lower requirements for an advancement into a next grade. This is the explanation of 2020 outlier.

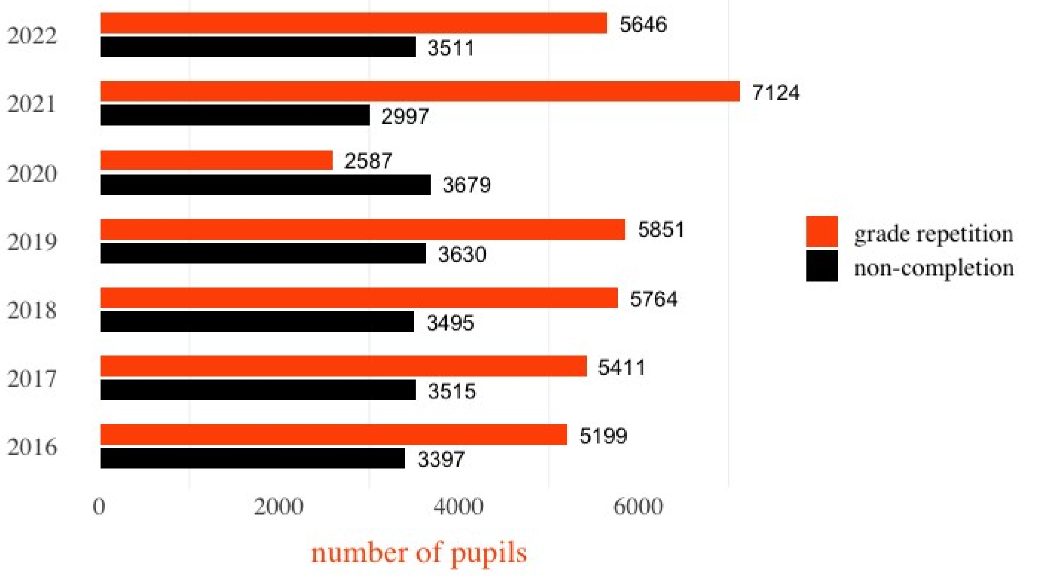
MŠMT's decree also affected the statistics about a number of pupils not completing the 9th grade. As we stated in the previous paragraph, the data about a number of pupils not completing the 9th grade is one report *behind* the data about a number of pupils repeating a grade. Thus, the number of pupils not completing the 9th grade is the lowest in report 2021. Yet the difference is not as large as in case of a number of pupils repeating a grade.

We address the noise in the data inflicted by MŠMT's recommendation in two ways. First, although the total number of students was affected by the Covid period, we still may assume that the difference among schools were not significantly affected.

Second, in our analyses we primarily use the means of the periods – (i) before treatment and (ii) after treatment. For before treatment period, we use a mean of reports 2016-2018. For after treatment period, we use a mean of reports 2019-2022. As after treatment period captures the data of four report, including one below-average and second above-average, the noise coming from Covid measures is minimised.

As we documented before, between years 2016 and 2022 number of TA at Czech elementary schools tripled. Thus, as a 'treatment', we refer to a significant (positive) change in a number of TAs.

Figure 5.1: Educational Outcomes 2016-2022



source: report about elementary school (M03) 2016-2022, MŠMT

5.2 Share of Socially Disadvantaged Pupils

There is significant heterogeneity in the share of socially disadvantaged pupils at elementary schools. Higher share of socially disadvantaged pupils can both attract more TA support and worsen academic attainments. Both effects could thwart analyses of causal effect we are about to study. It is thus necessary to separate the effects of the share of socially disadvantaged pupils on our models.

Therefore, we add to our models information to what extent a school faces a challenge of a higher share of socially disadvantaged pupils. The data on the modelled share of socially disadvantaged schools come from the estimation of Prokop and Hovorka (2021) conducted for the MŠMT in 2021. The estimation was carried out for the purposes of targeted aid, in form of the provision of digital devices and other equipment, to schools in socially disadvantaged conditions.

Although there are data about number of socially disadvantaged pupils at school, there is strong evidence that they are heterogeneously underreported. This was the motivation for the creation of a model which primarily adjusted a share of socially disadvantaged students at schools with reported 0 of socially disadvantaged pupils. The significant predictors for this model was:

i. a number of pupils (higher percentage of socially disadvantaged students is in smaller schools);

ii. a type of a founder higher percentage of socially disadvantaged students is in public schools);

iii. index of social exclusion in municipalities (Agentura pro sociální začleňování);

iv. binary indicator of whether school is located either in Karlova Vary region or Ústí nad Labem region;

v. number of students who dropped out of distance learning in the year 2020/2021 (Prokop & Hovorka, 2021).

6 Methodology

The purpose of the chapter is to introduce a reader into the methods applied to answer the research question. We decided to employ three methods to answer our research questions, *ordinary least squares* (OLS), *propensity-score matching* (PSM), and *two-stage least squares* (2SLS).

First, we start with describing our OLS models and explain why these models cannot provide a robust causal evidence of the effect of TA support on educational outcomes.

Second, we present a workflow of our propensity score matching. We introduce a set of variables applied to estimate propensity scores and assess balance of propensity scores and variables both before and after matching.

Third, we present an applied geolocating method which we use to estimate the distance of a directorate of schools from the nearest EAF necessary for our 2SLS models.

Last, we introduce our instrumental variable estimation models, specifically 2SLS models. We start with a description of the first stage and continue with the second stage.

As a TA is supposed to help primarily pupils with difficulties, we believe that TA support should be measurable by the rate at which student fail their grade or not complete the 9th grade. Nonetheless, the set of our 2 educational outcomes is far from ideal.

First, our educational outcomes are of binary nature. Either a pupil advances into a next grade or not. Either a pupils finished the 9th grade of elementary school or not. The educational outcomes do not capture any other information between as, for example, PISA score or any other inter-school comparative tests would do. Nonetheless, these educational outcomes are particularly substantial for socially disadvantaged pupils and pupils with SEN who are at risk of failing in school.

Second, although elementary schools in the Czech Republic share basic learning objectives, formulated in the framework curriculum set by the MŠMT, a director of school set classification criteria for her school individually (Parliament of the Czech Republic, 2004). Hence, some elementary schools might have stricter criteria than others. Moreover, some elementary school may prioritise grading according to the performance within a class (group relationship norm), other elementary school may prioritise grading according to a past performance (individual relationship norm). Additionally, there is also space for discrepancies among subjective grading styles of individual teachers.

The study by Münich and Protivínský (2022) documents that the classification of pupils with the same academic results varies on average by a whole classification grade between Czech schools. Pupils from advantaged socioeconomic backgrounds receive better grades than pupils from disadvantaged backgrounds who otherwise have the same level of tested skills.

6.1 Ordinary Least Squares

We provide standard OLS models to obtain a suggestive evidence. Although we are aware that our application violates basic OLS assumptions, we would like to enable a reader to have a possibility of comparing OLS results with results yielded by more robust methods.

As we outlined earlier, to minimise noise in the data related to Covid-19 pandemic measures, we study the effect of change in TA support on educational outcomes. Due to this, in our models, we employ the difference in the data between *post-treatment period* (mean of the reports 2019-2022) and *pre-treatment period* (mean of the reports 2016-2018). As a result, our outcome variables (*repetition rate* and *non-completion rate*) are in a model in the form of a difference between *post-treatment period* and *pre-treatment period.* In same way, we integrate the data about relative number of TAs at schools in the form of a difference. Covariates are integrated without taking a difference since we do not expect a significant changes between *pre-treatment* and *post-treatment period.*

We employ same regression form for both our outcome variables. The treatment is defined as the relative number of TAs to a number of pupils at school. Among our control variables, we selected:

i. *a modelled share of socially disadvantaged pupils at school,*

ii. *a number of pupils at school (mean of 2016-2022 reports),*

iii. *a number of pupils in a village/town (mean of 2016-2022 reports),*

iv. *and type of founder (either public, private, or religious).*

(I) $\Delta repetition = \alpha_1 + \beta_1 \Delta\#TAs + \gamma_1\, disadvantaged + \gamma_2\, \#pupils\_at\_school + \gamma_3\, \#pupils\_in\_town + \gamma_4\, founder$

(II) $\Delta non\text{-}completion = \alpha_1 + \beta_1 \Delta\#TAs + \gamma_1\, disadvantaged + \gamma_2\, \#pupils\_at\_school + \gamma_3\, \#pupils\_in\_town + \gamma_4\, founder$

However, as we suggested above, models have a major flaw in their design, namely the violation of the assumption of exogeneity. In order to fulfil the assumption of exogeneity, a relative number of TAs would have to be independent of an outcome variable. However, the literature and general knowledge suggest that pupil having a problem (e.g., bad grades) is a frequent and nearly necessary precondition to start the application for TA. Hence, our OLS models provide results for comparison but cannot fulfil the assumption of exogeneity.

6.2 Propensity Score Matching

In a scenario, in which we cannot fulfil the assumption of exogeneity, we may make use of methods which do not require so strict assumptions. One of these methods, is a propensity score matching estimation. The PSM approach is based on a simple principle – making sure that we are comparing 'apples with apples'. With this objective, we can calculate the probability of the treatment by a set of suitable observed variables. The whole process is thus a form of dimension reduction which provides one-dimensional *propensity score*, quantifying the probability of being treated.

The necessary assumption states that the observed variables are required to account for all possible confounders. Yet although it is often a case that some confounders are unobserved, matching usually achieves better balance than regression (Zhao et al, 2021).

We selected following variables for matching:

i. *a modelled share of disadvantaged pupils at school,*

ii. *a number of pupils at school,*

iii. *a number of pupils in a village/town,* *iv.* *administrative region*[4],

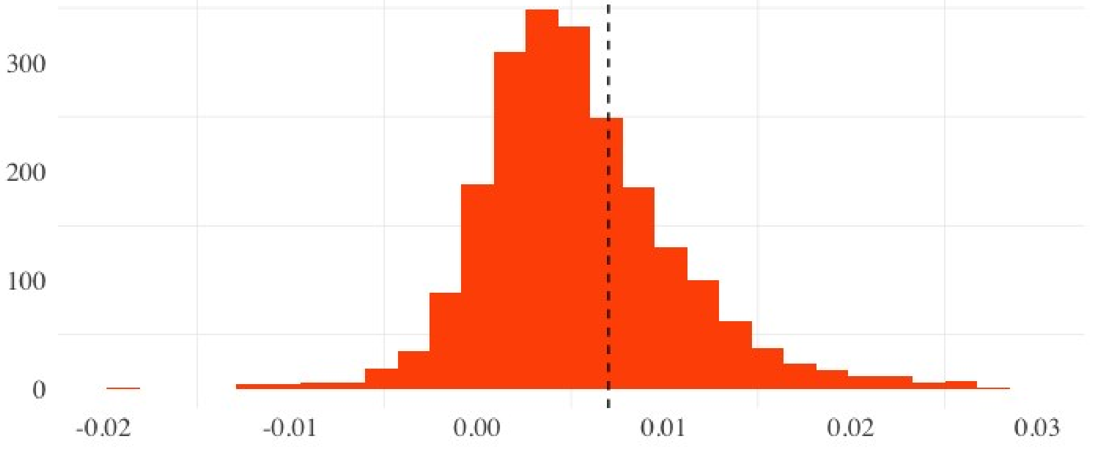
v. and *a type of a founder*.

We added a variable of an administrative region as the literature suggests that there are a significant differences in the provision of TA support across regions. The rationale behind this variable lies in the process of the provision of a TA for which a diagnostics by a EAF is necessary. Especially, in the rural areas, the visit to a EAF may pose a significant obstacle for many parents.

We decided to proceed with a binary variable of treatment. The chart below depicts the distribution of the change in a relative number of TAs between the 2016-2018 average and 2019-2022 average. The mean change was around 0.0055. In other words, on average between years 2016-2018 and 2019-2022 there was an average increase of a TA with a half-time per 100 pupils.

For the purposes of matching, an ideal ratio between the treated and control groups is, by rule of thumb, between 1:2 and 1:3. Thus, we define schools in which a change in relative number of TAs was higher than 0.007 as treated. Other schools remain in the control group. The final ratio is 32% treated and 68% untreated schools.

Figure 6.1: Histogram of Changes in a Number of TAs



[4] There are significant differences in the level of treatment across administrative regions.

Table 6.1: Covariate Balance

	type	standard. mean diff.
disadvantaged	continuous	0.343
#pupils at school	continuous	-0.650
#pupils in town	continuous	-0.357
private founder	binary	-0.008
public founder	binary	0.016
religious founder	binary	-0.008
Prague	binary	-0.061
Central Bohemia	binary	0.022
South Bohemian	binary	0.014
Pilsen	binary	0.009
Karlovy Vary	binary	-0.001
Ústí nad Labem	binary	0.057
Liberec	binary	0.009
Hradec Králové	binary	0.026
Pardubice	binary	0.015
Vysočina	binary	-0.031
South Moravian	binary	-0.018
Olomouc	binary	0.047
Zlín	binary	-0.043
Moravian-Silesian		-0.043

source: report about the directorate of schools (R13) 2016-2022, MŠMT

The standard workflow of matching consists of following steps. First, we explore the balance of the variables prior to matching. Second, we employ a suitable matching method. Third, we assess the balance of the variables after matching. If the treated and control groups are significantly imbalanced, we can try a different matching method. If we are satisfied with the balance of the groups, we can proceed to estimating our estimand, in our case average treatment effect (ATE).

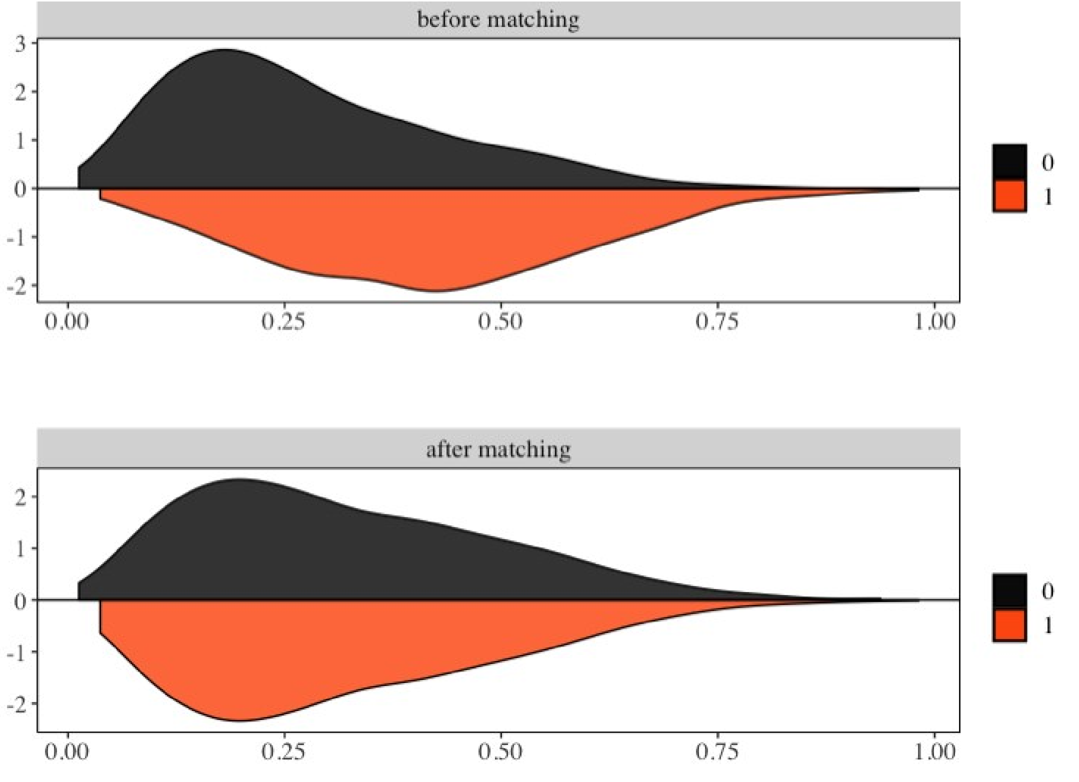
After assigning the binary variable whether a unit was treated, we can explore the balance of the variables before matching. For assessing the balance of samples, we use standardised mean difference to be able to compare variables among themselves. In our case, it is calculated as the mean/proportion of treated sample minus the mean/proportion of the control sample divided by the standard deviation.

We can observe that main differences are in a number of pupils at school, a number of pupils in town/village, and the modelled share of disadvantaged pupils. We can state that positive change in a relative number of TAs occurred disproportionately more often in a smaller schools, in a smaller towns or villages and at school with higher modelled share of disadvantaged pupils. It is consistent with the statement that the increase in relative number of TAs was least profound in an administrative region Prague.

To conduct matching, we decided for *MatchIt* R package (Ho et al., 2011). We opted for an optimal full matching as it enables the estimation of average treatment effect. It involves dividing the sample into subclasses, each containing one treated unit and one or more control units, or vice versa. The number of subclasses and the assignment of units to subclasses are determined based on the values of variables, with the goal of minimising the sum of the absolute differences between treated and control units within each subclass. After subclasses have been formed, weights are computed based on subclass membership and used to estimate the treatment effect, reducing the influence of confounding variables. For a distance measure, we picked classic logit model.

After conducting matching, we can observe how distribution of propensity score in treated and control group was balanced. We use *cobalt* R package to visualise the balance tests of our matching (Greifer, 2022). Prior to matching, the treated group had higher probability be treated than the control group, after matching both groups have very similar probability to be treated.

Figure 6.2: Propensity Score Distribution



note: cocreated by patchwork (Pedersen, 2022)

The change in the distribution of propensity score in treated sample is the result of assigning lower weights to units which are very similar to each other. We can compare the effective sample size of treated sample after matching with a total number of matched units. The Effective Sample Size is a metric that provides an estimate of the size of a sample needed to achieve the same level of precision as a simple random sample with the same number of observations. It takes into account the fact that the observations in a clustered or dependent sample are not independent of each other.

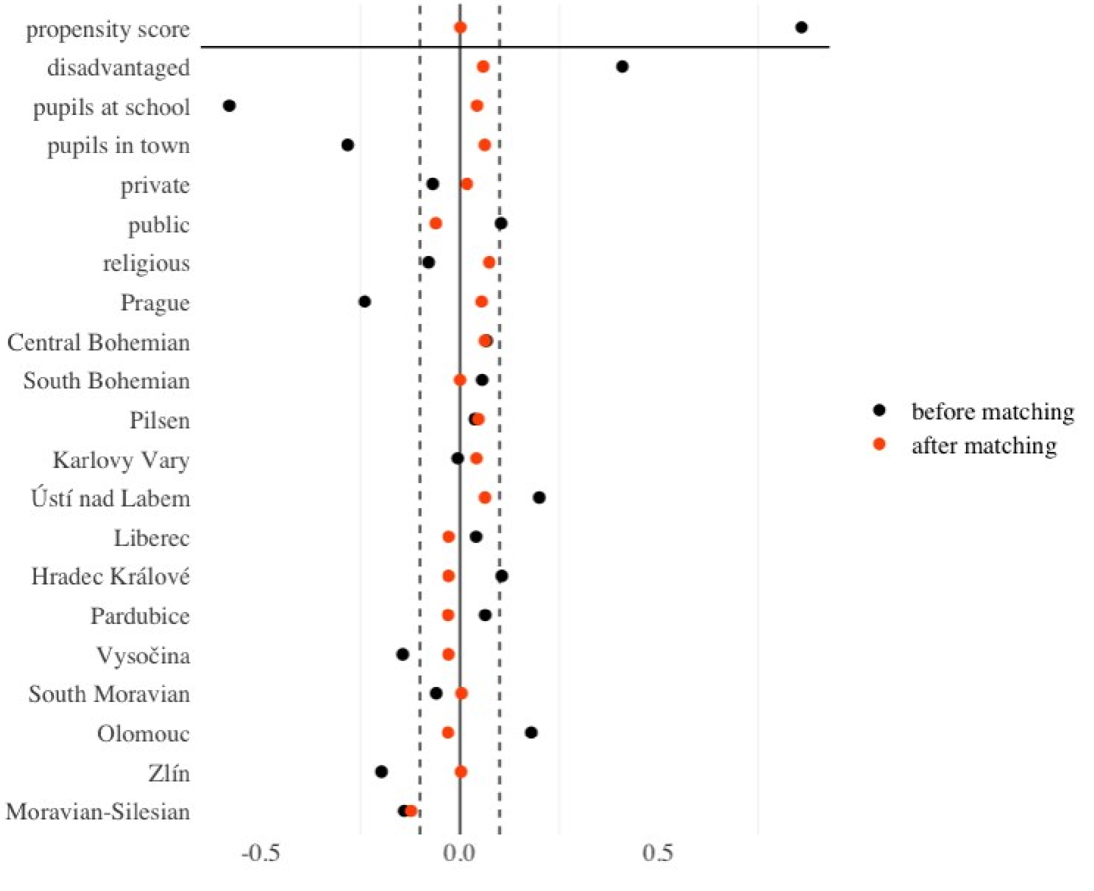
Table 6.2: Matching Results

	control	treated
all	1498.0	701.0
matched (ESS)	1224.4	327.6
matched (unweighted)	1498.0	701.0
unmatched	0.0	0.0

For example, in our treated sample, the observations within treated sample are more similar to each other than to observations in control sample. As a result, the information provided by a given number of observations in a treated sample is less than that provided by the same number of observations in a simple random sample. The ESS reflects this difference by reducing the sample size to account for the increased similarity within the samples.

Lastly, we check the balance of the variables after matching. Again, we use a standardised mean difference to assess balance after matching. The dashed lines in our 'Love' plot denote 0.1 standardised mean difference. We can see that only our binary variables denoting what share of schools in a sample is located in the Moravian-Silesian region is slightly higher than 0.1. Satisfied with the balance of our matched samples, we process with our propensity score matching models to estimate effect of treatment.

Figure 6.4: Covariate Balance



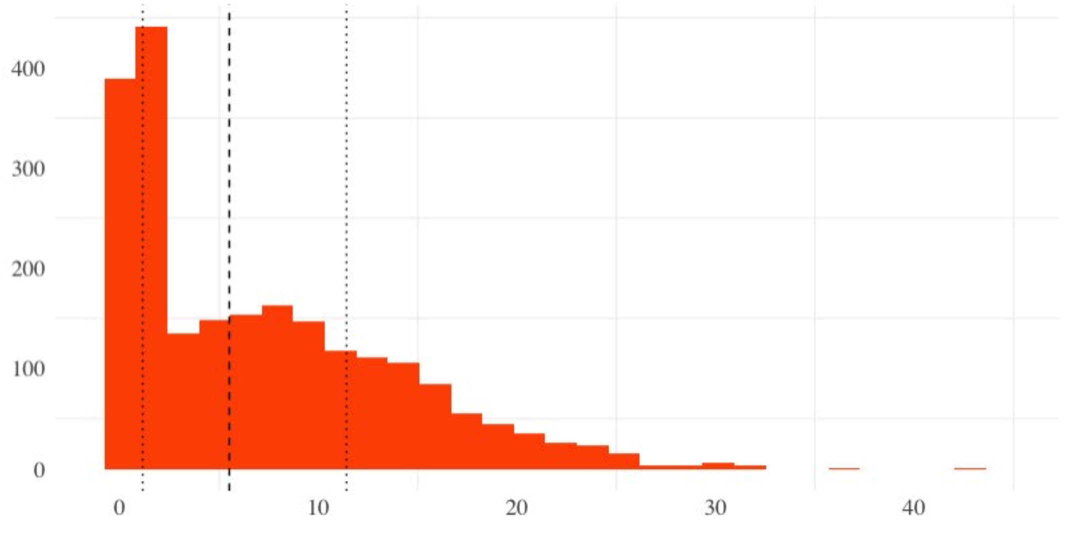
6.3 Geolocation

We employ a distance of a school from the nearest EAF (either PPA or SPS) as an instrument in our IVM. The measurement of a beeline between a school and the nearest EAF relies on the method called address geocoding. This process converts a human-readable address into geographic coordinates. In R, an open-source statistical language, we have a R package tidygeocoder (Cambon et al., 2021) which communicates with various Application Programming Interfaces (APIs) and lets them process complete (Baumer et al., 2021). We decided to employ 'HERE Geocoder API'[5] since it, in our user case of Czech addresses, produces constant and reliable results.

From our selection of schools fulfilling conditions described in the Data section, we have 308 schools out of 2,674 which do not have a unique identifier RED_IZO. Usually, these cases are the individual branches of one school at different addresses. The maximum is that 4 different addresses share one RED_IZO. Hence, for cases which do not have a unique identifier RED_IZO we used the coordinates of the point in the middle of the addresses as the reference point. The fact that in majority of cases the individual addresses are not very far from each other should ensure that this approximation does not challenge the validity of the analysis. Moreover, the relative sparsity of PPAs and SPCs and the median value of the distance of 5.5 kilometres mean that the approximation in the order of metres is relatively insignificant.

[5] https://developer.here.com/products/geocoding-and-search

Figure 6.2: Histogram of Beeline Distances from the Nearest EAF



note: a dashed line depicts a median, dotted lines depict the 25th and 75th percentile

6.4 Two-Stage Least Squares

The standard assumption of the linear regression that cofounders and the error term are uncorrelated often cannot be met. If this is a case, we speak about the problem of endogeneity. One of the most common methods to address this problem makes use of so-called *instrumental variables* (Greene, 2019, Chapter 8).

Using an instrumental variables for purposes of studying research question related to educations has a strong tradition at least since the often-cited analysis of David Card published in 1993. The idea was to quantify the effect of schooling on earnings. As there are many variables which affect both the length of schooling and the level of earnings, a researcher requires an exogeneous source of variation in education choices. Card proposed a proximity to a college as an exogeneous variables which he employed in instrumental variable estimation to quantify the relationship between schooling and earnings.

A ‘good’ instrument has to satisfy three requirements:

i. *First stage*: the instrument has a causal effect on the variable whose effects we are trying to capture.

ii. *Independence assumption*: the instruments is randomly assigned or 'as good as randomly assigned,' in the sense of being unrelated to the omitted variables we might like to control for.

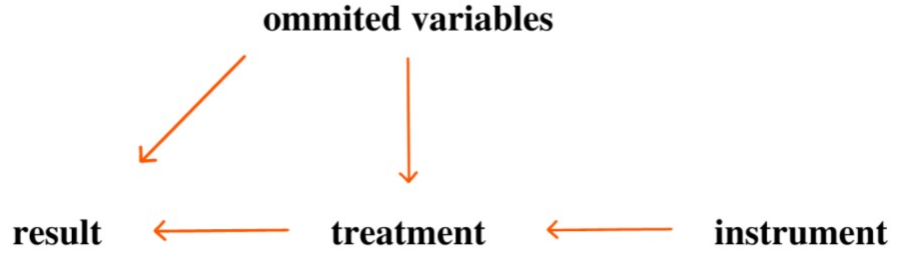
iii. *Exclusion restriction:* there is a **single** channel through which the instrument affects outcomes. The exclusion restriction cannot be quantitatively tested (Angrist & Pischke, 2015, Chapter 3).

As such, we argue that the distance of a school from the nearest EAF may be a good instrument. First, our theory states that the distance to the nearest EAF has a negative impact on the likelihood of the provision of a TA (*instrumental hypothesis*). The relationship is not ideal as it is often case that pupils are not diagnosed in the nearest EAF. Still, we will test the predictive power of the *distance from the nearest in the EAF* in the first stage of 2SLS model.

Second, we are not aware of any direct relationship between our instrument variable and one of our control variables. In rural areas, we expect schools with higher share of socially disadvantaged pupils as well as school with lower share. Third, we see no relationship between the *distance from the nearest in the EAF* and either of our outcome variables – neither *grade repletion rate*, nor *non-completion rate*.

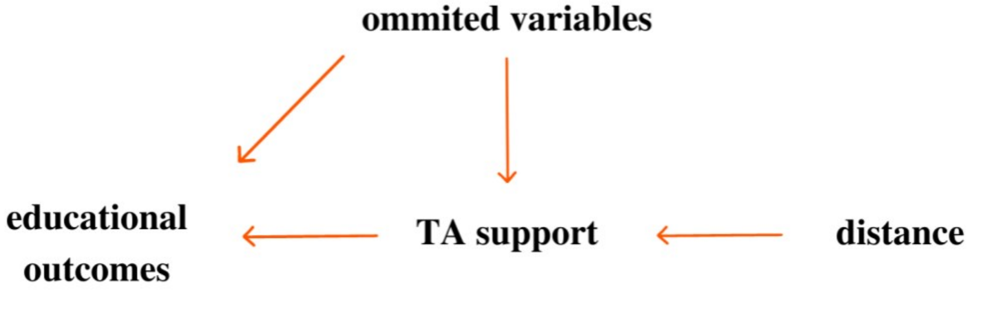
The method is graphically described in diagram 1.

Diagram 1: General IVM



In our case, the treatment is the number of TAs relative to the number of pupils at school. As a possible instrumental variables, we propose to use the distance of school from the nearest EAF. The fact that parents need to take their children to the EAF so that the pupil has a possibility of obtaining a TA may justifiably pose a severe obstacle for many parents, assumingly especially for parents from unstable socio-economic background. Thus, we may argue that the distance from the nearest EAF has a plausible effect on the relative number of TAs (*first stage*) and, at the same time, we see no direct relationship between the distance from the nearest EAF and (i) educational outcomes (*exclusion restriction*) or (ii) confounders affecting educational outcomes (e.g., practice of an individual EAF) (*independence assumption*). The relationships are graphically illustrated in diagram 2.

Diagram 2: Specific IVM



6.4.1 First Stage of 2SLS Estimation

The first stage of 2SLS estimation addresses our instrumental hypothesis and second hypothesis:

Instrumental Hypothesis

The beeline distance of school from the nearest EAF have negative effect on TA support provision.

Hypothesis #2

The different characteristics of a school have an impact on the provision of TA support.

An *instrumental variables* is one of the variables in the first stage regression form. The dependent variable is a *treatment* which in our case is the relative number of TAs in a school. Among other cofounders, we included (i) a modelled share of disadvantaged pupils at school, (ii) a number of pupils at school, (iii) a number of pupils in a village/town, and (iv) a type of a founder. We employed the regression form firstly on the data of the difference between means of reports 2016-2018 and 2019-2022 (as in previous models). Then, we applied same regression form on the solely 2019-2022 mean data.

The regression forms can be, thus, summarised as:

mean of 2019-2022 reports – mean of 2016-2018 reports

(I) $$\#\Delta TAs = \alpha_1 + \beta_1\, distance\_EAF + \gamma_1\, disadvantaged + \gamma_2\, \#pupils\_at\_school + \gamma_3\, \#pupils\_in\_town + \gamma_4\, founder$$

mean of 2019-2022 reports

(II) $$\#TAs = \alpha 1 + \beta 1\, distance\_EAF + \gamma 1\, disadvantaged + \gamma 2\, \#pupils\_at\_school + \gamma 3\, \#pupils\_in\_town + \gamma 4\, founder$$

6.4.2 Second Stage of 2SLS Estimation

The first stage of 2SLS estimation addresses our primary hypothesis:

Hypothesis #1

The relative number of TAs have positive impact on primary school pupils' educational outcomes.

The regression forms can be summarised as:

(I) $repetition = \alpha 1 + \beta 1\ TA\ support + \gamma 1\ disadvantaged + \gamma 2\ \#pupils\_at\_school + \gamma 3\ \#pupils\_in\_town + \gamma 4\ founder$

(II) $non\text{-}completion = \alpha 1 + \beta 1\ TA\ support + \gamma 1\ disadvantaged + \gamma 2\ \#pupils\_at\_school + \gamma 3\ \#pupils\_in\_town + \gamma 4\ founder$

7 Results

In this chapter, we present the results of our model. The structure is based on the structure of the previous chapter. First, we present the results of OLS models, then the results of PSM models, and last the results of the 2SLS models.

7.1 Ordinary Least Squares

The OLS models were employed on 2,199 directorate of schools to study the effects on a change in grade repletion rate and on 2,199 directorate of schools to study the effects on a change in non-completion rate. Both models did not fulfil the assumption of homoskedascity and, thus, we used function *coeftest*() from the *lmtest* package (Zeileis & Hothorn, 2002) in combination with the function *vcovHC()* from the *sandwich* package (Zeiles, 2004) to obtain heteroscedasticity robust standard errors and p-values.

For a change in the rate of grade repetition, we found only one statistically significant variable – *a modelled share of socially disadvantaged pupils.* We may then speak about the decrease of a grade repetition rate at schools with larger modelled share of socially disadvantaged pupils vis-à-vis schools with smaller modelled share of socially disadvantaged pupils. The constant itself was not found statistically significant and, thus, between years 2016-2018 and 2019-2022 there was not significant average change in a grade repetition rate. Statistically insignificant constant may be associated with indirect effect of Covid lockdown. In the medium-run, the online schooling may have affected heterogeneously the share of pupils who needed to repeat a grade, at some schools the rate may have increased and at some school the rate may have decreased.

In case of a non-completion rate, another variable was found to be statistically significant. Having a founder of religious background had a 'positive' impact on a change in number of pupils not completing the 9th grade.

However, neither for grade repetition rate, nor for non-completion rate, the *change in a relative number of TAs'* was found to be statistically significant variables. We have already mentioned that OLS models are not suitable for answering our research question and we carried out OLS models, primarily, for explorative purposes.

Table 7.1: OLS Results

	grade repetition	**non-completion**
number of TAs	0.013 p = 0.0615	-0.026 p = 0.866
disadvantaged	**-0.015** p = 0.004	-0-044 p = 0.162
pupils at school	-0.0000003 p = 0.585	-0.000002 p = 0.604
pupils in town	0.000 p = 0.876	0.000 p = 0.760
private	0.0003 p = 0.754	-0.003 p = 0.431
religious	-0.001 p = 0.691	**0.0013** p = 0.045
constant	0.0005	-0.003
N	2199	2199
F Statistic	3.868	1.465

7.2 Propensity Score Matching

After conducting matching and assessing balance of our matched samples, we can proceed to estimating average treatment effect. We employ *marginaleffects* R package to construct linear models similar to our OLS models. In other word, we again use (i) a modelled share of socially disadvantaged pupils at school, (ii) a number of pupils at school (iii) a number of pupils in a village/town (v) and type of founder (either public, private, or religious as our variables to estimate the effect of treatment on grade repetition and non-completion rates.

However, results of neither grade repetition rate model, nor non-completion model are statistically significant. Therefore, our PSM models revealed that the treatment of increase higher than 0.007 of relative number of TAs to a number of pupils did not have statistically significant effect on a change in educational outcomes.

7.3 First Stage of 2SLS Estimation

The first stage of 2SLS estimation should examine our *instrumental hypothesis* that the beeline distance of a school from the nearest EAF have a negative effect on the provision of TA support. The results with robust standard errors denoted a distance from the nearest EAF was statistically significant only for data of the mean of 2019-2022 reports (p-value of 0.012). We also used analysis of variance (function *anova()*) to compare models with an instrument (including control variables) versus models without an instrument (including control variables). The analyses of variance showed that only in case of the data for the mean of 2019-2022 reports a more complex model with an instrument is significantly better at capturing variance.

Therefore, whilst the beeline distance from the nearest EAF did not prove to be a statistically significant of a change in a relative number of TAs between the mean of 2019-2022 reports and the mean of 2016-2018 reports, it proved to be statistically significant determinant of a relative number of TAs for the mean of 2019-2022 reports.

Table 7.2: First Stage 2SLS Results

	(I) difference of means	**(II) 2019-2022 mean**
distance	0.00003 p = 0.170	**0.0001** p = 0.012
disadvantaged	**-0.030** p = 0.000	**-0.071** p = 0.000
pupils at school	**-0.000004** p = 0.000	**-0.00001** p = 0.000
pupils in town	**-0.000** p = 0.004	-0.000 p = 0.529
private	-0.003 p = 0.336	**-0.011** p = 0.003
religious	**-0.003** p = 0.050	**0.006** p = 0.076
constant	**0.006**	**0.014**
N	2199	2199
F Statistic	35.812	93.474

However, the results are contradictory to our expectations and instrumental hypothesis. The results suggest that a beeline distance of a school from the nearest EAF has a positive effect on the provision of TA support. As our hypothesis is not confirmed, we consider our instrument as inappropriate and our 2SLS estimation cannot be employed to study the effect of TA support on educational outcomes.

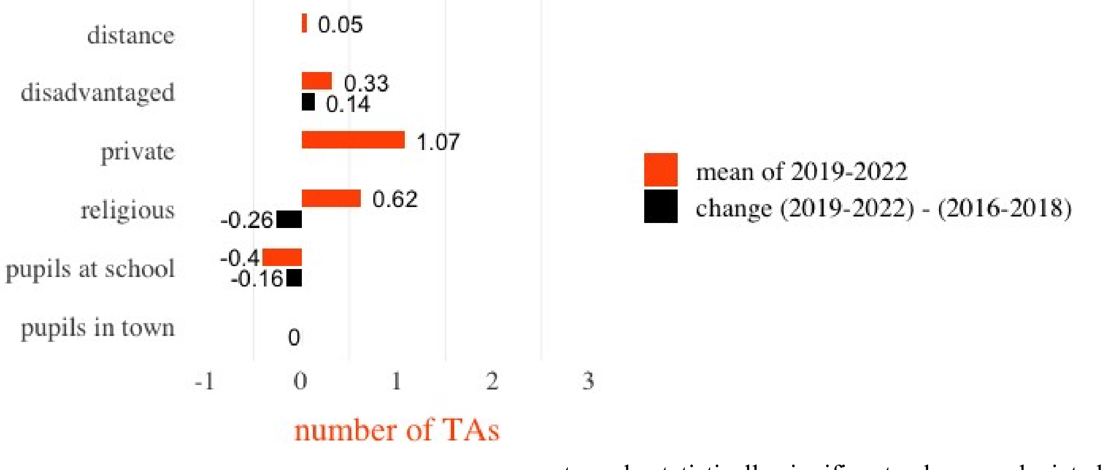
The fact that, in contrast to our theory, a distance of school from the nearest EAF was found to have a positive effect on the provision of TA support may have more explanations. The most probable explanations lies in the possibility thar our covariate *a modelled share of socially disadvantaged pupils at school* does not address the problem of reverse causality. As, for instance, mapavzdelavani.cz (Prokop et al, n.d.) visually suggests, in rural areas, we could expect more pupils with SEN and, consequently, higher demand for TA support. We used an above-mentioned covariate to address the reverse causality of demand but there might be other factors specific for rural areas (i) which are not captured in *a modelled share of socially disadvantaged pupils at school* and (ii) which increases demand for TA support.

Other explanation provides a recent study on the determinators of Roma pupils segregation in Czech school system (Hoření et al, 2023). The qualitative investigation into the process of providing TA support implies that EAF staff help schools in socially excluded localities. Typically, EAF staff go on a large scale to segregated schools, the school management ensures that pupils and their parents are present, and EAF staff acknowledge the entitlement for TA support for multiple pupils. In this way, the position of TA is more stable as the entitlement for TA support for multiple pupils avoids the loss of TA position in case one of the pupils with the entitlement moves away.

These findings question the validity of our instrumental hypothesis. If EAF staff visits segregated school intentionally to provide TA support, a distance from the nearest EAF stops being an obstacle for the provision of TA support.

Nevertheless, the first stage of 2SLS estimation provides a valuable insight into how school characteristics affect the provision of TA support. To compare the rate of the effect of individual determinators, we constructed a graph depicting the size of the coefficient per 100 pupils. In case of *beeline distance from the nearest EAF, a modelled share of socially disadvantaged pupils, pupils at school,* and *pupils in town/village*, we multiplied coefficients by the median value of the respected variable. For instance, the median beeline distance from the nearest EAF in our dataset was around 5.5 km, thus, the median effect of a beeline distance from the nearest EAF is around 0.05 (more of full-time TA working hours).

Figure 7.1: Median Effects on the Provision of TA Support (per 100 pupil)

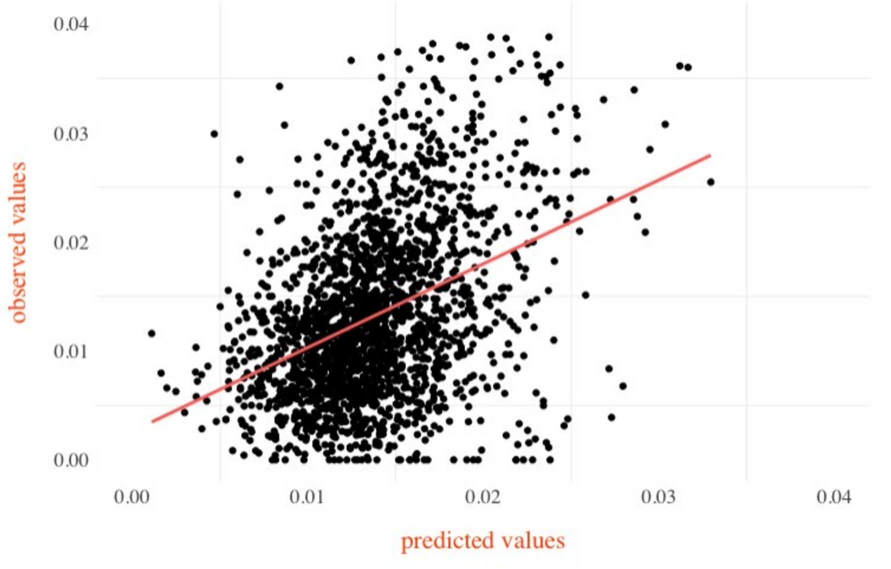


note: only statistically significant values are depicted

The most significant determinator of the provision of TA support is a type of founder. Private schools have 1.07 and religious schools have 0.62 more full-time TA working hours than private schools. However, the change of the provision of TA support between the mean of 2019-2022 report and mean of 2016-2018 reports was higher at public school than at private or religious schools.

We also constructed a plot of observed and predicted values for the first stage model employed on a data for the mean of 2019-2022 reports. The visual control indicates that our selected first stage model is *imperfect* at explaining the variance.

Figure 7.2: Observed vs. predicted values (2019-2022 mean)



7.4 Second Stage of 2SLS Estimation

Although the first stage of our 2SLS estimations showed that our instrument is inappropriate for our estimation, we provide the results of the second stage for educational purposes.

The results of the second stage of 2SLS estimation suggest that a relative number of TAs in statistically significant neither for grade repetition rate, nor for non-completion rate. Provided that our instrument were appropriate, we would conclude that the second stage of 2SLS estimation suggests that a relative number of TAs has no statistically significant effect on either grade repetition rate or non-completion rate.

Table 7.3: Second Stage 2SLS Results

	grade repetition	non-completion
number of TAs	0.227 p = 0.536	2.692 p = 0.269
disadvantaged	**0.086** p = 0.002	**0.506** p = 0.006
pupils at school	-0.0000005 p = 0.914	0.00002 p = 0.528
pupils in town	**-0.000000002** p = 0.00002	**-0.0000002** p = 0.000
private	-0.002 p = 0.543	-0.037 p = 0.168
religious	-0.002 p = 0.579	-0.016 p = 0.512
constant	-0.001	-0.029
N	2112	2112

7.5 Summary of Results

OLS models found no statistically significant relationship between a change in a relative number of TAs and a change in either grade repletion rare or non-completion rate. Yet, as we discussed above, OLS models alone could not provide robust causal evidence since the assumption of exogeneity is not fulfilled.

Therefore, we applied additionally two quasi-experimental approached: (i) propensity score matching and (ii) instrumental variable regression. Propensity score matching models revealed that we cannot reject a null hypothesis. In other words, there was not a statistically significant difference in a change of either grade repetition or non-completion rate between school which experienced substantial increase in a relative number of TAs and school which did not.

The instrumental variable regression in the specific form of the two-least square regression made use of a beeline distance from the nearest EAF as an exogenous instrument. In the first stage, we tested a statistical significance of the instrument as a determinator of a relative number of TAs at elementary schools. We found, after controlling for the selected set of covariates, that when employed on a data for the mean of 2019-2022 our instrument is statistically significant in explaining the variance of a relative number of TAs at elementary schools. However, in contrast to our expectations and hypothesis, the effect was found to be marginally positive. Moreover, the visual control of observed and predicted values for relative number of TAs suggested that our instrument was imperfect at explaining the variance.

Nonetheless, we proceeded with the second stage and tried to estimate the effect of TA support on educational outcomes. Yet the effect on neither grade repetition rate nor non-completion rate was found to be statistically significant.

To summarise, our models found that TA support has no effect on educational outcomes of pupils in Czech elementary schools. Yet, this conclusion has many caveats we discuss in the following subsection. The provision of TA support in the Czech Republic was determined, in the descending order of magnitude, by (i) a type of founder, (ii) a number of pupils at schools, (iii) a modelled share of socially disadvantaged pupils, and marginally by (iv) a distance from the nearest EAF. The largest modelled difference is between a 100 pupils public elementary school and 100 pupils private school. In this modelled example, a private elementary school would have on average 0.4 fulltime TA support more than a public elementary school.

8 Discussion

In this section, we will firstly discuss possible explanations of the finding that TA support had no effect on educational outcomes. We may divide our explanations in two categories. First, explanations which do not question the quality of the data and explain why the presence of TA support does not improve educational progress of pupils. Second, explanations which discusses the quality of the data we used for our analyses. Then, we will outline what questions future research should study and what research design would be the most appropriate.

8.1 What Might Cause the Infectivity of TAs?

Provided that we accept the result of our analyses that TA support had no effect on educational progress of pupils, there are explanations in other literature explaining the infectivity of TA support. As a number of TAs in Czech elementary school had increased rapidly in recent years, the qualification they have may vary significantly. Thus, as one TA may prove to have a substantial effect on pupil's/pupils' progress, another with lesser qualification and skills may have an almost-zero effect, in some cases when TA excludes a pupil with SEN from the class, the effect may be negative. The factors which may affect the beneficially of a TA are many. We can, in accordance with reviewed literature, name the character of a TA, TA's experience, or a subjects knowledge of a TA.

Nonetheless, it is not just a TA underqualification which may limit the beneficially of a TA support. Since the presence of a TA is still a rather novel feature in the Czech educational system, many teachers and many school collectives may struggle with the effective integration of (a) pupils with SEN and (b) TAs.

8.2 Quality of Data & Robustness of Methodology

The other type of explanations is focused on the data and methodology we used in our analyses. As we stated previously, the fundamental limitations of the data we use is the binary structure of our outcome variables. We did not possess any data more suitable nation-wide data on the academic attainments of pupils and, hence, we had to employ the data for the grade repletion and non-completion rate. Moreover, qualification criteria are not standardised, each school sets its own criteria for classification. The subjectivity of the outcome variables is further increased by the heterogenous classification methods of individual teachers.

The nature of the data which is non-individual and observational led us to rely on quasi-experimental methods. Although we managed to obtain a good balance in covariates used for propensity score matching, we cannot guarantee that our set of variables is all-encompassing. The quasi-experimental methods enabled us to get as robust evidence as we could get from the available data. Yet, the quality of the data means that we cannot guarantee we addressed the problem of reverse causality and endogeneity properly.

8.3 Future Research

A more robust approach would simulate experimental methodology applied by Andersen, Beuchert, Nielsen, and Thomsen (2020). The use of randomised experiment can provide robust evidence not only for the estimation of the effect of TAs on pupils 'academic attainments, but also for the study of what qualification of a TA has the largest beneficial impact, what type of TA's participation is the most suitable, and other relevant research questions related to the introduction of TAs into primary and secondary schools.

Thus, we propose to link change in the system of the provision and funding of TAs with the small to medium sample randomised experiment to study above outlined questions. Although these questions were explored by Andersen, Beuchert, Nielsen, and Thomsen (2020), there is still limited evidence on these questions. Moreover, the domestic education-oriented applied research may have the potential spill-over effects on the other sectors of the governance. The importance of in-house research is underscored by the observation that the evidence-informed policymaking is often hindered by 'low trust in external sources of information, poor management of available information, weak senior commitment to analytical skills, and low ability to partner with external groups' (Head, 2016, pp. 470).

Future research could contribute also by studying effects of individual levels of TA. A study conducted by Andersen, Beuchert, Nielsen, and Thomsen (2020) is a good example how research can shed light on specific parameters of TAs‘ role in education. Currently, there are no data available on the numbers of TAs by their level in the Czech Republic. A new research with the objective to study effects of individual levels of TAs in relation to both the type and depth of pupil(s) with SEN and the role of TA in the classroom could stimulate a change in scope and structure of the data the MŠMT stores.

9 Policy Recommendations

The endeavour to robustly estimate the effect of TA support on educational outcomes provided rather limited evidence. Yet the results addressing our second research question and process itself enabled authors to gain insight into difficulties of evidence-based school policymaking in the Czech Republic. We believe that successful (inclusive) schooling requires policymakers to base decisions on evidence and expert knowledge. For this reason, we dedicate this section to policy recommendations which, in our view, would benefit the school policymaking in the Czech Republic.

Firstly, we would like to address the process of policymaking itself. The high-quality policymaking is based on the evidence and respects opinions of the experts. The system of TA support is widely used internationally and there also domestic experts with profound knowledge of the advantages and disadvantages of individual parameters of the system. Nevertheless, the praxis of the present policymaking suggests that the Czech school policymaking *lends an ear* to neither of those. The illustrating example was the introduction the current system of the provision and financing of TAs.

Our analysis provides evidence that the provision of TAs is disproportionately more frequent at private or religious schools than public schools. The study of the Faculty of Education Palacký University Olomouc (2013, pp.56) found that the probability that a pupil with similar SEN obtains a TA as a supporting measure varies significantly among administrative regions of the Czech Republic. These findings are in stark contrast to the Education Act (No. 561/2004) which refers the principle of equal access to education (Parliament of the Czech Republic, 2004). The inappropriateness of the current system is corroborated by the fact that MŠMT is proposing a change in the system of the provision of TA support.

The MŠMT introduced the current model of provision and financing TAs despite the fact it had at its disposal a document, titled ‘Proposal for a System of TA Funding’, which argued **persuasively** against it and proposed 3 alternative models. The primary drawback identified was the instability of the position of TA which is tied to the presence of a concrete pupil with diagnosed SEN (Felcmanová et al., 2015). Thus, in the current model, when a pupil entitled to TA support starts to attend a particular school, the school is required to hire one or less full-time equivalent TA. When this pupil leaves the school, the hired TA(s) lose their position unless a new pupil entitled to TA support starts to attend the school.

The process of the introduction of current model of the provision and financing of TA represents that the education policymaking of the MŠMT did not respect experts' opinion. Yet high-quality policymaking requires to learn from the mistakes of others and to invite experts into the process. Felcmanová and others (2015) provided one strong argument against the current model, our thesis adds another in the form of the documentation of severe inequalities in the probability of obtaining TA support among individual pupils with SEN and their classmates.

It is our contention that high-quality evidence-based education policymaking must be based on strong research and analytical capacities of the government. As our literature review suggests there is ample international evidence whether TA support exerts positive effect on pupils' academic attainments and what parameters can maximise positive effects. For instance, Rob Webster, the Director of the Education Research, Innovation and Consultancy (ERIC) Unit at the University of Portsmouth, published many books, intended for school leaders, teachers, TAs, and others, on how to make TA support work as best it can. The domestic education policymaker can look for this kind of international experts and their know-hows and use their insight for the designing of the domestic education policies.

At the same time, in order to make informed decisions, policymakers and stakeholders require access to high-quality evidence obtained through robust evaluation processes. Evidence obtained in this way can serve as the basis for designing policies that are grounded in empirical data and aimed at achieving specific outcomes. Furthermore, the commitment to sound evidence and appropriate consultation processes in decision-making can enhance transparency, accountability, and the legitimacy of policy decisions.

Thus, it can be argued that strengthening the government own research and analytical capacities is also a necessity for a high-quality policies. Brian W. Head (2016), a professor of policy analysis, summarises that a commitment to financing and utilizing evidence obtained through evaluations is crucial to promoting evidence-based policies and ensuring effective governance. The evidence-informed policymaking is conditional on 'long-term investment in data collection and analysis (on key social, economic, and environmental matters), as well as investment in technical and managerial skills for interpreting and utilizing information from multiple sources' (pp. 473).

The recent publication of the National Economic Council of the Government (NERV) (2023) is in the same vein. It documents that the insufficient government capacities for the regulatory impact assessment are not limited to the education policymaking but concerns general public administration. The members of the NERV state that, as a consequence, 'previous governments, including the current one, have weak support in the preparation, defense, and implementation of reforms, and in their advocacy to the public'.

Therefore, they recommend increasing and improving research and analytical capacities of (i) individual ministries, (ii) the government office, and (iii) individual university departments. For the last, the inspiration can be both international (e.g., Institute of Education, University College London) and domestic (e.g., Institute of Educational Sciences, Masaryk University). If the government based its arguments on international and domestic evidence in the past, it is plausible that the introduction of inclusive schooling in the Czech Republic would have been less controversial.

The research and analytical teams need reliable and comprehensive data for their work. With this purpose in view, a complex review of the structure of school reports might be beneficial for answering researchers' and policymakers' questions. However, the augmented benefit for education policymaking might consist of the introduction of anonymised unique pupil identifier. The possibility to track individual pupils' progress would enable researchers and policymakers to make more targeted analyses and answer a wider range of questions. The inspiration could come from the United Kingdom where unique pupil numbers are allocated at the point of a pupil's first entry into the state funded school sector to 'provide invaluable evidence on educational performance to inform independent research, as well as studies commissioned by the department' (Department of Education, 2019).

Yet as we outlined above, there is also a strong case for the review of the scope and structure of data the MŠMT has in disposal about Czech schools. Our research experience leads us to a conviction that the whole data system needs a review. At the moment, it is not in our capacity to provide recommendations for the comprehensive change, but we can provide recommendations for the data capturing information about TAs.

Future research, we believe, as well as policy evaluations from the MŠMT, could provide greater insight if there were following changes in the data management:

i. the data about TAs were available at the level of individual schools rather than directorate of schools;

ii. the data also included information about individual levels of TAs;

iii. there were information on whether TAs work in mainstream or special education classrooms;

iv. there were information about the experience and qualifications of individual TAs;

v. there were information on which specific assistant (e.g., level, experience) is assigned to which students with SEN (e.g., type, depth)

Besides, the difference between the number of TAs per a pupil between public schools on one side and private and religious schools on the other, raise a question of whether private and religious schools do not enjoy a preferential treatment in the volume of the government funding for TA positions. This inequality may further strengthen concerns about the role of private school as 'drivers of social segregation'. Since the Czech school system reproduces the socio-economic background of parents at high rate (Shewbridge et al., 2016), thus lowers the social mobility, it is in the interest of the government to closely study the impact of increasing number of private schools on the school system, particularly the impact on the educational and social mobility. Moreover, higher share of private school-goers might negatively affect the educational results of the whole system. 'At the system level, across all countries and economies, school systems with larger shares of students in private-independent schools tended to show lower mean performance in reading, mathematics and science, after accounting for per capita GDP (OECD, 2019, Chapter 7).

Rita Nikolai and Marcel Helbig (2021, 2015) state that the government should provide private schools with public subsidies to help with reducing educational inequalities and creating equal educational opportunities. The subsidies ought to be of the following types:

i. ‘the compensation of schools for the loss of tuition revenue. For example, private schools could completely remove school fees (like in Rhineland-Palatinate in Germany) or exempt parents from low-income families from paying school fees if they are not able to afford them;

ii. subsidies for state-supported private schools should be linked to the number of students from low-income families. In return, private schools must provide information – in anonymous form – about the social composition of their student body;

iii. there should be a limit on the total revenue of private schools. If the financial imbalances between public schools and private schools become too great, private schools will become more attractive and attract even more money. The regulation in North Rhine-Westphalia (one of the German states) might be a possible solution. In this federal state, the income from school fees is factored into the state funding. Too much private income leads to a decline in state funding.’

In conclusion, the fundamental policy recommendation is to invest in the research and analytical capacities of the government and public institutions, invite policy expert in the policy discussion, learn from the available evidence and ‘best practices’, and regularly evaluate introduced changes in public policies as well as long-term trends in the Czech education system.

10 Conclusion

The lively public debate about the introduction of *inclusive schooling* overshadowed the nature of education policymaking in the Czech Republic. Instead of focusing on gathering international evidence, modelling the benefits and drawbacks of different system parameters, and listening to experts, the NGOs and government officials sought to calm down a frightened society. We believe that if the state had made a more thorough preparation for the introduced reform, it would have had many arguments prepared in advance and the current situation, in which the government is trying to change the system of funding of TA after 7 years since the reform, would not have arisen.

In this thesis, we endeavoured to fill the gap in the evidence and, using various advanced econometric models, to estimate the effect of TAs on the educational outcomes and describe factors which have determined the provision of TAs in the current system. The quasi-experimental design and the nature of the data posed a severe limits which we described in detail in the *Discussion* section. We found that a relative number of TAs did not have any statistically significant effects on the grade repetition and non-completion rates. We also provide evidence that private and religious school have been able to provide more TAs per a pupil than public schools.

Yet the primary advantage of this work lies in its ability to demonstrate how policymaking can be effectively prepared and evaluated through the use of rigorous academic procedures. By drawing upon both extant literature and conducting our own data-oriented analyses, we are able to gain a comprehensive understanding of the strengths and weaknesses of the present system.

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Appendix: R Script

M03_upload

```
library(tidyverse)
library(readxl)
##################uploading an individual year ####################################
# Automation for years 2016-2022
rok_vector <- c(2016:2022)

for (rok in rok_vector) {
  data <-  read_excel(str_c("~/Documents/UK_FSV_2021:2022/Thesis I/Data/thesis_v2/data/R13_",
rok, ".xlsx"),
                      sheet = 3)

colnames(data) <- tolower(colnames(data))

data <- data %>%
  filter(red_izo %in% bez_specialnich, ####vyřazuji školy, které mají žáky ve speciálních třídách
         red_izo %!in% devata_trida, ####vyřazuji školy, ve kterých žádný žák neukončil docházku v 9.
třídě
         red_izo %in% red_izo_2022) |>  ###only school appearing in 2022 reprot
  group_by(red_izo) %>%
  summarise(n_TAs = `r1401d4`) %>%
  ungroup() %>%
  select(red_izo, n_TAs)  # na plně zaměstnané

######
assign(str_c("R13_", rok), data)

}

################
################
########combine
R13_19_22 <- bind_rows(R13_2022, R13_2021, R13_2020, R13_2019)  %>%
  group_by(red_izo) %>%
  summarise(n_TAs = mean(n_TAs))
```

```
########combine
R13_16_18 <-  bind_rows(R13_2018, R13_2017, R13_2016)  %>%
  group_by(red_izo) %>%
  summarise(n_TAs = mean(n_TAs))
```

R13_upload

```
library(tidyverse)
library(readxl)
#####

red_izo_2022 <- read_excel(str_c("~/Documents/UK_FSV_2021:2022/Thesis
I/Data/thesis_v2/data/M03_2022.xlsx"),
                                   sheet = 1) |>
              pull(red_izo)




# Automation for years 2016-2022
rok_vector <- c(2016:2022)

for (rok in rok_vector) {
  data_I <-  read_excel(str_c("~/Documents/UK_FSV_2021:2022/Thesis I/Data/thesis_v2/data/M03_",
rok, ".xlsx"),
                       sheet = 1)

  # Lower case all column names
  colnames(data_I) <- tolower(colnames(data_I))

  # Filter and summarize data
  data_I <- data_I %>%
    filter(red_izo %in% bez_specialnich,
           red_izo %!in% devata_trida,
           red_izo %in% red_izo_2022) |>  ###only school appearing in 2022 reprot
    group_by(red_izo) %>%
    summarise(ukoncili_v_7_8= sum(r01042 + r01052),
             ukoncili_v_9 = sum(r01062)) %>%
    ungroup()

  data_II <-  read_excel(str_c("~/Documents/UK_FSV_2021:2022/Thesis
I/Data/thesis_v2/data/M03_", rok, ".xlsx"),
```

```
                  sheet = ifelse(rok > 2016,
                                 9,
                                 2))

  # Lower case all column names
  colnames(data_II) <- tolower(colnames(data_II))

  # Filter and summarize data
  data_II <- data_II %>%
    group_by(red_izo) %>%
    summarise(pupils_at_school = sum(r03013),
              opakujic_rocnik = sum(r03017)) %>%
    ungroup()

  # Join data
  data <- left_join(data_I, data_II, "red_izo") %>%
    mutate(rok = rok)

  # Assign to new variable
  assign(str_c("M03_", rok), data)
}

#######how many pupils did I selected out?
sum(M03_2022$pupils_at_school)
sum(read_excel("~/Documents/UK_FSV_2021:2022/Thesis I/Data/thesis_v2/data/M03_2022.xlsx",
               sheet = 9)$r03013)

#####
####################################combining years
M03_19_22 <- bind_rows(M03_2022, M03_2021, M03_2020, M03_2019)  %>%
  group_by(red_izo) %>%
  summarise(ukoncili_v_7_8 = mean(ukoncili_v_7_8),
            ukoncili_v_9 = mean(ukoncili_v_9),
            pupils_at_school = mean(pupils_at_school),
            opakujic_rocnik = mean(opakujic_rocnik),
            non_complete = ukoncili_v_7_8/(ukoncili_v_7_8 + ukoncili_v_9),
            grade_repet = opakujic_rocnik/pupils_at_school) %>%
  ungroup()

M03_19_22
```

```
#

#
##
M03_16_18 <-  bind_rows(M03_2018, M03_2017, M03_2016)  %>%
  group_by(red_izo) %>%
  summarise(ukoncili_v_7_8 = mean(ukoncili_v_7_8),
            ukoncili_v_9 = mean(ukoncili_v_9),
            pupils_at_school = mean(pupils_at_school),
            opakujic_rocnik = mean(opakujic_rocnik),
            non_complete = ukoncili_v_7_8/(ukoncili_v_7_8 + ukoncili_v_9),
            grade_repet = opakujic_rocnik/pupils_at_school) %>%
  ungroup()
```

M03_filters

```
library(tidyverse)
library(readxl)
#####


####nejřív vyřadím ZŠ, které mají alespoň jednu třídu speciální
# list of dataset names
datasets <- list(
  M03_2016 = 9,
  M03_2017 = 10,
  M03_2018 = 10,
  M03_2019 = 10,
  M03_2020 = 10,
  M03_2021 = 10,
  M03_2022 = 10
)

# initialize the final vector
bez_specialnich <- numeric()

# loop through the list of dataset names
for (dataset in names(datasets)) {
  # read the dataset
  data <- read_excel(str_c("~/Documents/UK_FSV_2021:2022/Thesis I/Data/thesis_v2/data/", dataset,
".xlsx"), sheet = datasets[[dataset]])
```

```
  # determine the correct column name for the "red_izo" column based on the dataset name
  col_name <- ifelse(dataset %in% c("M03_2016", "M03_2017"), "RED_IZO", "red_izo")
  var_name <- ifelse(dataset == "M03_2016", "R3A0112", "r3a0112")
  # process the data
  processed_data <- data %>%
    filter(get(var_name) == 0) %>%
    pull(col_name)

  # append the results to the final vector
  bez_specialnich <- unique(c(bez_specialnich, processed_data))
}

bez_specialnich



#zároveň chci jen školy, které mají 9. třídou
datasets <- list(
  M03_2016 = 2,
  M03_2017 = 9,
  M03_2018 = 9,
  M03_2019 = 9,
  M03_2020 = 9,
  M03_2021 = 9,
  M03_2022 = 9
)
# initialize the final vector
devata_trida <- numeric()

# loop through the list of dataset names
for (dataset in names(datasets)) {
  # read the dataset
  data <- read_excel(str_c("~/Documents/UK_FSV_2021:2022/Thesis I/Data/thesis_v2/data/", dataset,
".xlsx"), sheet = datasets[[dataset]])

  colnames(data) <- tolower(colnames(data))

  # process the data
  processed_data <- data %>%
    group_by(red_izo) |>
```

```
  summarise(nine_grade = sum(r03123)) |>
  filter(nine_grade == 0) %>%
  pull(red_izo)

 # append the results to the final vector
 devata_trida <- unique(c(devata_trida, processed_data))
}

devata_trida
```

Graph educational outcomes

```
library(tidyverse)
library(readxl)

rok_vector <- c(2016:2022)

for (rok in rok_vector) {
 data_I <-  read_excel(str_c("~/Documents/UK_FSV_2021:2022/Thesis I/Data/thesis_v2/data/M03_", rok, ".xlsx"),
                      sheet = 1)
 # Lower case all column names
 colnames(data_I) <- tolower(colnames(data_I))

 # Filter and summarize data
 data_I <- data_I %>%
  group_by(red_izo) %>%
  summarise(ukoncili_v_7_8= sum(r01042 + r01052)) %>%
  ungroup()

 data_II <-  read_excel(str_c("~/Documents/UK_FSV_2021:2022/Thesis I/Data/thesis_v2/data/M03_", rok, ".xlsx"),
                       sheet = ifelse(rok > 2016,
                                      9,
                                      2))

 # Lower case all column names
 colnames(data_II) <- tolower(colnames(data_II))

 # Filter and summarize data
 data_II <- data_II %>%
```

```
    group_by(red_izo) %>%
    summarise(opakujic_rocnik = sum(r03017)) %>%
    ungroup()

  # Join data
  data <- left_join(data_I, data_II, "red_izo") %>%
    mutate(rok = rok)

  # Assign to new variable
  assign(str_c("M03_graph_", rok), data)
}



M03_total <- bind_rows(bind_rows(M03_graph_2022, M03_graph_2021, M03_graph_2020,
M03_graph_2019,
                                 M03_graph_2018, M03_graph_2017, M03_graph_2016)  %>%
                         group_by(rok) %>%
                         summarise(ukoncili_v_7_8 = sum(ukoncili_v_7_8),
                                   opakujic_rocnik = sum(opakujic_rocnik)) %>%
                         ungroup()) |>
  select(rok, ukoncili_v_7_8, opakujic_rocnik)

M03_total <- pivot_longer(M03_total, cols = c(ukoncili_v_7_8, opakujic_rocnik)) |>
  mutate(rok = as.character(rok),
         name = fct_relevel(name, "ukoncili_v_7_8", "opakujic_rocnik"))



####
ggplot(M03_total, aes(y = rok, x = value, label = value,
                      fill = name, group = name)) +
  geom_col(position = position_dodge(0.7),
           width = 0.6) +
  geom_text(position = position_dodge(0.7),
            hjust= -0.25) +
  scale_fill_manual(values = rev(c("#ff5500", "black")),
                    labels = rev(c("grade repetition", "non-completion"))) +
  theme_minimal() +
  theme(legend.position = "right",
        legend.title = element_blank(),
        text = element_text(size=16, family="serif"),
```

```
    plot.title = element_text(margin=margin(10,0,10,0),
                              hjust = 0.125,
                              color = "#ff5500"),
    plot.title.position = "plot",
    plot.caption.position =  "plot",
    axis.title.y = element_blank(),
    axis.title.x = element_text(margin = margin(t = 10, r = 0, b = 0, l = 0),
                                color = "#ff5500"),
    panel.grid.major = element_blank(),
    panel.spacing = unit(2, "lines")) +
  xlab("number of pupils") +
  ggtitle("Educational Outcomes 2016 - 2022") +
  guides(fill = guide_legend(reverse = TRUE)) +
  coord_cartesian(clip = "off")
```

Geolocation schools

```
library(readxl)
library(tidyverse)
library(sf)
library(tidygeocoder)



#######
data <-  read_excel(str_c("~/Documents/UK_FSV_2021:2022/Thesis
I/Data/thesis_v2/data/M03_2022.xlsx"),
                    sheet = 1) %>%
  filter(red_izo %in% bez_specialnich, ####vyřazuji školy, které mají žáky ve speciálních třídách
         red_izo %!in% devata_trida) |>   ####vyřazuji školy, ve kterých žádný žák neukončil docházku v
9. třídě)
  select(red_izo, p_izo, vusc3, misto, ulice)

####uprava pro geolokaci
data <- data %>%
  mutate(misto = case_when(str_starts(misto, "Praha") ~ "Praha",
                           T ~ misto),
         adresa = str_c(coalesce(str_remove(ulice, "č.p. "), ""),
                        " ",
                        coalesce(misto, ""),
                        " ",
```

```
                    "Czechia")) %>%
  select(red_izo, adresa)
###
data

###start_geocode
data_geo <- data %>%
  geocode(address = adresa,
          method = "here") %>%
  sf::st_as_sf(coords = c("long", "lat"), crs = 4326)

############pro sdílená red_iza určit prostřední bod
data_geo_v2 <- data_geo %>%
  group_by(red_izo) %>%
  summarise() %>%
  st_centroid() %>%
  ungroup()



##################################
assign(str_c("M03_geo"), data_geo_v2)
```

Geolocation SPC

```
library(readxl)
library(tidyverse)
library(sf)
library(tidygeocoder)



####
rok <- 2022
#######
data <-  read_excel(str_c("~/Documents/UK_FSV_2021:2022/Thesis I/Data/thesis_v2/data/Z33_", rok, ".xlsx"),
                   sheet = 1) %>%
  select(red_izo, p_izo,vusc, misto, ulice)

####uprava pro geolokaci
data <- data %>%
  mutate(misto = case_when(str_starts(misto, "Praha") ~ "Praha",
```

```
                        T ~ misto),
         adresa = str_c(coalesce(str_remove(ulice, "č.p. "), ""),
                        ", ",
                        coalesce(misto, ""),
                        ", ",
                        "Czechia")) %>%
  select(red_izo, p_izo, adresa)
###
data

###start_geocode
data_geo <- data %>%
  geocode(address = adresa,
          method = "here") %>%
  sf::st_as_sf(coords = c("long", "lat"), crs = 4326)
##############PROVIZORNÍ#############
assign(str_c("Z33_geo_", rok), data_geo)
```

Geolocation PPP

```
library(readxl)
library(tidyverse)
library(sf)
library(tidygeocoder)



####
rok <- 2022
#######
data <-  read_excel(str_c("~/Documents/UK_FSV_2021:2022/Thesis I/Data/thesis_v2/data/Z23_", rok, ".xlsx"),
                      sheet = 1) %>%
  select(red_izo, p_izo,vusc, misto, ulice)

####uprava pro geolokaci
data <- data %>%
  mutate(misto = case_when(str_starts(misto, "Praha") ~ "Praha",
                        T ~ misto),
         adresa = str_c(coalesce(str_remove(ulice, "č.p. "), ""),
                        ", ",
                        coalesce(misto, ""),
```

```
                    ", ",
                    "Czechia"),
        adresa = replace(adresa, adresa == "J. A. Bati 5520, Zlín, Czechia",
              "Jana Antonina Bati 5520, Zlín, Czechia")) %>%
  select(red_izo, p_izo, adresa)
###
data

###start_geocode
data_geo <- data %>%
  geocode(address = adresa,
         method = "here") %>%
  sf::st_as_sf(coords = c("long", "lat"), crs = 4326)
##############PROVIZORNÍ#############
assign(str_c("Z23_geo_", rok), data_geo)
```

Measuring Distance

```
library(dplyr)
library(sf)



#########3) PPP + SPC
poradny_geo <- bind_rows(Z23_geo_2022, Z33_geo_2022)

index_poraden <- st_nearest_feature(M03_geo, poradny_geo)

distance <- as.numeric(st_distance(M03_geo, poradny_geo[index_poraden,], by_element=TRUE))

data_III <- M03_2022 %>%
  mutate(distance = distance,
        SPZ = poradny_geo [index_poraden, 2],
        SPZ_p_izo = SPZ$p_izo) %>%
  select(red_izo, distance, SPZ_p_izo)

###############
vzdalenosti <- data_III

vzdalenosti
```

Graph Distance

```
library(tidyverse)
library(readxl)

summary(merged_19_22$distance)

####
ggplot(data = merged_19_22, aes(x = distance)) +
  geom_histogram(fill = "#FF5500") +
  theme_minimal() +
  theme(legend.position = 'none',
        legend.title = element_blank(),
        text=element_text(size=16, family="serif"),
        plot.title = element_text(margin=margin(10,0,10,0),
                                  hjust = 0.125,
                                  color = "#FF5500"),
        plot.title.position = "plot",
        plot.caption.position =  "plot",
        axis.title=element_blank(),
        panel.grid.major = element_blank(),
        panel.spacing = unit(2, "lines")) +
  ggtitle("Histogram of a Beeline Distance from the Nearest EAF") +
  geom_vline(xintercept = 1.135, linetype="dotted") +
  geom_vline(xintercept = 5.498, linetype="dashed") +
  geom_vline(xintercept = 11.403, linetype="dotted") +
  xlim(c(-1,45))
```

Merge

```
library(tidyverse)


#
'%!in%' <- function(x,y)!('%in%'(x,y))
#
##########2019_2022
merged_19_22 <- M03_19_22 %>%
  left_join(R13_19_22, "red_izo") %>%
  left_join(vzdalenosti, "red_izo") %>%
  left_join(kraj, "red_izo") %>%
  left_join(model, "red_izo") %>%
  left_join(pupils_in_town, by = "misto") |>
```

```
  group_by(red_izo) |>
  summarise(pupils_in_town = mean (pupils_in_town),
            across(everything(), first)) |>
  mutate(r_TAs = n_TAs/pupils_at_school,
         distance = distance/1000)  |>
  select(red_izo, znevyh_share_predr, pupils_in_town, zriz, region, distance, grade_repet,
non_complete, r_TAs, pupils_at_school)

#bind %>% filter(rowSums(is.na(.)) > 0)

merged_16_18 <- M03_16_18 %>%
  left_join(R13_16_18, "red_izo") %>%
  left_join(vzdalenosti, "red_izo") %>%
  left_join(kraj, "red_izo") %>%
  left_join(model, "red_izo") %>%
  left_join(pupils_in_town, by = "misto") |>
  group_by(red_izo) |>
  summarise(pupils_in_town = mean (pupils_in_town),
            across(everything(), first)) |>
  mutate(r_TAs = n_TAs/pupils_at_school,
         distance = distance/1000)  |>
  select(red_izo, grade_repet, non_complete, r_TAs)



############ ODEČET průměr 2020-2022 - průměr 2017-2019 ############
merged_19_22_v2 <- pivot_longer(merged_19_22, cols = c(grade_repet, non_complete, r_TAs))

merged_16_18_v2 <- pivot_longer(merged_16_18, cols = c(grade_repet, non_complete, r_TAs))

merged_rozdil <- merged_19_22_v2 |>
  left_join(merged_16_18_v2, by = c("red_izo", "name")) |>
  mutate(value = value.x - value.y) |>
  select(-value.x, -value.y)


merged_rozdil <- pivot_wider(merged_rozdil, names_from = name, values_from = value) |>
  filter(is.na(non_complete) == FALSE)    ###mám tam 17NAs for non_completes

merged_rozdil
```

```
#####
hist(merged_rozdil$r_TAs)
summary(merged_rozdil$r_TAs)

merged_19_22 %>% filter(rowSums(is.na(.)) > 0)
```

OLS

```
library(dplyr)
library(flextable)
library(broom)
library(lmtest)
library(sandwich)
#####



#########R O Z D Í L##########
#####1) nedokoncovani
model_nedokoncovani <- lm(non_complete ~
                 r_TAs + znevyh_share_predr + pupils_at_school + pupils_in_town + zriz,
                 data = merged_rozdil)

#####1) propadani
model_propadani <- lm(grade_repet ~
                  r_TAs + znevyh_share_predr + pupils_at_school + pupils_in_town + zriz,
                  data = merged_rozdil)

###test for heteroscedascity
par(mfrow = c(2, 2))
plot(model_nedokoncovani)

bptest(model_nedokoncovani)



###test for heteroscedascity
par(mfrow = c(2, 2))
plot(model_propadani)

bptest(model_propadani)
```

```
#######

rob.model_propadani     <- coeftest(model_propadani, function(x) vcovHC(x, type="HC0"),
                              save = TRUE)
rob.model_nedokoncovani  <- coeftest(model_nedokoncovani, function(x) vcovHC(x, type="HC0"),
                              save = TRUE)


######
library(stargazer)
stargazer(model_propadani, model_nedokoncovani,
        p = list(rob.model_propadani[,"Pr(>|t|)"], rob.model_nedokoncovani[,"Pr(>|t|)"]),
        header = FALSE,
        type = "text", digits = 3,
        digits.extra = 5,
        title = "OLS results",
        column.labels = c("grade repetition", "non-completion"),
        model.numbers = FALSE,
        covariate.labels = c("number of TAs", "disadvantaged", "pupils at school",
                          "pupils in town", "private", "religious", "constant"),
        dep.var.labels.include = FALSE,
        style = "ajps",
        out = "OLS.html",
        report=("vc*p"))
```

PSM

```
library(tidyverse)
library(MatchIt)
library(cobalt)
library(marginaleffects)
library(patchwork)
library(kableExtra)


#https://ngreifer.github.io/cobalt/articles/cobalt.html
#https://kosukeimai.github.io/MatchIt/articles/matching-methods.html
```

```
#####
merged_rozdil |>
  group_by(region) |>
  summarise(mean(r_TAs, na.rm = TRUE))



#############


data  <- merged_rozdil

PSM <- data |>
  mutate(treated = if_else(r_TAs >= 0.007, TRUE, FALSE)) |>
  filter(is.na(distance) == FALSE) |>
  mutate(disadvantaged = znevyh_share_predr,
         region_code = region,
         region = fct_reorder(region_code, .x = as.numeric(str_sub(region_code, start = 4))),
         founder = as.factor(recode(zriz,
                     "2" = "public",
                     "5" = "private",
                     "6" = "religious")),
         distance_EAF = distance) |>
  select(-znevyh_share_predr, -zriz, -distance)

PSM
#####

PSM %>%
  filter(rowSums(is.na(.)) > 0)



str(PSM)
#######pre-mstching balance test
m.out0 <- matchit(treated ~ disadvantaged + pupils_at_school + pupils_in_town
              + founder + region,
              data = PSM,
              method = NULL,
              distance = "glm")

bal <- bal.tab(m.out0)
#####
```

```
bal_kbl <- bal$Balance[-1,1:2] |>
  mutate(Diff.Un = round(Diff.Un, digits = 3))

colnames(bal_kbl) <- c("type", "standard. mean diff.")

kbl(bal_kbl) |>
  kable_minimal(full_width = F,
              html_font = "sans-serif") |>
  column_spec(c(1,3), color = "black") |>
  kable_styling(position = "center") |>
  save_kable(file = "balance.html", self_contained = T)
#######
bal_m1 <- bal.tab(m.out1)


bal_kbl_obs <- bal_m1$Observations |>
  mutate(control = round(Control, digits = 1),
       treated = round(Treated, digits = 1)) |>
  select(-Control, -Treated)


kbl(bal_kbl_obs) |>
  kable_minimal(full_width = F,
              html_font = "sans-serif") |>
  column_spec(c(1,3), color = "black") |>
  kable_styling(position = "center") |>
  save_kable(file = "balance_obs.html", self_contained = T)


as.data.frame(bal$Balance[-1])

kbl(bal)




#######
```

```
m.out1 <- matchit(treated ~ disadvantaged + pupils_at_school + pupils_in_town
                  + founder + region ,
                  data = PSM,
                  method = "full",
                  distance = "glm", #a method of estimating propensity scores
                  estimand = "ATE")

b0 <- bal.plot(m.out0,
               colors = c("black", "#FF5500"),
               var.name = "distance",
               mirror = TRUE,
               sample.names = "before matching",
               theme = theme_minimal()) +
  theme(legend.title = element_blank(),
        text=element_text(size=16, family="serif"),
        plot.title = element_text(margin=margin(10,0,10,0),
                                  hjust = 0.125,
                                  color = "#FF5500"),
        plot.title.position = "plot",
        plot.caption.position =  "plot",
        axis.title=element_blank(),
        panel.grid.major = element_blank(),
        panel.spacing = unit(2, "lines")) +
  ggtitle(lab = "Propensity Score Distribution")

b1 <- bal.plot(m.out1,
               colors = c("black", "#FF5500"),
               var.name = "distance",
               mirror = TRUE,
              sample.names = "after matching",
               theme = theme_minimal()) +
  theme(legend.title = element_blank(),
        text=element_text(size=16, family="serif"),
        plot.title = element_text(margin=margin(10,0,10,0),
                                  hjust = 0.125,
                                  color = "#FF5500"),
        plot.title.position = "plot",
        plot.caption.position =  "plot",
        axis.title=element_blank(),
        panel.grid.major = element_blank(),
```

```
    panel.spacing = unit(2, "lines")) +
  ggtitle(lab = "")

b1

b0/b1

##########B a l a n c e____T E S T##########

bal.tab(m.out1) #The effective sample size (ESS)

bal
####M.0.Un the mean of a control group
labels <- c(distance = "propensity score",
        pupils_at_school = "pupils at school",
        pupils_in_town = "pupils in town",
        founder_public = "public",
        founder_private = "private",
        founder_religious = "religious",
        region_CZ011 = "Prague",
        region_CZ021 = "Central Bohemian",
        region_CZ031 = "South Bohemian",
        region_CZ032 = "Pilsen",
        region_CZ041 = "Karlovy Vary",
        region_CZ042 = "Ústí nad Labem",
        region_CZ051 = "Liberec",
        region_CZ052 = "Hradec Králové",
        region_CZ053 = "Pardubice",
        region_CZ061 = "Vysočina",
        region_CZ062 = "South Moravian",
        region_CZ071 = "Olomouc",
        region_CZ072 = "Zlín",
        region_CZ081 = "Moravian-Silesian")

love.plot(m.out1, binary = "std",
```

```
        thresholds = c(m = .1),
        colors = c("black", "#FF5500"),
        var.names = labels,
        sample.names = c("before matching",
                         "after matching"),
        theme = theme_minimal()) +
  theme(legend.title = element_blank(),
       text=element_text(size=16, family="serif"),
       plot.title = element_text(margin=margin(10,0,10,0),
                               hjust = 0.125,
                               color = "#FF5500"),
       plot.title.position = "plot",
       plot.caption.position =  "plot",
       axis.title=element_blank(),
       panel.grid.major = element_blank(),
       panel.spacing = unit(2, "lines"))


######
m.out1
summary(m.out1)

####estimating TREATMENT EFFECTS
#https://kosukeimai.github.io/MatchIt/articles/estimating-effects.html
md <- match.data(m.out1, distance = "dist")

head(md)

###
fit_grade_repet <- lm(grade_repet ~ treated *
           (disadvantaged + pupils_at_school + pupils_in_town +  founder),
                data = md, weights = weights)



comp_grade_repet  <- comparisons(fit_grade_repet ,
                variables = "treated",
                vcov = ~subclass,
                wts = "weights")

summary(comp_grade_repet )
```

```
###
fit_non_complete <- lm(non_complete  ~ treated *
                (disadvantaged + pupils_at_school + pupils_in_town +  founder),
                data = md, weights = weights)

fit_non_complete <- comparisons(fit_non_complete,
                 variables = "treated",
                 vcov = ~subclass,
                 wts = "weights")

summary(fit_non_complete)
```

Visualising PSM

```
library(tidyverse)
library(MatchIt)
#https://kosukeimai.github.io/MatchIt/articles/MatchIt.html

#####
merged_rozdil |>
  group_by(region) |>
  summarise(mean(r_TAs, na.rm = TRUE))



##############H I S T O G R A M###########
mean(merged_rozdil$r_TAs)
hist(merged_rozdil$r_TAs, 500, xlim = c(-0.02, 0.02))
table(merged_rozdil$r_TAs >= 0.007)
nrow(filter(merged_rozdil, r_TAs >= 0.007))/nrow(merged_rozdil)

ggplot(data = merged_rozdil, aes(x = r_TAs)) +
  geom_histogram(fill = "#FF5500") +
  theme_minimal() +
  theme(legend.position = 'none',
        legend.title = element_blank(),
        text=element_text(size=16, family="serif"),
        plot.title = element_text(margin=margin(10,0,10,0),
                              hjust = 0.125,
                              color = "#FF5500"),
        plot.title.position = "plot",
        plot.caption.position =  "plot",
```

```
      axis.title=element_blank(),
      panel.grid.major = element_blank(),
      panel.spacing = unit(2, "lines")) +
  ggtitle("Histogram of a change in a number of TAs") +
  geom_vline(xintercept = 0.007, linetype="dashed") +
  xlim(c(-0.02,0.03))
```

1st stage 2SLS

```
library(tidyverse)
library(stargazer)
library(lmtest)
library(sandwich)

#########
merged_rozdil
colnames(merged_rozdil)

first_stage_r <- lm(r_TAs ~ distance + znevyh_share_predr + pupils_at_school + pupils_in_town +
              zriz,
          data = merged_rozdil)

first_stage_r_reduced <- lm(r_TAs ~ znevyh_share_predr + pupils_at_school + pupils_in_town +
                 zriz,
               data = merged_rozdil)

anova(first_stage_r_reduced, first_stage_r)



###

###test for heteroscedascity
par(mfrow = c(2, 2))
plot(first_stage_t)

bptest(first_stage_r)

###
merged_19_22
colnames(merged_19_22)
```

```
first_stage_t <- lm(r_TAs ~ distance + znevyh_share_predr + pupils_at_school + pupils_in_town +
            zriz,
          data = merged_19_22)

first_stage_t_reduced <- lm(r_TAs ~ znevyh_share_predr + pupils_at_school + pupils_in_town +
            zriz,
          data = merged_19_22)

anova(first_stage_t_reduced, first_stage_t)

summary(first_stage_t)



###test for heteroscedascity
par(mfrow = c(2, 2))
plot(first_stage_t)

bptest(first_stage_t)

######
rob.first_stage_r   <- coeftest(first_stage_r , function(x) vcovHC(x, type="HC0"),
                  save = TRUE)
rob.first_stage_t   <- coeftest(first_stage_t , function(x) vcovHC(x, type="HC0"),
                  save = TRUE)



####
stargazer(first_stage_r, first_stage_t,
     p = list(rob.first_stage_r[,"Pr(>|t|)"], rob.first_stage_t[,"Pr(>|t|)"]),
     report=("vc*p"),
     header = FALSE,
     type = "text", digits = 3,
     digits.extra = 20,
     title = "first stage 2SLS",
     column.labels = c("(I) difference of means", "(II) 2019-2022 mean"),
     model.numbers = FALSE,
     covariate.labels = c("distance", "disadvantaged", "pupils at school",
               "pupils in town", "private", "religious", "constant"),
     dep.var.labels.include = FALSE,
     add.lines = list(c("", "","")),
```

```
    style = "ajps",
    out = "first_stage.html")



#########visual test###########
merged_rozdil$pred_r_TAs <- predict(first_stage_r, merged_rozdil)

ggplot(merged_rozdil, aes(x = pred_r_TAs, y = r_TAs)) +
  geom_point(fill = "#ff5500")+
  geom_smooth(se = FALSE,
        method = "lm",
        aes(color = "#ff5500")) +
  theme_minimal() +
  theme(legend.position = "none",
     text = element_text(size=16, family="serif"),
     plot.title = element_text(margin=margin(10,0,20,0),
                  hjust = 0.125,
                  color = "#ff5500"),
     plot.title.position = "plot",
     plot.caption.position =  "plot",
     axis.title.x = element_text(margin = margin(t = 15, r = 0, b = 5, l = 0),
                   color = "#ff5500"),
     axis.title.y = element_text(margin = margin(t = 0, r = 15, b = 0, l = 5),
                   color = "#ff5500"),
     panel.grid.major = element_blank(),
     panel.spacing = unit(2, "lines")) +
  xlim(c(0, 0.012)) +
  ylim(c(-0.01, 0.04)) +
  xlab("predicted values") +
  ylab("observed values") +
  ggtitle("Observed vs. predicted values") +
  coord_cartesian(clip = "off")



#######
merged_rozdil$pred_r_TAs <- predict(first_stage_r, merged_rozdil)
```

```
ggplot(merged_rozdil, aes(x = pred_r_TAs, y = r_TAs)) +
  geom_point(fill = "#ff5500")+
  geom_smooth(se = FALSE,
              method = "lm",
              aes(color = "#ff5500")) +
  theme_minimal() +
  theme(legend.position = "none",
        text = element_text(size=16, family="serif"),
        plot.title = element_text(margin=margin(10,0,20,0),
                                  hjust = 0.125,
                                  color = "#ff5500"),
        plot.title.position = "plot",
        plot.caption.position =  "plot",
        axis.title.x = element_text(margin = margin(t = 15, r = 0, b = 5, l = 0),
                                    color = "#ff5500"),
        axis.title.y = element_text(margin = margin(t = 0, r = 15, b = 0, l = 5),
                                    color = "#ff5500"),
        panel.grid.major = element_blank(),
        panel.spacing = unit(2, "lines")) +
  xlim(c(0, 0.012)) +
  ylim(c(-0.01, 0.04)) +
  xlab("predicted values") +
  ylab("observed values") +
  ggtitle("Observed vs. predicted values") +
  coord_cartesian(clip = "off")
```

Visualise 1st stage 2SLS

```
library(tidyverse)
library(patchwork)


#########visual test###########
merged_rozdil$pred_r_TAs <- predict(first_stage_r, merged_rozdil)

g1 <- ggplot(merged_rozdil, aes(x = pred_r_TAs, y = r_TAs)) +
  geom_point(fill = "#ff5500")+
  geom_smooth(se = FALSE,
              method = "lm",
              aes(color = "#ff5500")) +
  theme_minimal() +
```

```
  theme(legend.position = "none",
        text = element_text(size=16, family="serif"),
        plot.title = element_text(margin=margin(10,0,20,0),
                                  hjust = 0.125,
                                  color = "#ff5500"),
        plot.title.position = "plot",
        plot.caption.position =  "plot",
        axis.title.x = element_text(margin = margin(t = 15, r = 0, b = 5, l = 0),
                                    color = "#ff5500"),
        axis.title.y = element_text(margin = margin(t = 0, r = 15, b = 0, l = 5),
                                    color = "#ff5500"),
        panel.grid.major = element_blank(),
        panel.spacing = unit(2, "lines")) +
  xlim(c(-0.001, 0.04)) +
  ylim(c(-0.001, 0.04)) +
  xlab("predicted values") +
  ylab("observed values") +
  ggtitle("Observed vs. predicted values (difference of means)") +
  coord_cartesian(clip = "off")



#######
merged_19_22$pred_r_TAs <- predict(first_stage_t, merged_19_22)

g2 <- ggplot(merged_19_22, aes(x = pred_r_TAs, y = r_TAs)) +
  geom_point(fill = "#ff5500")+
  geom_smooth(se = FALSE,
              method = "lm",
              aes(color = "#ff5500")) +
  theme_minimal() +
  theme(legend.position = "none",
        text = element_text(size=16, family="serif"),
        plot.title = element_text(margin=margin(10,0,20,0),
                                  hjust = 0.125,
                                  color = "#ff5500"),
        plot.title.position = "plot",
        plot.caption.position =  "plot",
        axis.title.x = element_text(margin = margin(t = 15, r = 0, b = 5, l = 0),
                                    color = "#ff5500"),
```

```
    axis.title.y = element_text(margin = margin(t = 0, r = 15, b = 0, l = 5),
                                color = "#ff5500"),
    panel.grid.major = element_blank(),
    panel.spacing = unit(2, "lines")) +
  xlim(c(0, 0.04)) +
  ylim(c(0, 0.04)) +
  xlab("predicted values") +
  ylab("observed values") +
  ggtitle("Observed vs. predicted values (2019-2022 reports mean)") +
  coord_cartesian(clip = "off")

g2
```

2nd Stage 2SLS

```
library(ivreg)

#https://stats.stackexchange.com/questions/134789/interpretation-of-ivreg-diagnostics-in-r



second_STAGE_grade <-  ivreg(grade_repet ~ r_TAs + znevyh_share_predr + pupils_at_school +
pupils_in_town + zriz|
                             distance + znevyh_share_predr + pupils_at_school + pupils_in_town + zriz,
                        data = merged_19_22)



summary(second_STAGE_grade,
    diagnostics = TRUE)



###test for heteroscedascity
par(mfrow = c(2, 2))
plot(second_STAGE_grade)

bptest(second_STAGE_grade)




##
second_STAGE_non <-  ivreg(non_complete ~ r_TAs + znevyh_share_predr + pupils_at_school +
pupils_in_town + zriz|
```

```
                    distance + znevyh_share_predr + pupils_at_school + pupils_in_town + zriz,
                  data = merged_19_22)


summary(second_STAGE_non,
       diagnostics = TRUE)



###test for heteroscedascity
par(mfrow = c(2, 2))
plot(second_STAGE_non)

bptest(second_STAGE_non)



####
######
rob.second_STAGE_grade  <- coeftest(second_STAGE_grade , function(x) vcovHC(x, type="HC0"),
                              save = TRUE)
rob.second_STAGE_non  <- coeftest(second_STAGE_non , function(x) vcovHC(x, type="HC0"),
                            save = TRUE)




####



stargazer(second_STAGE_grade, second_STAGE_non,
         p = list(rob.second_STAGE_grade [,"Pr(>|t|)"], rob.second_STAGE_non [,"Pr(>|t|)"]),
         report=("vc*p"),
         header = FALSE,
         type = "text", digits = 3,
         digits.extra = 20,
         title = "second stage 2SLS",
         column.labels = c("grade repetition rate", "non-completion rate"),
         model.numbers = FALSE,
         covariate.labels = c("number of TAs", "disadvantaged", "pupils at school",
                    "pupils in town", "private", "religious", "constant"),
         dep.var.labels.include = FALSE,
         add.lines = list(c("", "","")),
```

```
        style = "ajps",
        out = "second_stage.html")
```

Effects Visualisation

```
library(tidyverse)
library(readxl)

summary(merged_19_22$distance)
summary(merged_19_22$znevyh_share_predr)
summary(merged_19_22$pupils_in_town)
summary(merged_19_22$pupils_at_school)



348.6*-1.283984e-06
####
vis_diff <- tibble(variable = factor(c("distance", "disadvantaged", "private", "religious",
                                "pupils at school", "pupils in town"),
                           levels = rev(c("distance", "disadvantaged", "private", "religious",
                                   "pupils at school", "pupils in town"))),
                   value = c(NA, 2.989435*0.046, NA, -0.2594,
                          -4.467123e-04*348.6, -1.283984e-06*752.86),
                   data = "change in a number of TAs")



vis_19_22 <- tibble(variable = factor(c("distance", "disadvantaged", "private", "religious",
                                 "pupils at school", "pupils in town"),
                              levels = rev(c("distance", "disadvantaged", "private", "religious",
                                      "pupils at school", "pupils in town"))),
                    value = c(0.01*5.498, 7.1*0.046,  1.073, 0.6238,
                           -1.158479e-03*348.6, NA),
                    data = "number of TAs (mean of 2019-2022)")
```