The Impact of Commuting on Higher Education Students' Academic Performance

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Abstract

Commuting is part of the daily lives particularly in large urban areas. We use a campus reallocation as a source of exogenous variation of commuting times to estimate the impact of commuting on students' outcomes. This is the first quasi-experimental study of the impact of commuting on higher education students' academic achievement. Our results show that an increase of 10 minutes in commuting time leads to a decrease between 6 p.p and 8 p.p of a standard deviation in the students' GPA.

1 Introduction

Commuting is part of our daily routines, carrying multiples consequences for our well-being. According to Eurofound (2015), before the COVID-19 global pandemic, a European worker spent, on average, 40 minutes in a one-way commuting journey. Sweden was the European country with the highest commuting time, with an average of 50 minutes per travel, while Cyprus was the European country with the lowest, with an average of 22 minutes per commute. Thus, on average, an European spent around 6 hours and 40 minutes in weekly commuting if he traveled 5 days per week.

Although we normally associate commuting to workers, it is also relevant for students that have to travel between home and school daily. Schirmer, Orr and Gwosc (2017) analyzed the median commuting times for higher education students in the European Union and found that, in 2010, the median time of a one-way commute for a European higher education student living with his parents was around 36 minutes, while for a student living in a student hall was around 15 minutes.

Our study intends to understand how commuting times impact higher education students' academic performance. The understanding of this relation will contribute to the debate of the costs and benefits of remote learning, which has recently gain visibility due to COVID-19 pandemic.

In what concerns higher education, during the pandemic, between 2020 and 2021, most students experienced some periods of remote classes. In one hand, one of the most claimed advantages of remote learning is the time saved on commuting. On the other hand, remote learning comes with many costs. For example, there is evidence that it increases the gap between low and high ability students, (Cacault et al., 2021).

As stated, we intend to understand how commuting impact students' GPAs. However, commuting is much likely an endogenous, since, for example, more attentive parents could choose to live closer to the best high schools and higher education institutions. Therefore, it could be the case that students who live in the city center and normally have lower commuting times are simultaneously those who are more prepared for higher education. Thus, to be able to establish a causal impact, we will take advantage of an exogenous shock: a campus reallocation in Portugal. Nova School of Business and Economics (Nova SBE), was settled in the Lisbon city center, in the area of Campolide, until the 2017/2018 academic year. However, in the fall of 2018, the school moved to Carcavelos, a town that belongs to the neighbouring of Cascais. The new campus is about 21 km away from the old one, the equivalent to 19 minutes traveling by car with no traffic. Figure 3, in the appendix, shows a map depicting the old and the new location of the campus. This reallocation led to exogenous variations in students' commuting times, which we use to get closer to causal estimates.

When applying to higher education institutions, the commuting times and their impacts on achievement are relevant variables for students' decisions. Some, whose family house is in a different region, must reallocate, which implies deciding on accommodation and on how much time they are willing to spend on commuting. Others, although living in the school's region, have to face long commutes and need to decide if they prefer to move to a place closer to the school, or to commute longer and stay with their parents. Besides, students might prefer to choose an institution closer to their homes. Therefore, information regarding the impacts of commuting may help students to make these important decisions.

The results of this study are also important in terms of policy-making mainly for universities that usually promote initiatives to help students with accommodation and transportation issues but also for other educational and governmental bodies. Besides, as stated, this study also contributes to enrich the debate regarding the advantages and disadvantages of remote learning, measuring the true impact of commuting when classes take place in person [1].

[1] Since we are using a campus reallocation that occurred in 2018 and only considering data before the transition to online classes.

2 Literature Review

According to Wolpin (2003), students' achievement is determined by the current and previous family and school's inputs, and by the student's cognitive endowment. This emphasizes that parents' attentiveness, school and teaching quality, and the student's ability are the most relevant factors that impact student's outcomes. Regarding higher education students, several studies find past academic outcomes as being the strongest predictor of academic achievement (McKenzie and Schweitzer, 2001; Danilowicz-Gösele et al., 2017; Silva et al., 2020). Smith and Naylor (2001) obtain that family background and professional occupation of the parents are also relevant predictors of higher education students' academic performance.

Regarding the impact of commuting times on students' academic performance, especially higher education ones, the literature is scarce. However, in what concerns the relationship between commuting and labor-related outcomes, the literature is more abundant.

Ommeren and i Puigarnau (2011) explore the effects of commuting distances on worker's absenteeism using a 9-year German Socio-Economic Panel Survey. To recover causal estimations, Ommeren and i Puigarnau (2011) only select workers whose workplace has been reallocated, but their house and job kept the same. Their results show that there is a positive relationship between commuting and absenteeism and that absenteeism could be between 15% and 20% lower if commuting times were negligible.

Another study by Ma and Ye (2019) addresses the topic of how commuting affects work productivity, measuring productivity with absenteeism and self-reported measures of performance. The data used in the study was collected through an online survey, and an IV approach was applied to control for sources of endogeneity, using the variables "population density at home location", and "population density at job location" as instruments for the commuting distance. Their results show a significant positive relation between commuting distance and absenteeism and a negative but only "marginally significant" relationship between commuting distance and job performance.

Xiao, Wu and Kim (2021) explore how commuting impacts a very specific class of workers:

inventors. In this study, the authors use a different measure of productivity: the quantity and quality of the patents registered by the inventor. To guarantee a clear identification strategy, like Ommeren and i Puigarnau (2011), Xiao, Wu and Kim (2021) use a source of exogenous variation of commuting distances by focusing on workers whose companies have reallocated. In line with the previous literature, the researchers find that when an inventor sees a 10km increase in his commuting distance, the quantity of patents is estimated to decrease by 5%. Overall, these results evidence a negative relationship between daily commutes and productivity.

Regarding the relationship between commuting and academic performance, the literature is scarce. Tigre, Sampaio and Menezes (2017) studied the impact of daily travels between home and school on Brazilian 6th graders, through surveys on students, teachers, and parents from 118 schools in Recife. The surveys included different socio-economic and educational aspects and specific questions regarding commuting times between home and school. Student's performance was measured by the student's grade on a standardized math test designed by the research team. Additionally, the researchers use the average distance to the two closest schools as an instrumental variable to capture exogenous variations of commuting times. Their results show that, all else constant, if travel between home and school increases by one hour, students' grades are, on average, 0.75 of a standard deviation lower.

Falch, Lujala and Strøm (2013), analyse how travel time between a student's house and the closest high school influences high school students' "propensity" to graduate in Norway. The "commuting time" variable was instrumented by using two different variables related to the student's municipality characteristics: the percentage of the population (in the municipality) living in rural zones and the "square kilometer per inhabitant". The results from the instrumental variable approach indicate a negative relation between commuting time and the propensity to graduate. The authors conclude that a student who is half an hour distant from the nearest high school is 2.3 percentage points less likely to graduate on time than a student with a negligible commute.

Kobus, Van Ommeren and Rietveld (2015) develop a theoretical framework to understand the impacts of daily traveling between home and the university on the academic achievement of university students. The model is tested empirically by using data from a survey conducted at the University of Amsterdam. The authors use an instrumental variable for commuting time: "the average travel time to the nearest two universities". Their results indicate that students who commute more tend to visit the university fewer times, but when they do, they tend to stay longer, in such a way that the total weekly hours spent at the university doesn't depend on the student's commuting time. Furthermore, their results show that when there is an increase of one standard deviation in commuting times, students' average grades decrease by one third of a standard deviation.

The majority of the studies we have analyzed argue that commuting times might negatively affect a vast array of student and labor outcomes. However, the literature concerning students is still very limited as most of the studies do not rely on experimental or quasi-experimental identification strategies. Moreover, the literature regarding higher education students and commuting is even more limited. In fact, this is the first quasi-experimental study on this unexplored topic of how commuting impacts higher education students' academic performance. Using an exogenous source of commuting variation that is induced by the reallocation of a school campus in Portugal, we intend to get closer to causal estimates and to measure the true impact of commuting on students' GPA.

3 Data

Our database is an administrative data set that contains information for 5,546 Bachelor's students from Nova SBE. The data goes from the 2007/08 up to the 2019/20 academic year. However, we disregarded the second semester of 2019/20 due to the COVID-19 crisis that led to a national lockdown and to the transition to online classes.

The data contains information about students' scores for each course throughout the program, and other personal information such as nationality, date of birth, the national math exam scores held at the end of the secondary education, high school final GPAs, needed-base scholarships, international mobility, parents' qualifications, students' zip codes, and a variable that indicates whether the student has reallocated in the beginning of his studies.

As we are looking at commuting times, we would need the students' addresses for each semester. However, this personal information, such as the zip codes and the reallocation status, is only provided in first-year enrollment and is not updated thereafter. Besides, among the students who reported to have reallocated in their first year, some disclose their new home address in Lisbon and others report their parents' home address in their original cities. Furthermore, for students that reallocated in their first year, the probability of them changing their location over the 3 years of the program is high, and as they only provide their address in their first-year enrollment, it is very difficult to be sure about their actual address on a given academic year. Thus, for this study, we will focus our analysis on students that we can assume that kept living in the same address during the three years of the program: students that didn't reallocate in their first year, and whose address belongs to the university's commuting zone.

According to Afonso and Venâncio (2016), a commuting zone is an area where most residents work, live, or study. Afonso and Venâncio (2016) define the Portuguese commuting zones using the methodology developed by Tolbert and Sizer (1996). Using data from the Portuguese 2001 Census, Afonso and Venâncio (2016) compute an index that captures the intensity of commuting relations among each pair of Portuguese municipalities and then perform an hierarchical clustering analysis to gather the municipalities that have stronger commuting ties. The authors found 91 commuting zones in mainland Portugal. Lisbon and Cascais, the municipalities of the old and the new campus, respectively, belong to the same commuting zone along with other fourteen municipalities.

Therefore, in this study, we consider students who live within the same commuting zone of the university and who have not reallocated. So, we keep in our sample 3,355 students that live in the following municipalities that constitute one commuting zone: Alcochete, Almada, Amadora, Barreiro,Cascais,Lisbon, Loures, Moita, Montijo,Odivelas, Oeiras, Palmela, Seixal, Sesimbra, Setúbal, and Sintra.

Our outcome variable is the student's GPA in a given semester. To compute the GPA we consider the first time the student was enrolled in a given course [2]. Moreover, we have normalized the semester GPA across students within the 1^{st}, the 2^{nd}, and the 3^{th} years [3].

3.1 Computation of the commuting distances

Our database contains information regarding student's zip codes. To obtain student's commuting distances to school, we have used the distance matrix API (Application Programming Interface), developed by Google web services, and computed a set of variables related to commuting times and distances. This API uses a matrix comprised of origins and destinations as inputs, and returns the distance in kilometers and the travel time in minutes between two points. It is also possible to choose a means of transportation such as "car" or "public transports".

We computed three different variables: commuting distance in kilometers; commuting time traveling by car in minutes; and commuting time traveling by public transports in minutes. The variable that contains the commuting times when traveling by public transports is the fuzziest one since Google has no access to the complete offer of public transportation and since some zones have limited offer of public transports.

Google computes commuting times choosing the fastest routes based on past information regarding traffic and road conditions. In reality, a student might prefer to commute by a more distant route to save money from tolls or might use a mixed way of transportation, some days traveling by car, and, other days, commuting by public transports. Therefore, our measures of commuting are estimates of the real commuting time of the students.

Table 1 exhibits the summary statistics for our main variables.

[2] We didn't consider students whose GPA was zero. However, we have performed our estimations also considering these students and the results were robust.

[3] Figure 4 in the appendix 6 displays the evolution of the students' GPA across program years. As one can observe in the figure, the students' GPA increase as they progress in the program.

Table 1: Summary Statistics

	(1) N	(2) mean	(3) sd	(4) min	(5) max
High_School_Average_Grade	2,893	170.8	10.99	126	200
National_Math_Exam_Grade	2,893	177.9	13.39	98	200
Admission Grades (50% Exam + 50% High School)	3,082	173.2	15.24	14.70	198.5
Father_higher_education	2,983	0.71	0.45	0	1
Mother_higher_education	2,810	0.76	0.43	0	1
Scholarships	3,355	0.031	0.18	0	1
Gender	3,355	0.49	0.5	0	1
Distance_km	16,320	13.45	10.95	0.21	78.44
Time_Commuting_Car	16,320	16.79	7.51	0.85	53.63
Time_Commuting_Pub_Transports	15,162	44.62	21.3	2.88	179.32
Semester_Average_GPA	18,001	11.79	4.05	0.75	19.43

Note: A student appears repeatedly in our data set since we have one observation per student, per semester

4 Methodology

4.1 Identification Strategy

We aim to understand the causal impact of commuting on students' academic achievement. As an OLS estimation of the GPAs against commuting times might not be sufficient to recover causal estimations, we will also use a source of exogenous variation of commuting: the Nova SBE campus reallocation which led to exogenous variations of students' commuting times to school.

As stated, in this study we will focus on students for whom it is reasonable to assume that they didn't reallocate after the campus transition. This is, we consider students who live within the same commuting zone of the university and who have not reallocated in their first year of studies.

4.1.1 The impact of the exogenous shock in student's commuting times

It is important to understand how the campus reallocation impacted students' commuting. As figure (1) (a) illustrates, before the campus transition, the average distance between home and school for our sample was around 12 km, and, after the reallocation, it increased to 22 km. Regarding commuting times, the average one-way commute between home and school, traveling by car, increased from 16 to about 22 minutes, and by public transports, it increased from 39 to 53 minutes.[4] Furthermore, besides the increase in the average commuting distances and times, we also observe an increase in the standard deviation of the commutes.[5]

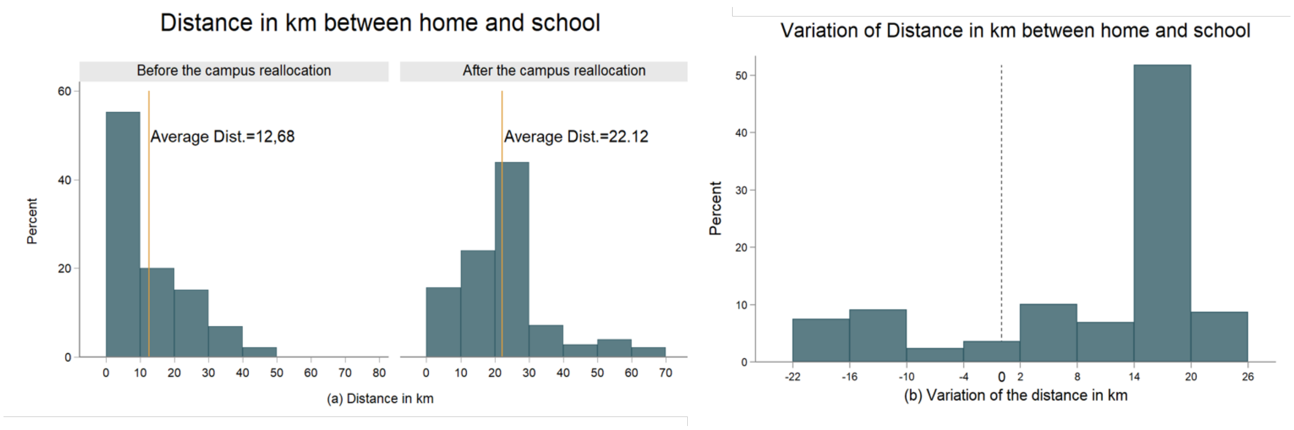

Figure 1: (a): Distance in km of a one-way journey between home and school before and after the shock; (b): Exogenous variations of the commuting distances in km after campus reallocation

As we can observe in figure 1 (b) that displays the distribution of the variations of the distance in km, although the majority of the students had seen an increase in their commuting, some have benefited from a decrease in their travel distances.[6]. Therefore, we conclude that the effect of the reallocation on students' commuting times was heterogeneous, benefiting some students, but being detrimental for the majority.

[4]Figure (5) and (6) in the appendix.

[5]The standard deviation of the distance went from 11 to 13 km, the standard deviation of the commuting time traveling by car increased from 7 to 9 minutes, and the standard deviation of the commuting time traveling by public transports increased from 22 to 30 minutes.

[6]The graphs 8 and 9 in the appendix exhibit the histograms for the variation in minutes traveling by car and by public transports after the exogenous shock of the campus reallocation.

4.2 First Approach

$$Semester\_std\_GPA_{iyt} = \alpha + \delta Commuting\_Time/Distance_{iyt} + S_i + T_{yt} + \epsilon_{iyt} \qquad (1)$$

To take advantage of the exogenous change of the campus, in this estimation we only consider students that were in the 1^{st} or 2^{nd} year of their program in 2017/18 and moved to the 2^{nd} or 3^{th} year of their program in 2018/19, respectively, since the campus reallocation occurred in the 2018/19 academic year. These are the students that have faced the transition between both campuses' locations, and whose commuting time to school has seen an exogenous variation[7].

In equation 1, $Semester\_std\_GPA_{iyt}$ stands for the standardized semester GPA[8] of student i, in academic year y, and semester t. $CommutingTime/Distance_{iyt}$ represents the commuting distance in km or the commuting time in minutes traveling by car, or by public transports, for each student i, in each academic year and each semester. S_i stands for the students' fixed effects. T_{yt} represents the dummies for each semester in each academic year, α represents the constant, and ϵ_{iyt} stands for the error term of the model.

Using student fixed effects, in this estimation, we are washing out any potential effect of time-invariant unobservable variables that could lead to biased estimates. Thus, in this model we explore the within variation for the students who have been through the campus reallocation. δ measures the effect of commuting on students' semester GPA.

4.3 Second Approach

As an alternative, we also consider a model which takes variations on commuting within each student for different periods and regresses the variations of the students' standardized semester GPA[9] on the variations of students' commuting distances/times, as one can observe in equation 2.

[7] As stated, we will only use students that live within the Lisbon commuting zone and have not reallocated from their parents' house.

[8] The semester GPAs were standardized within the student program year as explained in section 3.

[9] The semester GPAs were standardized within the student program year as explained in section 3.

Again, we estimate different regressions for the three different variables measuring commuting.

As the campus reallocation occurred in the 2018/19 academic year, in this estimation we only consider students that were in the 1^{st} or 2^{nd} year of their program in 2017/18 and moved to the 2^{nd} or 3^{th} year of their program in 2018/19, respectively. These are the students that have faced the transition between both campuses' locations.

In equation 2, $\Delta Semester\_std\_GPA_i$ represents the variation of the standardized semester GPA, for each student i, between the first semester spent in the new campus, the 1st semester of 2018/19, and the last semester spent in the old campus, the 2nd semester of 201718[10].

$$\Delta Semester\_std\_GPA_i = \alpha + \beta X_i + \delta \Delta Commuting\_Time/Distance_i + \epsilon_i \tag{2}$$

$\Delta Commuting\_Time/Distance_i$ stands for the variation of the commuting distance, or the variation of commuting time in minutes traveling by car, or by public transports, calculated as the difference between the time/distance traveled between home and school after the campus reallocation, and the time/distance traveled between home and school before the campus reallocation.

As the variation of commuting time is an exogenous variable for thw sample considered, this allows us to identify our model and overcome potential endogeneity issues.

X_i represents the set of controls used. In this model, we use controls for student's high-school grades [11], parents' education, and needed-base scholarships. Besides, we control for enrollment in the Erasmus mobility program between 2017/18 and 2018/19, and we also use a dummy that indicates whether the student has moved from the first to the second year, or from the second to the third year. α is the constant and ϵ_i corresponds to the error term of the model.

[10]For a student that went abroad within the Erasmus program in the second semester of 2017/18, we consider the grades of the semester immediately before (S1 of 2017/18) and, for a student that went abroad in the first semester of 2018/19, we consider grades of the semester immediately after (S2 2018/19).

[11]We use the admission grade that considers 50% of high school final grade and 50% of the national math exam grade. However, we have also run regressions using both grades as separate controls, and the qualitative results are the same.

5 Results

5.1 First Approach Results

In table 2 we observe the results for the OLS and our fixed effects estimation described in equation 1. Columns (1) to (3) display the results of the OLS model that considers the whole sample of students that meet our location criteria since 2007/08 academic year until the 1st semester of the 2019/2020 academic year. Columns (4) to (6) present the results for the OLS model considering only the students who have been through the campus reallocation, this is, students who were in the 1st or 2nd year in 2017/18 and moved to the 2nd or 3rd year in 2018/19, the year of the campus' reallocation. Columns (7) to (9) column exhibits the results of the student's fixed effects estimation.

Table 2: Commuting distances/times and semester standardized GPAs

	OLS - All Years			OLS - only for the transition years			Student Fixed Effects		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Distance_variation_km	-0.002***			-0.007***			-0.005**		
	(0.001)			(0.002)			(0.002)		
Time_variation_car		-0.003***			-0.008**			-0.006*	
		(0.001)			(0.003)			(0.003)	
Time_variation_pub_transports			0.000			0.001			-0.001
			(0.000)			(0.001)			(0.001)
Year_Semester_Dummies	YES	YES	YES	YES	YES	YES	YES	YES	YES
Controls	YES	YES	YES	YES	YES	YES	NO	NO	NO
Observations	12,571	12,813	12,813	760	766	766	760	760	760
R-squared	0.169	0.149	0.148	0.149	0.129	0.123	0.889	0.889	0.888

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

As table 2 exhibits, commuting is negatively associated with the standardized semester GPA. The coefficients for the variable "Distance in km" and for the variable "Commuting time by car" are negative and statistically significant either for the fixed effects or for the OLS estimations.

According to our fixed effects model, all else constant, an extra kilometer in commuting leads, on average, to a decrease of 0.5 p.p of a standard deviation in the student's semester GPA, and an extra minute of commuting by car is associated with a decrease of 0.6 p.p of a standard deviation in the student's semester GPA.

The results from the OLS estimation including all students are the lowest. This is reasonable since we are including many students who did not suffer the campus reallocation - all the ones who graduated before 2017/2018. On the other hand, the results from the OLS estimation restricted for the students enrolled in the program during the campus reallocation are closer to the results of the fixed effects estimation in spite being a little stronger. The results considering the public transports' variable are not significant in any of the models presented, which is reasonable since this is our least quality variable.

5.2 Second Approach Results

As presented in 4.3, our second approach uses the variation of commuting distances/times before and after the campus reallocation as the independent variable, and the variation of the semester GPA as the dependent variable. Table 3 presents the results of this estimation for three different samples:

1. Overall sample: Comprises all students from the Lisbon metropolitan area that didn't reallocate, and that faced the campus reallocation.
2. Only 1st to the 2nd year: Comprises the students from the Lisbon metropolitan area that didn't reallocate, and that faced the campus reallocation between their 1st and 2nd year.
3. Only 2nd to the 3rd year: Comprises the students from the Lisbon metropolitan area that didn't reallocate, and that faced the reallocation between their 2nd and 3rd year.

From the regression on the overall sample presented in table 3, we observe that there is a significant negative relationship between the variation of commuting distances in kilometers, and the variation of the semester standardized GPAs. The results from the estimation including all years show that all else constant, an increase of one kilometer in a student's commute will lead, on average, to a decrease of 0.6 p.p of a standard deviation in the student's semester GPA. This coefficient is significant at a 5% level of confidence. Moreover, the table also shows a negative

Table 3: Variations of commuting distances/times and variations of semester standardized GPAs

	All Students			Only 1st to the 2nd year			Only 2nd to the 3rd year		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Distance_variation_km	-0.006**			-0.007*			-0.006*		
	(0.002)			(0.004)			(0.003)		
Time_variation_car		-0.008**			-0.008			-0.008	
		(0.004)			(0.005)			(0.005)	
Time_variation_pub_transport			-0.001			-0.003			-0.000
			(0.001)			(0.002)			(0.002)
Year_Program_Dummy	YES	YES	YES	YES	YES	YES	YES	YES	YES
Erasmus Dummy	YES	YES	YES	YES	YES	YES	YES	YES	YES
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	372	372	372	170	170	170	202	202	202
R-squared	0.026	0.021	0.012	0.037	0.032	0.031	0.041	0.037	0.024

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

relationship between the commuting variation in minutes traveling by car and the variation of GPAs. The coefficient associated with this relationship is also statistically significant at a 5% confidence level. On the other hand, the coefficient of the regression with commuting time in minutes traveling by public transports as the independent variable is not statistically significant, which may result from the fuzzier measurement of this variable.

Regarding the results of the 1st to the 2nd year estimation and the results for the 2nd to the 3rd year estimation, the regressions using commuting time variations by car and by public transports as independent variables don't present significant coefficients. However, when using commuting distance in kilometers as the independent variable, we find a negative significant effect of the variation of commuting distance on the variation of the semester GPA.

In all cases, the point estimates show a coherent negative sign, but, in some cases, without the power to be statistically significant. Thus, these results suggest a negative impact of commuting on students' GPAs, implying that the longer the commute, all else constant, the lower the student's GPA. These results are in line with the results from the OLS and fixed effects estimations.

Figure 2 presents three graphs that display the impact of a change in the variation of commuting distance/time on the variation of the semester standardized GPA.[12]. The line corresponds to the average impact, and the shaded region represents the 95% confidence intervals of our estimates.

[12]These graphs were based on the overall sample.

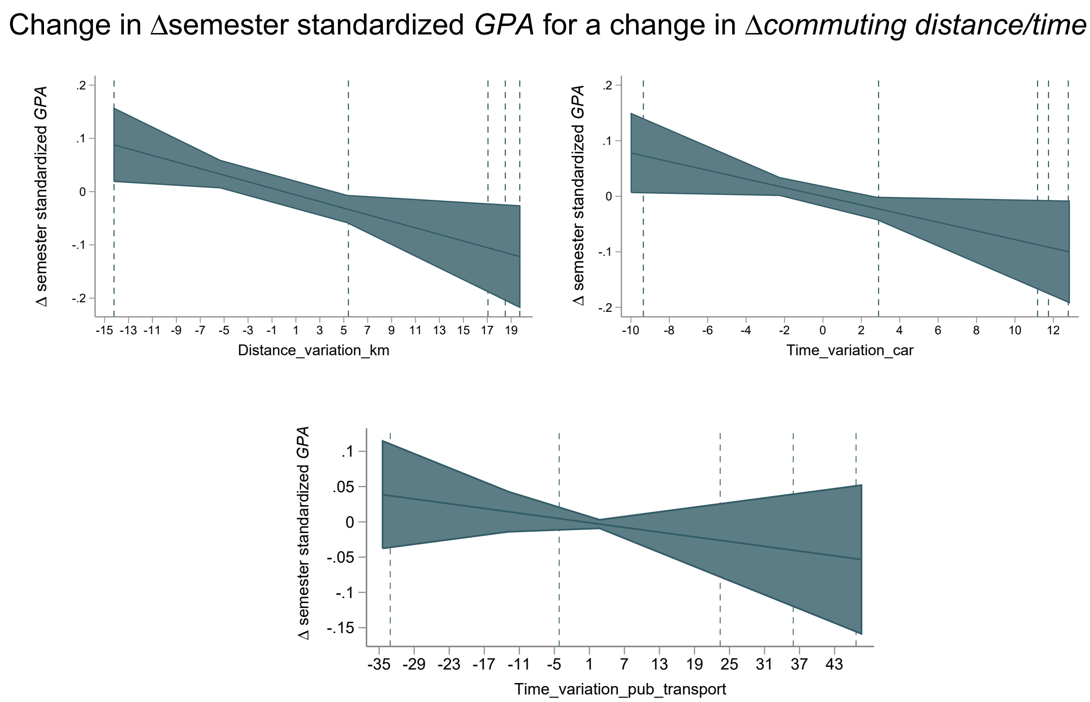

Figure 2: The effects of a change in the variation of commuting distance/time on the variation of the semester standardized GPA. The vertical dashed lines refer to the students in the 10th, 30th, 50th, 70th, and 90th percentiles of the distribution of each independent variable. The shaded regions correspond to the confidence intervals bands.

As we can observe in figure 2, while an increase of one kilometer in a student's commute leads to a decrease of 0.6 p.p of a standard deviation in the student's GPA, an increase of 15 km in commuting distance leads to a decrease of 9 p.p of a standard deviation in the student's GPA.

The five dashed lines in each graph correspond to the students in the 10th, 30th, 50th, 70th, and 90th percentiles of the distribution of each independent variable. For example, in the first graph, our independent variable is the "Distance Variation in Km", and student in the 10th percentile of the distribution is a student that has seen a decrease of his commuting distance of about 14km after the campus reallocation. This student benefits from an increase of 8.4 p.p of a standard deviation in his average semester grade. On the other hand, a student in the 90th percentile of the distribution of the distance variation in kilometers, this is, a student that has seen an increase of around 19 km in his commuting distance, observes a decrease of 11.4 p.p of a standard deviation in his average semester grade.

5.3 Placebo Test

As a robustness check, we also run a placebo test where we have considered all the students that meet our location criteria but didn't go through the reallocation process. So, we have considered students from 2007/08 until 2017/18 and simulated a campus reallocation. With the simulated variations of distances and commuting times, we have estimated the same model presented in equation 2.

Table 4: Variations of commuting distance/time and variations of semester standardized GPA

	(1)	(2)	(3)
Distance_variation_km	0.000		
	(0.001)		
Time_variation_car		0.000	
		(0.001)	
Time_variation_pub_transport			-0.000
			(0.000)
Year_Program_Dummy	YES	YES	YES
Erasmus	YES	YES	YES
Controls	YES	YES	YES
Observations	3,407	3,407	3,144
R-squared	0.027	0.027	0.023

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

As we observe in table 4, all the point estimates are zero. This means that the simulated variations of commuting distances had no impact on the variations of students' standardized semester GPAs. If the variations of GPAs we observed in the previous results were driven by unobserved variables, we would expect to observe GPA's variations in this placebo specification as well. Therefore, these placebo results support our estimates from section 5.2 and subsection 5.4, reinforcing the causal link between commuting and grades.

We have also performed this placebo test for a more comparable sample, only containing students between 2014/15 and 2016/17 academic years [13] The results were consistent with the ones provided in table 4.

[13]The results are presented in table 9 in the appendix 6.

5.4 Heterogeneous effects

The results presented suggest that commuting has a negative impact on students' GPA. Nevertheless, these effects might vary across students with different characteristics. To pursue this heterogeneity analysis, we will focus on our second estimation approach described in 4.3.

Firstly, to analyze whether the impact of commuting on grades varies across the level of income of the students we use parents' education as a proxy for income.

Table 5: Variations of commuting distances/times and variations of semester standardized GPA, depending on the parents' educational level

	(1) Both	(2) None	(3) Oly One	(4) Both	(5) None	(6) Oly One	(7) Both	(8) None	(9) Oly One
Distance_variation_km	-0.005	-0.009	-0.008						
	(0.003)	(0.006)	(0.006)						
Time_variation_car				-0.007	-0.008	-0.009			
				(0.004)	(0.009)	(0.008)			
Time_variation_pub_transport							-0.001	-0.004	-0.001
							(0.001)	(0.003)	(0.003)
Both-None		0.28			0.01			1.39	
Both-Only One		0.18			0.01			0	
None-Only One		0			0			0.96	
Year_Program_dummy	YES	YES	YES	YES	YES	YES	YES	YES	YES
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES
Erasmus Dummy	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	247	48	77	247	48	77	247	48	77
R-squared	0.028	0.060	0.048	0.028	0.034	0.035	0.018	0.069	0.021

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

"Both" refers to students who have both parents graduated from higher education;"None" refers to students with no parent graduated from higher education; and "Only One" refers to students who have only one parent graduated from higher education; The lines "Both-None", "Both-Only One", and "None-Only One" present the values of the chi-squared test statistic to evaluate whether the coefficient for the respective regressions are statistically different from each other.

In table 5 we find the results for the different estimations, depending on parents' education level, where the "Both" columns show the results for the students who have both parents graduated from higher education; the "None" columns display the results for the students with no parent graduated from university; and the "Only One" columns show the results for students who have only one parent graduated from university.

When splitting the sample into these three groups - Both, None, and, Only One - we end up with a small number of observations per regression, especially in the groups of parents with lower educational levels. This might be one of the reasons the coefficients in these regressions are non-significant. Therefore, we cannot conclude that the effects of commuting vary across the level of education of the parents. Besides, testing the hypothesis on the differences between the coefficients, we don't find any statically significant differences, as expected.

We also analysed if commuting impacts boys and girls the same way. In table 6 we present the results of the estimations calculated separately for boys and girls.

Table 6: Variation of commuting distances/times and variation of semester standardized GPA, depending on gender

	Girls	Boys	Girls	Boys	Girls	Boys
	(1)	(2)	(3)	(4)	(5)	(6)
Distance_variation_km	-0.004	-0.008**				
	(0.003)	(0.004)				
Time_variation_car			-0.005	-0.011**		
			(0.005)	(0.005)		
Time_variation_pub_transport					-0.000	-0.002
					(0.002)	(0.002)
Girls-Boys[1]	0.59		0.66		0.8	
Year_Program_Dummy	YES	YES	YES	YES	YES	YES
Erasmus Dummy	YES	YES	YES	YES	YES	YES
Controls	YES	YES	YES	YES	YES	YES
Observations	179	193	179	193	179	193
R-squared	0.049	0.040	0.045	0.035	0.039	0.022

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

[1] This line presents the values of the chi-squared test statistic to evaluate whether the coefficient for Girls and Boys regressions are statistically different from each other

Looking at point estimates of table 6, the negative effect of commuting seems to be stronger for boys. Testing the hypothesis on the differences between the coefficient on boys and girls, we find that the differences are not statistically significant, as we would expect given the large standard errors for the girls' regressions.

Finally, we looked at different commuting impacts for students with higher and lower baseline achievement levels. In this estimation, we added an interaction term between the commuting independent variable and the standardized admission score of the student which is a proxy for student previous achievement.

As we can observe in table 7, the interaction term is not statistically significant in any of the regressions with the different independent variables. Therefore, we cannot state that commuting impacts students differently depending on their previous achievement level.

Table 7: Variation of commuting distances/times and variation of semester standardized GPA with an interaction term for standardized admission grades

	(1)	(2)	(3)
Distance_variation_km	-0.006**		
	(0.002)		
Time_variation_car		-0.008**	
		(0.004)	
c.Time_variation_car#c.Admission_grade_std		-0.005	
		(0.004)	
Time_variation_pub_transport			-0.001
			(0.001)
c.Time_variation_pub_transport#c.Admission_grade_std			-0.001
			(0.001)
Year_Program_Dummy	YES	YES	YES
Erasmus	YES	YES	YES
Controls	YES	YES	YES
Observations	372	372	372
R-squared	0.030	0.027	0.014

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Overall, we don't identify any heterogeneity in our results depending on student's characteristics.

6 Discussion & Conclusion

This work is the first quasi-experimental study exploring how commuting impacts higher education students academic performance. Our results suggest a negative causal relationship between commuting and students' GPAs. We conclude that an increase of 10 minutes in commuting time, traveling by car, is associated with a decrease between 6 p.p and 8 p.p of a standard deviation in the students' GPA. Besides, an increase in 10 km in commuting distance is associated with a decrease between 5 p.p and 6 p.p of a standard deviation in the students' GPA. Comparing our results with Kobus, Van Ommeren and Rietveld (2015) for students from the Univeristy of Amsterdam, we observe that our coefficients are lower. In fact, they estimate that one standard deviation increase in commuting times (about 30 minutes) leads to a decrease of one-third of a standard deviation in the average grades of higher education students. However, the two studies were conducted with different methodologies, since Kobus, Van Ommeren and Rietveld (2015) use survey data and an IV estimate, and we use administrative data and an exogenous shock to identify our model.

Regarding the mechanisms behind the relation we have encountered, our database is not sufficient to analyze them. However, we briefly discuss some possible hypothesis based on the existing literature. It is probably the case that students who commute more study fewer time. According to Stinebrickner and Stinebrickner (2007), Stinebrickner and Stinebrickner (2004), and Plant et al. (2005) the time spent on study and the quality of the study are positively associated with the students' GPA. So, it is plausible to think that students who commute more might be studying less hours. Besides, it is also possible that students with longer commutes engage in fewer extracurricular activities and have less leisure time. According to different studies such as, Hunt (2005) and Muñoz-Bullón, Sanchez-Bueno and Vos-Saz (2017), these activities are important and positively associated with having good academic performance. So, it could also be the case that students who commute more, dedicate fewer time to other activities which might be detrimental for their academic success. Lastly, students who commute more, might also sleep less. Hershner (2020) and Okano et al. (2019) report, sleep is positively associated with grades and sleep patterns could explain up to 25% of the college students' GPAs variance. So, it might be the case that students who commute longer, sleep less, which could have substantial impact on their academic performance, explaining the variation we observe among students with different commuting patterns.

Despite no clear results on heterogeneous effects, some evidence arises that the effect may be stronger for boys than for girls. However, more definitive conclusions would need a larger sample to increase the power of the presented estimations.

Overall, the results of this work evidence that students benefit from lower commuting distances to school, but it also shows that the impacts are not substantial. This consideration is important mainly when thinking about policy implications.

Different measures could help to facilitate or diminish the commuting time for students. For example, more public transportation in the university areas or more residences closer to universities.

However, these policies are relatively expensive. On the other hand, there is the possibility of providing some remote classes. Regarding this topic, our study clearly identifies that commuting less is beneficial for students. However, as shown, the impacts are not substantial. So, it is also essential to account for the costs of remote classes in order to be able to make decisions that truly benefits higher education students.

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Appendix

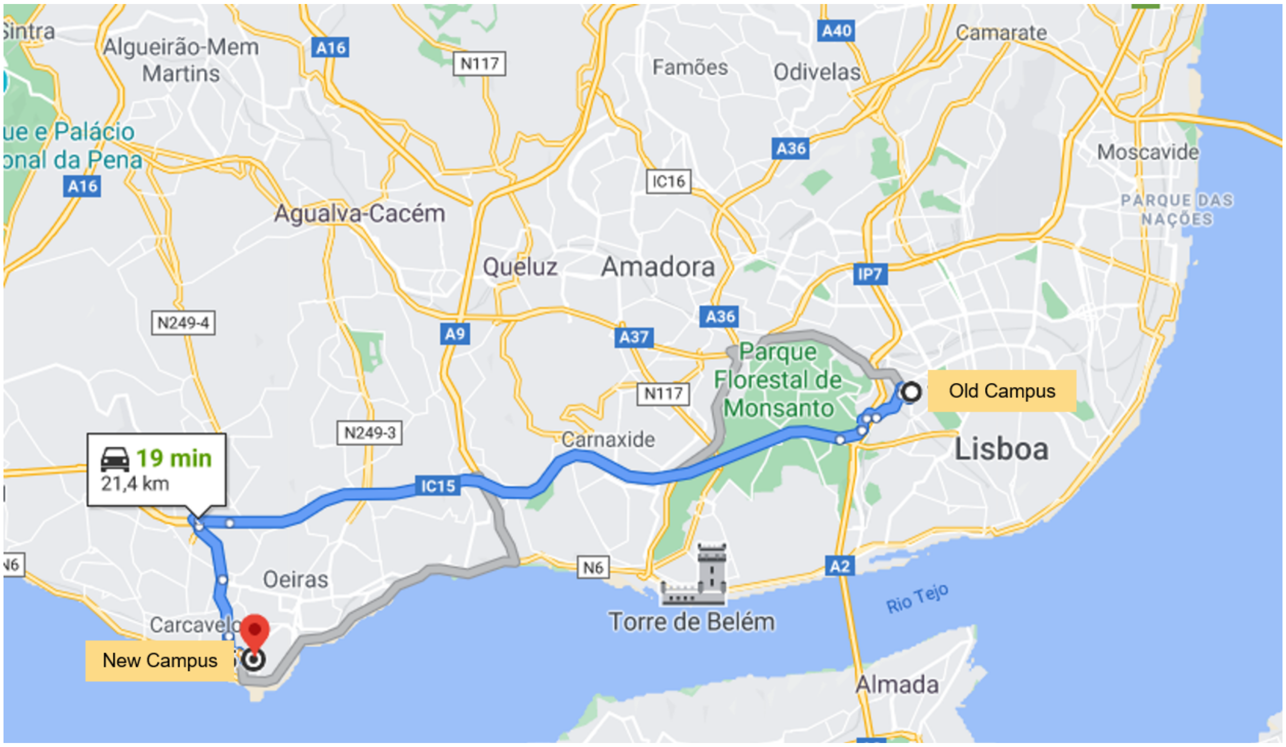

Figure 3: The campus reallocation from the Lisbon city center to Carcavelos

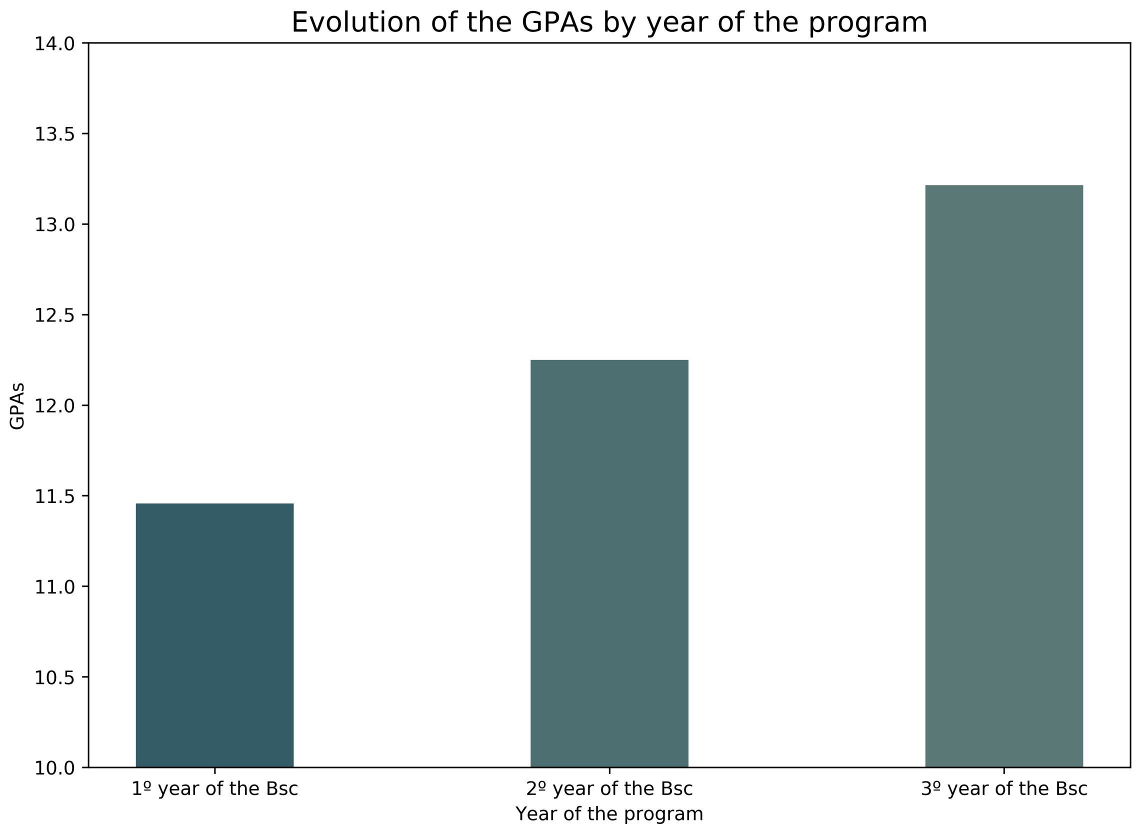

Figure 4: Evolution of the students' GPAs per year of the bachelor's program

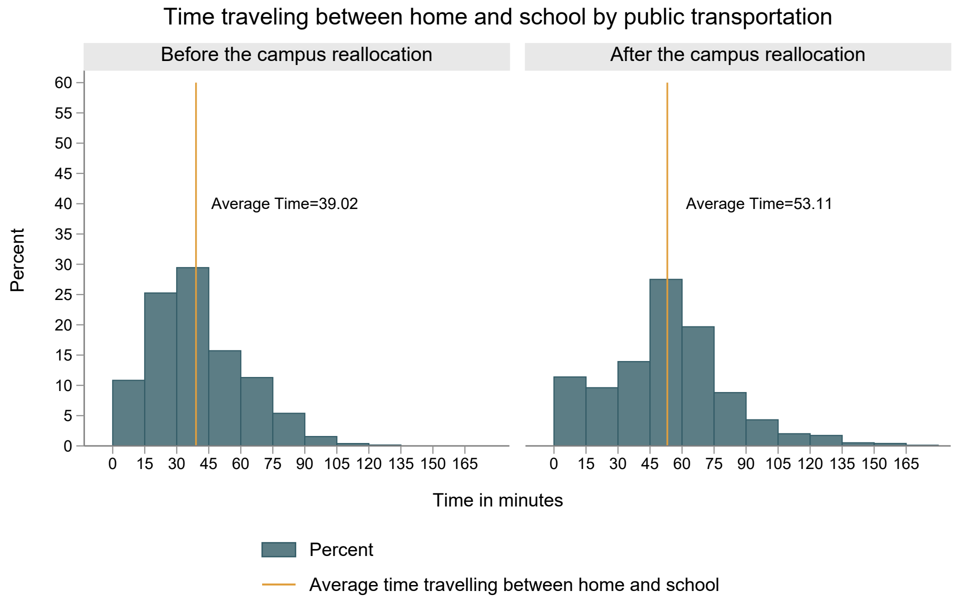

Figure 5: Time traveling in a one-way journey between home and school before and after the shock (by public transports)

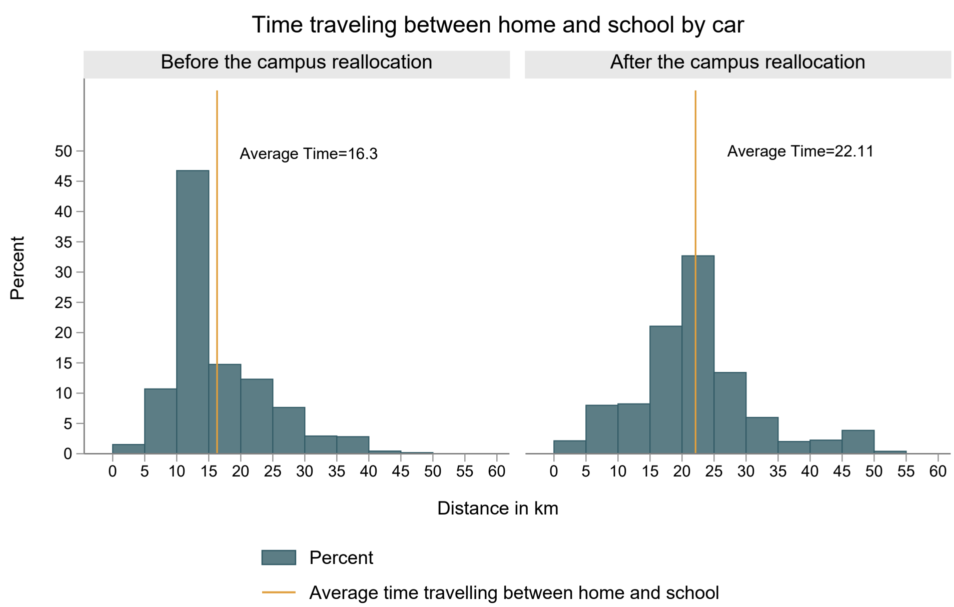

Figure 6: Time traveling in a one-way journey between home and school before and after the shock (by car)

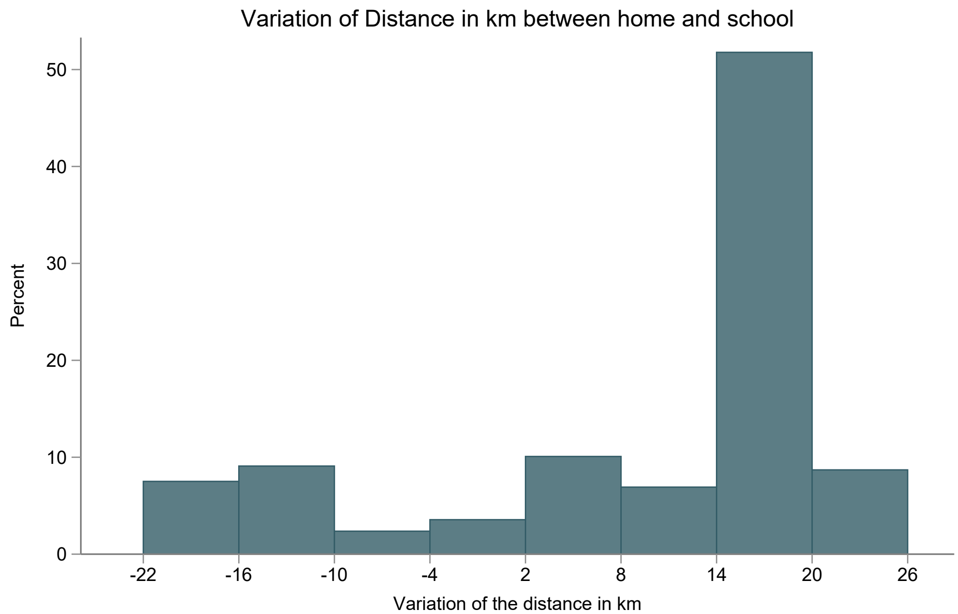

Figure 7: Exogenous variation of the distance in km between home and school due to the campus reallocation

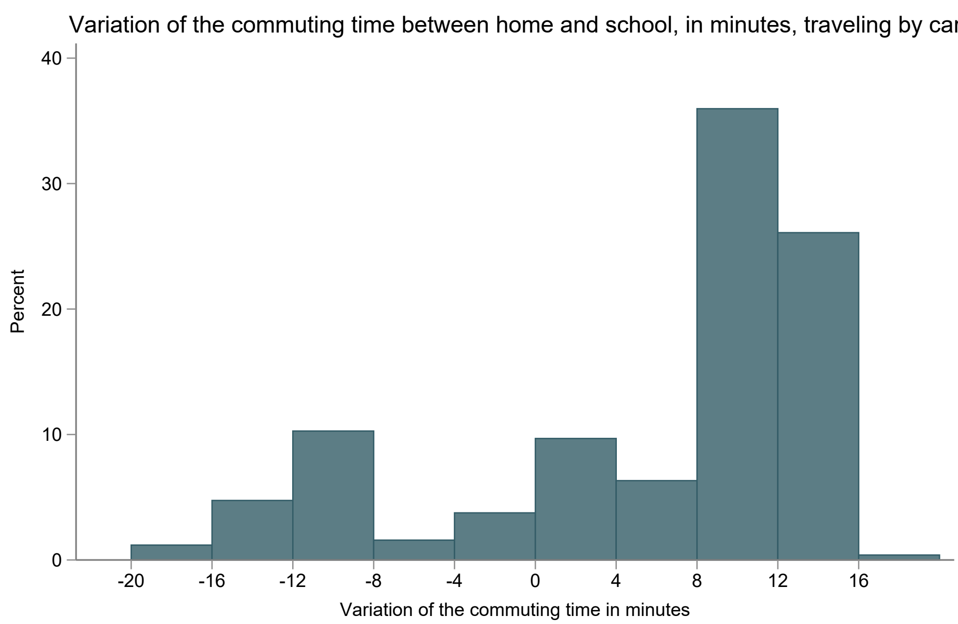

Figure 8: Exogenous variation of the commuting time, travelling by car, due to the campus reallocation

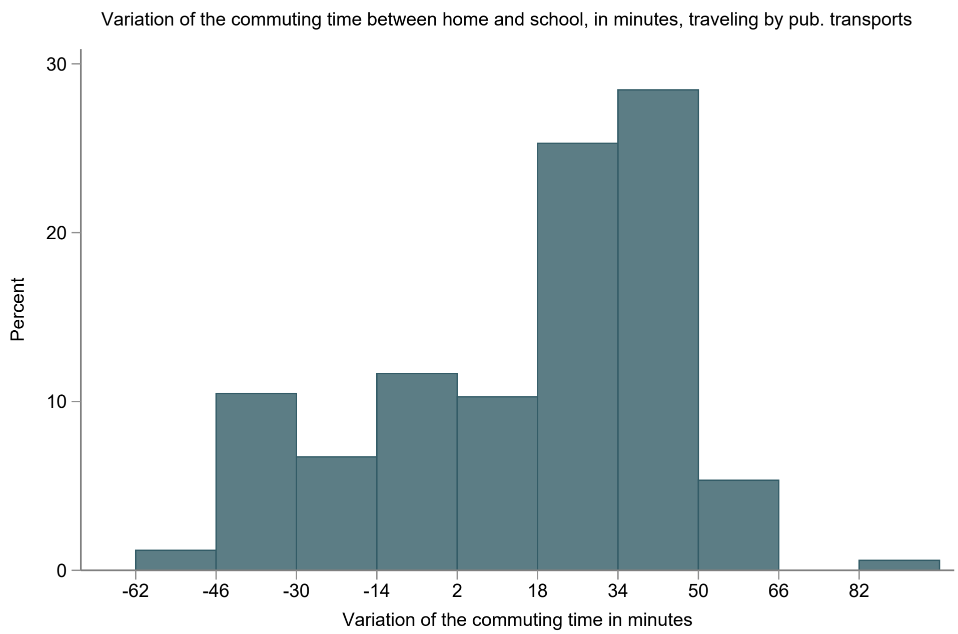

Figure 9: Exogenous variation of the commuting time, travelling by public transports, due to the campus reallocation

Table 8: Variations of commuting distances/times and variations of semester standardized GPAs

	All Students			Only 1st to the 2nd year			Only 2nd to the 3rd year		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Distance_variation_km	-0.006**			-0.007*			-0.006*		
	(0.002)			(0.004)			(0.003)		
Time_variation_car		-0.008**			-0.008			-0.008	
		(0.004)			(0.005)			(0.005)	
Time_variation_pub_transport			-0.001			-0.003			-0.000
			(0.001)			(0.002)			(0.002)
High School Grades	-0.004	-0.004	-0.004	-0.000	-0.000	-0.000	-0.005	-0.005	-0.005
	(0.004)	(0.004)	(0.004)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Mother_Higher_Education	0.085	0.080	0.065	-0.036	-0.039	-0.055	0.134	0.129	0.108
	(0.089)	(0.089)	(0.089)	(0.133)	(0.133)	(0.133)	(0.123)	(0.124)	(0.124)
Father_Higher_Education	-0.010	-0.014	-0.010	0.040	0.033	0.045	-0.023	-0.024	-0.013
	(0.082)	(0.082)	(0.082)	(0.118)	(0.119)	(0.119)	(0.116)	(0.116)	(0.117)
Scholarships	-0.002	-0.007	0.010	-0.228	-0.231	-0.193	0.335	0.329	0.322
	(0.135)	(0.136)	(0.136)	(0.173)	(0.174)	(0.173)	(0.234)	(0.234)	(0.236)
ERASMUS Dummy	-0.074	-0.078	-0.085	-0.027	-0.030	-0.008	-0.134	-0.141	-0.156
	(0.097)	(0.097)	(0.098)	(0.138)	(0.139)	(0.141)	(0.138)	(0.138)	(0.139)
Year_Program_Dummy	0.073	0.073	0.083						
	(0.097)	(0.097)	(0.098)						
Constant	0.679	0.671	0.654	0.190	0.171	0.124	0.988	0.988	1.054
	(0.762)	(0.763)	(0.767)	(1.081)	(1.084)	(1.084)	(1.073)	(1.075)	(1.083)
Observations	372	372	372	170	170	170	202	202	202
R-squared	0.026	0.021	0.012	0.037	0.032	0.031	0.041	0.037	0.024

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 9: Variations of commuting distances/times and variations of semester standardized GPAs

	(1)	(2)	(3)
Distance_variation_km	0.001		
	(0.001)		
Time_variation_car		0.002	
		(0.002)	
Time_variation_pub_transport			0.000
			(0.001)
Year_Program_Dummy	YES	YES	YES
Erasmus	YES	YES	YES
Controls	YES	YES	YES
Observations	1,209	1,209	1,117
R-squared	0.029	0.029	0.024

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1