CERIS

CENTRE FOR ECONOMIC RESEARCH
ON INCLUSIVITY AND SUSTAINABILITY

The Commuting Paradox for Female College Students

Working Paper Series 2023/02

Cite as: Cullinan J, Flannery D (2023) The Commuting Paradox for Female College Students, Centre for Economic Research on Inclusivity and Sustainability (CERIS) Working Paper Series, 2023/02.

The Commuting Paradox for Female College Students

John Cullinan[a*] and Darragh Flannery[b]

[a] J.E. Cairnes School of Business & Economics, University of Galway, Ireland.

[b] Kemmy Business School, University of Limerick, Ireland.

* Corresponding author. J.E. Cairnes School of Business & Economics, University of Galway, University Road, Galway, H91 TK33, Ireland. Email: john.cullinan@universityofgalway.ie. Telephone: 091 493996.

Abstract

We study the relationship between living arrangements, commute time, and wellbeing for full-time undergraduate college students in Ireland. Exploiting geographic variation in system-wide accessibility to higher education as an instrumental variable, we use a partial identification approach to show that living at home reduces wellbeing by between 0.07 and 0.13 of a standard deviation. We find these effects are driven mainly by female students and show that long commutes are independently associated with very large increases in poor wellbeing for female students living at home. Our results challenge the theory that disutility from commuting is compensated by other factors relating to where an individual lives, providing new evidence on the so-called *commuting paradox*.

Keywords

Commuting; Living arrangements; Wellbeing; College students.

Statements and declarations

The authors declare no competing financial or non-financial interests.

1 Introduction

Prevalence rates of psychological distress and mental ill-health among students in higher education are high and increasing in many countries (Bolotnyy et al. 2022; Lewis and Bolton 2023; Lipson et al. 2019). Coupled with the growing use of wellbeing and quality of life measures as explicit policy objectives in the sector and more generally (American Council on Education 2021; Frijters et al. 2020; O'Donnell et al. 2014), there is now a burgeoning literature focusing on college student wellbeing and its determinants. For example, previous research in the higher education context has shown that female, ethnic minority, and sexual and gender minority students all have poorer mental health on average, as do students from lower socioeconomic backgrounds (Eisenberg et al. 2007; Larcombe et al. 2016; Lipson et al. 2022). This paper considers the relationship between living arrangements, commute time, and mental wellbeing for college students. Analysing data on full-time undergraduate students in Ireland, it exploits geographic variation in system-wide accessibility to higher education as an instrumental variable to estimate the total effect of living at home on wellbeing and models the relationship between wellbeing and commute time for those living at and away from home. It also considers a range of pathways and mechanisms through which commuting can impact wellbeing.

Despite the increased focus on college student wellbeing, there is very little literature examining the impacts of living arrangements and/or commuting for this group. This is somewhat surprising given that commuting to college is a prominent feature of student life in many countries (Hauschildt et al. 2021; National Centre for Education Statistics 2016) and invariably linked to a student's living arrangements/housing during their studies. In addition, there is also widespread evidence that commuting can impose a significant disutility on individuals, with commuting identified as the daily activity that produces the fewest positive feelings and the most negative ones (Kahneman et al. 2004). Indeed, a large body of empirical research has demonstrated a negative relationship between commute time and wellbeing for the general population (Frey and Stuzer 2014; Friman et al. 2017; Jacob et al. 2019; Kuun-Nelen 2015; Liu et al. 2022; Simón et al. 2020; Stuzer and Frey 2008; Tao et al. 2023). Stuzer and Frey (2008) label this the *commuting paradox*, since it contradicts the theory that commuting is a choice that is compensated through better housing, labour market, or other outcomes[1].

In addition to the personal consequences for students themselves, including unhappiness, social isolation, and decreased enjoyment of life, concerns relating to poor student wellbeing and mental ill-health are well-placed for several other reasons. First, there is evidence linking lower levels of student wellbeing to poorer academic engagement, performance, and outcomes, including increased dropout rates (Bruffaerts et al. 2018; Eisenberg et al. 2009; Hysenbegasi et al. 2005). While this is obviously important for students themselves, it also has implications for higher education institutions (HEIs), in terms of performance metrics, and the wider economy, due to reduced productivity in the future. Second, there are also potential dynamic effects of lower levels of wellbeing in younger ages. For example, there is evidence that young adults who report lower life satisfaction grow up to earn less income later in life (De Neve and Oswald 2012). In addition, research has shown that mental ill-health during early adulthood can have long-term adverse effects on labor market functioning (Goldman-Mellor et al. 2014; Niederkrotenthaler et al. 2014), relationship functioning (Kerr and Capaldi 2011), and health (Scott et al. 2016). Third, as measures of student satisfaction and experience are increasingly being used as inputs in well-known HEI rankings[2] and

[1] There are some studies that have found no relationship between commuting and overall life satisfaction, e.g. Dickerson et al. (2014) and Lorenz (2018), though the latter did find that longer commutes were related to lower satisfaction with some specific life domains, such as family life and leisure time.
[2] For example, the Times Higher Education Impact Rankings explicitly recognises the importance of student mental health and wellbeing by including mental health support for students under their good health and wellbeing SDG metric.

performance-based funding (PBF) schemes, the wellbeing of the student population may have implications for student recruitment and funding allocations for HEIs. For example, a recent policy change in Australia means the distribution of State funds within a PBF scheme will be partly determined by the quality of the overall student experience (Australian Department of Education, Skills and Employment 2019).

The rising interest in student wellbeing comes at a time of already high and increasing numbers of students commuting to college in many countries, often with long daily commutes. For example, the median one-way travel time for students not living on campus is more than 45 minutes (mins) in a number of European countries, including Austria, Czech Republic, France, Hungary, Ireland, Netherlands, Poland, Sweden, Switzerland, and Turkey (Hauschildt et al. 2021). In the United Kingdom (UK), Donnelly and Gamsu (2018) estimate that around 25% of full-time students are commuters, though this figure jumps to almost 45% for those from lower income backgrounds. In the United States (US), close to 30% of postsecondary students live with their parents while in college (Kelchen 2018), while 16% take more than 30 mins to get to their place of study (National Centre for Education Statistics 2016).

How far or long a student commutes to college is directly related to where they choose to live while in higher education. For example, on average 34% of students across 24 European countries live with their parents while in college, with these students facing an average one-way commute time of 40 mins. This compares to an average one-way commute of under 20 mins for those not living with their parents, with the difference between these groups largest in the Netherlands, France, Switzerland, Ireland, Poland, Sweden, and Portugal, and lowest in countries such as Estonia and Lithuania (Hauschildt et al. 2021). Notably, students living with their parents tend to express lower levels of satisfaction with their commute time but are more satisfied about both the costs and condition of their accommodation (Hauschildt et al. 2021). This suggests that some college students may be trading off the disutility of commuting with the benefits that come with living at home.

To better understand the relationship between living arrangements, commute time, and college student wellbeing, we analyse responses to the WHO-5 Wellbeing Index measure for 5,562 full-time undergraduate students. We first estimate the effect of living at home on wellbeing by exploiting geographic variation in system-wide accessibility to higher education as an instrumental variable. In Ireland, college students tend to study at HEIs that are close to where they live/come from and this is a result of a wide range of transaction costs associated with participation (Cullinan and Flannery 2022; Spiess and Wrohlich 2010). Examples include direct financial costs such as accommodation, living, and travel/transport costs. As a result, there is evidence of highly localised patterns of transitions to higher education in Ireland (Cullinan and Halpin 2017), while, in addition, previous research has shown strong preferences amongst prospective college students for HEIs that are closer to home (Walsh and Cullinan 2017; Walsh et al. 2018). One implication of this is that students who come from more accessible areas are more likely to live at home and have, on average, longer commutes. This is because commuting is unlikely to be an option for students from poor accessibility areas, due to the long travel distances involved. As a result, they are much more likely to move away from home and reside on or close to campus.

Employing a partial identification approach based on Nevo and Rosen (2012), we show that living at home reduces wellbeing by between 0.07 and 0.13 of a standard deviation, with much larger effects for female students compared to males. We also show that for female students living at home, one-way commutes of 45 mins or more are independently associated with an increased likelihood of poor wellbeing of 13.6 ppts compared to similar students living close to college. We provide evidence for the credibility of our results using sensitivity analysis tools and we investigate a range of potential pathways and mechanisms through which commuting might impact wellbeing. These include various aspects of a student's college experience, as well as health and health behaviours. Our analysis has a range of implications for HEIs and policymakers and is especially relevant in a time of increased focus on student wellbeing.

The paper is structured as follows: Section 2 presents a review of the literature, including relevant theoretical considerations and empirical evidence. Section 3 discusses the setting for our study, Section 4 describes the data, and Section 5 presents our empirical approach. Our main results are presented and discussed in Section 6, while Section 7 considers the implications of our findings and concludes.

2 Literature

2.1 Theory

As a starting point, and taking a standard microeconomic perspective, Stutzer and Frey (2008) draw from the urban location theory of Alonso (1964), Muth (1969) and Huriot and Thisse (2000), as well as from public economic theory with Tiebout's (1956) model of fiscal competition between areas, to outline a helpful conceptual framework of commuting. Their model suggests that individuals make labour market and housing decisions that involve longer commutes if compensated by higher wages and/or improved living conditions. This framework can easily be extended to consider decisions relating to higher education, whereby students may choose to enrol at a college that involves a longer commute if they are compensated by better educational prospects/experiences and/or improved housing/living/social conditions. This suggests that commuters are compensated by either a fulfilling job/study environment or better housing, so that their utility is equalised over all combinations of alternatives in the housing and labour/education markets. In other words, even if commuting produces disutility, the compensation argument implies it should not affect overall individual wellbeing and therefore no correlation between commuting and reported life satisfaction should be observed (Simón et al. 2020). However, it is important to note that such a framework relies upon an assumption of perfect housing and labour/education markets, which for reasons discussed below is very unlikely to hold in higher education contexts in many countries. In particular, for many students, the only option to participate in higher education may be to live at home and commute.

An alternative framework for considering such decisions, particularly when examining an individual's experience of choice outcomes, rather than choice processes, involves the concept of experienced utility. Such an approach is closely related to wellbeing and has gained prominence through the work of Kahneman et al. (1997), Diener (2009), and others. It suggests that utility can also refer to the experience of feelings and emotions that result from the outcome of a choice, and ultimately the wellbeing of an individual (Ettema et al. 2010).

There are several possible explanations as to why different living situations and commuting patterns may impact wellbeing, either positively or negatively (Coates et al. 2021; De Vos et al. 2013; De Vos et al. 2016; Ettema et al. 2010; Giménez-Nadal et al. 2023; Roberts et al. 2011). For example, the experience of commuting itself may bring about increased levels of stress if stuck in traffic or experiencing unreliable public transport. On the other hand, some individuals may feel greater levels of contentment on trips in relatively peaceful environments (Abou-Zeid and Ben-Akvira 2012; De Vos et al. 2013; Ettema et al. 2010). There are also potential spillover effects if stressful or otherwise low-quality travel to an activity (e.g. attending class) adversely influences participation in that activity and indirectly affects wellbeing (Bergstad et al. 2011; Ettema et al. 2010). For example, a student with a bad commuting experience may not have the same concentration levels in class as other students, which may impact their relative wellbeing. At the same time, if the student is living at home, the negative experience of commuting may be counteracted by better family supports and/or better housing conditions.

Another way in which wellbeing may be affected is through the social opportunity costs of living at home and time spent commuting. In particular, living with ones' parents and longer commutes may reduce social opportunities and engagement, which are a common feature of college life. This may result in social exclusion and, as a result, lower levels of wellbeing. From a theoretical perspective, this mechanism can be linked to Amartya Sen's capability approach whereby the wellbeing of an individual is related to the extent of their opportunity set and of their freedom to choose among this set (Coates et al. 2021; Sen 1993; Stiglitz et al. 2009). A potential counterargument here is that students living at home are likely to have lower or even zero rental costs, implying an increased budget set and greater consumption capabilities compared to students paying rent.

2.2 Empirical evidence

2.2.1 Commuting and wellbeing

In terms of empirical findings relating to the general population, numerous studies and systematic reviews have shown a consistent pattern of longer commutes associated with poorer wellbeing and mental health (Chatterjee et al. 2020; De Vos et al. 2013; Liu et al. 2022). For example, Wang et al. (2019) found that every additional 10 mins of commuting increased the likelihood of being screened with depression by 0.5%, while Stutzer and Frey (2008) estimated the impact of commuting an extra 18 mins to work (one-way) is about one-eighth as bad for life satisfaction as becoming unemployed. Both Roberts et al. (2011) and Jacob et al. (2019) showed that general mental health, assessed *via* a GHQ-12 benchmark using UK data, decreased with longer commutes and that this effect was stronger for women. This seems to be a result of women's greater responsibility for day-to-day household tasks, as opposed to shorter working hours or weaker occupational position[3]. In addition, commuting has also been found to be a major source of stress stemming from its unpredictability and perceived loss of control (Evans et al. 2002; Gottholmseder et al. 2009; Koslowsky et al. 1995), while boredom (Gatersleben and Uzzell 2007) and social isolation (Putnam 2000) amongst commuters have also been highlighted.

Despite the vast literature on the general population, there are only a few commuting studies focussing specifically on college students, and none from the economics literature. Some of these have examined commuter satisfaction levels with different modes of transport, showing that longer commute times, particularly commutes involving non-active travel modes such as buses and cars, are negatively associated with travel satisfaction (Ettema et al. 2011; St-Louis et al. 2014). In addition, a number of other studies have described the negative effect of commuting on campus participation and academic achievement (Allen and Farber 2018; Coutts et al. 2018; Kobus et al. 2015; Webb and Turner 2020). Only two studies we are aware of have explored the relationship between college students' wellbeing or mental health and commuting directly. Using a sample of Italian university students (*N*=4,700), Porru et al. (2021) found that students who commuted reported a significantly higher level of psychological distress compared to those studying in their hometown and those who moved for studying. Similarly, Parker et al. (2023) examined associations between perceived family support and psychological distress among students who attended a small suburban commuter college in the US (*N*=201), finding high distress levels on average in this group. However, the empirical analysis in both studies was largely descriptive in nature and limited by potential endogeneity concerns due to selection effects and omitted variable bias.

[3] There is also a wider emerging literature that considers commuting choices and gender in the general population – see, for example, Gu et al. (2021), Le Barbanchon et al. (2021), Liu and Su (2022).

Overall, our review of the empirical literature suggests that commuting is negatively associated with wellbeing in the general population and that studies relating to college students are rare. Furthermore, as noted by Chaterjee et al. (2020) and Liu et al. (2022), most studies to date use cross-sectional data and are based on observational research designs, with little consideration of the causal effects of commuting[4].

2.2.2 Living arrangements

While there is some (limited) evidence on the relationship between commuting and college student wellbeing, modelling this is complicated by the fact that a significant proportion of students choose to leave home to participate in higher education. This means that the impact that commuting, and commute time in particular, has on student wellbeing is directly related to this decision. For example, while commuting may contribute to lower wellbeing by placing additional stresses upon students, there may also be benefits to living at home if they can avail of family and/or other social supports, or if the quality of accommodation at home is better. However, relative to those who live on or close to campus, such students may also experience lower engagement with college life from an academic and social perspective, which could also impact their wellbeing (Chickering 1974; Kuh et al. 2007; Thomas and Jones 2017). Empirical research around the effects of different living arrangements on student wellbeing is surprisingly rare with no previous studies in the economics or education literatures. However, evidence around other more academic-focused outcomes do exist. For example, Lockwood-Reynolds (2020) and Webb and Turner (2020) found that residing on (or near) campus did not have any effect on student retention but did have a positive effect on student grade point average, for first year students in the US and UK respectively. Such outcomes may have a knock-on effect on, or be related to, student wellbeing.

[4] Some notable exceptions are Roberts et al. (2011) and Stutzer and Frey (2008) who both employed fixed effects models.

3 Institutional setting and context

To help characterise our study setting, explain the rationale for our empirical approach, and inform the generalisability of our results, it is important to highlight some key features of the Irish higher education system. There are currently four main types of HEIs, namely universities, technological universities (TUs), institutes of technology (ITs), and colleges of education (CEs), as well as a small number of other independent (mainly private) colleges. TUs are a relatively new type of HEI in Ireland and are the result of a number of amalgamations of ITs since 2019[5]. Prior to this, including in 2013 when our survey data was collected, the system consisted mainly of universities, ITs and CEs. Like other countries, these types of institutions differ with respect to entry requirements and programme offerings. While students can attain degrees in all types of HEIs, universities tend to be more selective and have a greater intake in areas such as health, humanities, law, and business, relative to both TUs and ITs.

Figure 1 presents the spatial distribution of HEIs in Ireland for the year 2013. The seven universities were mainly located in larger urban centres (this has not changed), with four in the greater Dublin area, whereas ITs were much more geographically dispersed. There is an extensive literature examining student mobility and enrolment patterns in Ireland, which has generally found that proximity to a HEI strongly influences where a student enrols (Cullinan and Duggan 2016; Cullinan and Halpin 2017; Flannery and Cullinan 2014; Walsh et al. 2015). In the context of the empirical approach adopted in this paper, these spatial patterns of enrolment are important, particularly as Walsh et al. (2017) highlighted significant inequalities in geographic accessibility to different types of higher education in Ireland.

[5] There is no evidence that these amalgamations have affected course offerings or admission patterns since their introduction.

There are no direct tuition fee differences at undergraduate level in Ireland with students facing a flat €3,000 charge regardless of HEI or field of study. Living costs tend to be relatively high for students and to vary by region, and students in Ireland living away from home reported the highest level of dissatisfaction with the cost of their accommodation out of 20 European countries (Hauschildt et al. 2021). Financial aid and assistance from the State is available to help alleviate potential inequalities in accessing higher education. For example, students who meet certain criteria based on parental income levels can apply to pay either a reduced tuition fee, be exempt from paying any tuition fee, and/or receive a maintenance grant while in college. The financial support available has good scope with around 40% of undergraduates in Ireland receiving some type of support. However, the scale of the supports is relatively low, estimated to cover just under 33% of student living costs on average (Indecon 2022). There are also significant accommodation pressures with high levels of excess demand for student housing. This is, in part, a result of significant growth in higher education participation in recent years.

Consistent with international evidence (Eisenberg et al. 2007; Lipson et al. 2022), Cullinan et al. (2022) shows high rates of psychological distress amongst college students in Ireland, with 24.5% and 14.8% of students classified in 'mild to moderate' and 'severe to extremely severe' ranges for stress respectively. In terms of mobility and commuting, roughly 20% of Irish students are estimated to live on campus, with 40% living with their parents and the remainder in private accommodation (Hauschildt et al. 2021). The proportion living with their parents compares to a European average of 34% and is similar to countries such as the Netherlands, Slovenia, and Poland (Hauschildt et al. 2021)[6]. As mentioned previously, commute times are significantly longer for those living at home relative to other students, with the median commute times for Irish students across different living arrangements comparable to many

[6] Matsudaira (2016) notes that, in general, many young people choose to live at home since they cannot afford to live independently.

other countries across Europe (Hauschildt et al. 2015; Hauschildt et al. 2021). In terms of transport mode, it is notable that Ireland is relatively car-centric, reporting a much higher proportion of students (40%) using a car as their primary means of getting to their HEI relative to other European countries[7].

4 Data and variables

4.1 Data

The Eurostudent project studies the social, living, and economic conditions of higher education students in Europe and undertakes regular repeated cross-sectional surveys across more than 20 participant countries. In this paper, we analyse data from the Eurostudent Survey for Ireland from 2013 (Wave 5 of 8), as this is the latest wave for which all our required variables are available. Data collection was primarily undertaken by online survey (>99%) with some self-completed mailed versions and the survey was based on a stratified sample i.e. sampling took place separately from different strata in the population/sampling frame (Harmon and Foubert 2013). Fieldwork was undertaken from 01/04/2013 to 31/05/2013, which coincides with a busy time for study and examinations in the Irish system. This is important for two reasons. First, the overall response-rate of 5.1% in Wave 5 was lower than that of previous and subsequent Eurostudent surveys (7.5–10.0%), which were undertaken earlier in the academic year. Second, levels of stress, anxiety, and mental ill-health could be higher during the study/examination period, which would likely affect student wellbeing.

In total, survey responses were received from 10,110 students from 26 HEIs. For our analysis we only consider full-time undergraduate students who entered *via* the traditional Leaving

[7] For example, the comparable proportions for France, Poland, and the Netherlands are 25%, 18%, and 12% respectively.

Certificate route[8]. This is because this is the group of students that are most likely to be making regular visits to their college campus and for whom the commuting-related questions we examine are most relevant. We exclude distance learners, students who studied outside Ireland before entering higher education, as well as so-called 'mature students'[9]. This gives an estimation sample of *N*=5,562 after data cleaning. In general, non-response to the survey questions of specific interest to our analysis was very low and missing data was not an issue.

4.2 Key variables and descriptive statistics

Table 1 presents variable definitions and sample descriptive statistics for the key variables used in this paper. For our main analysis we consider two dependent variables, namely subjective wellbeing (*SWB*) and poor wellbeing (*Poor SWB*). *SWB* is measured using the World Health Organisation-Five (WHO-5) Well-Being Index. This is a short self-reported measure of mental wellbeing and was first introduced in its present form in 1998 (WHO 1998). It can be reported by children and young people and has been administered in a wide variety of settings. The WHO-5 has been found to have adequate validity in screening for depression and in measuring outcomes in clinical trials. Item response theory analyses in studies of younger persons indicate that the measure has good construct validity as a unidimensional scale measuring wellbeing in this population (Topp et al. 2015).

In terms of scoring and interpretation, the WHO-5 consists of five statements, relating to mental wellbeing *in the preceding two weeks*:

- I have felt cheerful and in good spirits;
- I have felt calm and relaxed;
- I have felt active and vigorous;

[8] The Leaving Certificate is a high stakes examination taken at the end of secondary school in Ireland. Performance in the Leaving Certificate largely determines what college programmes a student is eligible to enrol in.
[9] These are students who entered higher education for the first time after the age of 23.

- I woke up feeling fresh and rested; and,
- My daily life has been filled with things that interest me.

Respondents rate each statement on a 0-5 scale, with 5 representing a response of ‘all of the time’ and 0 representing a response of ‘at no time’. The full questionnaire is shown in Appendix A Figure A1. A raw score is then calculated by aggregating the five answers so that a respondent’s WHO-5 score can range from 0 to 25, with 0 representing the worst possible and 25 representing the best possible quality of life. Table 1 shows an average WHO-5 score of 12.3 across the sample, with a standard deviation (SD) of 5.1. Appendix A Table A1 provides sample descriptive statistics for the individual components of the index.

The responses from the WHO-5 can also be used as an indicator of poor mental wellbeing, with scores below 13 used as an indication for testing for depression. We use this cut-off to define our second dependent variable: *Poor SWB*. Table 1 shows that 50.7% of the sample are classified as having poor wellbeing based on this measure. Importantly, both *SWB* and *Poor SWB* are based on responses that relate to the past two weeks and are therefore measures of current mental wellbeing.

Our first main independent variable of interest is an indicator denoting if a respondent lives at home (*Home*). This variable was constructed on the basis of responses to survey questions relating to what type of accommodation a student lives in during the study term/semester (e.g. parents’ property, private landlord’s property, student accommodation, etc.) and who they live with (e.g. parents, partner, landlord, students, etc.)[10]. Overall, almost one-half (46.2%) of our

[10] This classification is motivated, in part, by a taxonomy of commuter students presented in Maguire and Morris (2018). They distinguish between ‘residential students’, ‘social commuter students’, ‘home commuter students’, and ‘higher-risk commuter students’ depending on who a student lives with (i.e. other students or parents) and whether they live close or distant from their place of study. Maguire and Morris (2018) stress that the more specific term ‘commuter student’ is in general ill-defined. This is because some students who live at home (often used as a proxy for being a commuter student) have very short commutes, while some students who have moved away from home (and would not be not considered commuters using this proxy) have relatively long commutes. As shown below, this is the case for our sample. For this reason, we avoid the term commuter student, focussing instead on if the student lives at home or not, and then considering the issue of commute time.

sample live at home, the vast majority with their parents, and commute daily/regularly to college, while 53.8% have moved away from home[11].

The second key independent variable in our analysis is commute time (*Time*). This variable is based on responses to the question "On a typical day during the current semester, what is the time you cover from where you live to your higher education institution?", with respondents asked to indicate their "minutes on average (one way)"[12]. Table 1 shows an average one-way commute time of 31.2 mins, though with considerable variation across the analysis sample (SD = 29.7 mins). This variation, as well as differences in the distributions of commute times for students who live at, or away from, home, is illustrated in Figure 2. Unsurprisingly, it shows longer commute times on average for those who live at home. In fact, the average commute time for students living at home is 47.1 mins (SD = 31.1 mins), while for students living away from home it is 17.6 mins (SD = 20.0 mins).

A further indication of the difference in the distribution of commute times between *Home* and *Away* students is presented in Table 2. It disaggregates the numbers and proportions in each group by commute time quartile (defined on the basis of the full analysis sample)[13]. It shows that while 31.4% and 46.4% of students living at home have one-way commutes of 20-45 mins and 45+ mins respectively, the vast majority of students living away from home, in contrast, have a commute time of less than 20 mins (80.6%)[14].

Table 1 also presents details of the control variables used in the main analysis. These include a

[11] We subsequently denote those living at home as *Home* students and those living away from home as *Away* students.
[12] Respondents were not asked to report the frequency of these trips e.g. number per week.
[13] These quartiles are also used subsequently in our econometric models. In particular, *Time* Quartile 1 (Q1) represents a one-way commute of 0-10 mins, Quartile 2 (Q2) a one-way commute of 10-20 mins, Quartile 3 (Q3) a one-way commute of 20-45 mins, and Quartile 4 (Q4) a one-way commute of 45 mins or more.
[14] Table 2 also shows that some *Home* students have very short commutes while some *Away* students have relatively long commutes. Again, this would complicate the classification of students as commuters or non-commuters based on where, or with whom, they live. In general, the term commuter student tends to be used for those living at home with relatively long regular commutes, which as shown in Table 2, would comprise the majority of *Home* students.

range of personal controls, namely a student's age, sex, nationality, if they have children, and extent of any disability. There are also a range of higher education related variables that are used as controls. These include the HEI (college) a student attends, as well as their course, year, and programme of study. (Descriptive statistics for some of these variables are included in Appendix B given the large numbers of categories). Finally, the socioeconomic controls included are income and social class. It should be noted that the Eurostudent survey also includes a range of additional variables that are used in additional supplementary analyses, as well as sensitivity and robustness checks. Descriptive statistics relating to these variables are available from the authors on request.

5 Empirical strategy

Figure 3 presents an overview of the assumed relationship between living at home, commute time, and wellbeing that informs our empirical approach. We start by assuming two potential 'directed paths' from $Home$ to SWB: a 'direct effect' of $Home$ on SWB (i.e. $Home \longrightarrow SWB$) and an 'indirect effect' that operates through the mediator variable $Time$ (i.e. $Home \longrightarrow Time \longrightarrow SWB$). In this set-up, controlling for $Time$ in a regression of SWB on $Home$ would block some of the effect of $Home$ and therefore bias the average treatment effect (ATE) estimate. This is a result of 'overcontrol bias' as it violates the 'back-door criterion' that necessitates that controls that are descendants of the treatment along paths to the outcome are excluded (Cinelli et al. 2022; Pearl 2009). If, on the other hand, we are interested in the controlled direct effect (CDE) of $Home$ on SWB (i.e. the effect of $Home$ while holding commute time constant), then adjusting for $Time$ could be appropriate. Moreover, if we are willing to assume that $Home$ and $Time$ are exogenous, then it is straightforward to undertake a mediation analysis and estimate the proportion of any total effect of $Home$ on SWB that operates through commute time.

There are, however, a number of potential sources of bias that could undermine such an approach – see Figure 4. First, if there are unobserved confounders U related to both $Time$ and SWB, this could introduce collider bias by opening a backdoor path from $Home$ to SWB through U (i.e. $Home \longrightarrow Time \longleftarrow U \longrightarrow SWB$). One possible example would be if students have preferences for living in "nicer" neighbourhoods, defined in some sense, and these neighbourhoods typically involve longer commutes but are also related to, say, better wellbeing. In this case, the ATE estimate and any subsequent mediation analysis would be biased. Second, if there are also unobserved confounders that determine both *Home* and *SWB*, this would introduce omitted variable bias (OVB). An obvious example here would be selection effects whereby students choose to live at or move away from home based on factors related to their wellbeing. For example, if students with supportive parents and/or social networks at home are more likely to live at home, and this is related to better wellbeing, then this 'positive selection' would bias the ATE upwards. On the other hand, some students may chose to live at home and commute because of caring responsibilities and/or other family-member health issues, which can lead to mental health spillovers (Henry and Cullinan 2021). This would cause the ATE estimate to be biased downwards. *A priori*, it is not clear which type of selection effects dominate and, hence, what is the likely direction and magnitude of any bias. Thus, given such concerns, our identification strategy is to use an instrumental variables (IV) approach where we use system-wide accessibility to higher education (*Access*) as a source of exogenous variation for *Home*.

In terms of estimation, we proceed as follows. We first estimate naïve regression models of *SWB* using ordinary least squares (OLS), focussing initially on the 'total effect' of *Home*. More specifically, we start by estimating the following baseline specification:

$$SWB_i = \beta_0 + \beta_1 Home_i + \delta_1 \mathbf{X}_i^P + \delta_2 \mathbf{X}_i^{HE} + \delta_3 \mathbf{X}_i^{SE} + \varepsilon_i \quad [1]$$

where *SWB* is modelled as a linear function of *Home* and vectors of personal ($\mathbf{X}^P$), higher education ($\mathbf{X}^{HE}$), and socioeconomic ($\mathbf{X}^{SE}$) controls (as listed and defined in Table 1). This model can be easily augmented to estimate the CDE of *Home* by including *Time* as a covariate, such that:

$$SWB_i = \beta_0 + \beta_1 Home_i + \beta_2 Time_i + \delta_1 \mathbf{X}_i^P + \delta_2 \mathbf{X}_i^{HE} + \delta_3 \mathbf{X}_i^{SE} + \varepsilon_i \quad [2]$$

In this set-up, identification requires the strong assumption that *Home* and the error term (ε) are unrelated i.e. selection on observables. To get a sense of the extent to which any unobserved confounders are likely to bias the estimate of β_1, we employ sensitivity analysis tools for regression models developed by Cinelli and Hazlett (2020). Their approach allows us to consider questions such as how strong an unobserved confounder (or group of confounders) would have to be to change our conclusions, as well as how strong confounding would need to be, relative to the strength of observed covariates, to change the answer by a certain amount. It uses a partial R^2 parameterisation of the familiar OVB framework and assesses how including hypothetical omitted variables would change the results based on assumptions about how strongly the unobserved confounders relate to the treatment and the outcome. The key parameters in the sensitivity analysis are $R^2_{H\sim C|\mathbf{X}}$, the share of residual variance of the 'treatment' variable H (i.e. *Home*) explained by some omitted confounding variable(s) C after accounting for the covariates $\mathbf{X}$, and $R^2_{Y\sim C|H,\mathbf{X}}$, which is the share of residual variance of the outcome variable Y (i.e. SWB) explained by C, after accounting for H and $\mathbf{X}$.

Nonetheless, even after undertaking such sensitivity analysis, endogeneity concerns may remain. To address this, we use system-wide accessibility (*Access*) to higher education from a student's 'county of origin' (i.e. where they were living prior to entering higher education) as an instrument for *Home*. To compute this variable, we used GIS network analysis techniques (Cullinan et al. 2008) to calculate, for each county, the road network travel distance from it's population-weighted centroid to each of the 26 HEIs in our sample. We then weighted the inverse of these distances by the size of each HEI (measured by total undergraduate enrolments), summed these, and took the natural logarithm of the sum. This approach follows a number of previous studies that have used similar system-wide accessibility measures (Flannery and Cullinan 2014; Sa et al. 2004; Walsh et al. 2017).

In terms of the rationale for this IV, as noted in Section III, there is considerable variation in geographic accessibility to higher education in Ireland, and to universities in particular (Cullinan and Duggan 2016; Walsh et al. 2015; Walsh et al. 2017). Previous research has shown that this is not only a key determinant of whether school leavers progress to higher education (Cullinan et al. 2013), but also where and what they study (Cullinan and Duggan 2016; Flannery and Cullinan 2017). As discussed in Section I, this also implies that students who come from more accessible areas are more likely to live at home and have, on average, longer commutes. The reason for this is that, due to the travel distances involved, commuting is less likely to be an option for students from areas with poor accessibility. These students are therefore more likely to move away from home, which implies shorter commutes than for those who choose to live at home. Figure 5 provides supporting evidence for this. First, Panel (a) presents system-wide accessibility to higher education at county level by quintile of accessibility, showing accessibility is greatest in the east and parts of the south and west of the country. In terms of commuting, students from these areas tend to have the longest commute times on average (Panel (b)) and are more likely to be living with their parents (Panel (c)) and less likely to be living with other students (Panel (d)).

Given this instrument, we specify the following IV model, which we estimate using two-stage least squares (2SLS):

$$SWB_i = \beta_0 + \beta_1 Home_i + \delta_1 \mathbf{X}_i + \varepsilon_i$$

$$Home_i = \pi_0 + \pi_1 Access_i + \delta_2 \mathbf{X}_i + \eta_i \quad [4]$$

where again, *SWB* is the outcome variable of interest, *Home* is the potentially endogenous treatment variable, and **X** is a vector of exogenous control variables which includes $\mathbf{X}^P$, $\mathbf{X}^{HE}$, and $\mathbf{X}^{SE}$. Using this approach, identification rests on three assumptions. First, instrument relevance assumes that *Access* has an effect on *Home*, and this is easily tested. Second, the independence assumption states that *Access* is uncorrelated with any confounders of the *SWB*-*Home* relationship i.e. $Corr(Access, \varepsilon) = 0$. Third, and relatedly, the exclusion restriction assumes that *Access* affects *SWB* only through *Home*. The latter two conditions relate to the validity of the instrument and, if they hold along with instrument relevance, then 2SLS generates a local average treatment effect (LATE) estimate for 'compliers' i.e. the effect of living at home on *SWB* for those induced to do so as a result of coming from a region with good system-wide accessibility to higher education.

It is important to stress here that while the dependent variable relates to a student's *current* wellbeing, the IV relates to accessibility of the area they lived in *prior to* entering higher education. Given this, it seems reasonable to assume that, conditional on the controls included in our model, which include the HEI a student is attending, the instrument and error term are uncorrelated[15]. Nonetheless, in most settings where the IV is not randomly assigned, concerns inevitably arise around the validity of an instrument. For example, in our case, if students with stronger preferences for living at home have higher *SWB* on average, and students from good accessibility regions tend to have stronger preferences for living at home, then $Corr(Access, \varepsilon) \neq 0$[16]. In other words, the independence assumption might not hold and

[15] We also estimated models excluding HEI, which showed very similar findings.
[16] Another example would be if there are systematic differences in current wellbeing between students who come from urban and rural locations, given that students from urban areas generally have better access to higher education.

Access could be a so-called 'imperfect instrument' (Clarke and Matta 2018; Nevo and Rosen 2012). In such circumstances IV estimates will themselves be biased and one possibility to address this is to use partial identification to determine a range of feasible values (i.e. bounds) under weaker, and therefore more credible, assumptions.

To do so, we use Nevo and Rosen's (2012) imperfective IV approach which involves replacing the zero correlation assumption between the IV and the error term with an assumption related to the 'sign' of the correlation[17]. In particular, we assume that (i) the endogenous independent variable (*Home*) and the instrument (*Access*) have the same direction of correlation with the unobserved error term in the IV structural equation and (ii) *Access* is less endogenous than *Home*. This implies that our IV estimate from Equation [4] is a lower bound on the effect of *Home*, but also allows us to estimate an upper bound under these more plausible/credible assumptions. It is also possible to estimate confidence intervals (CIs) associated with these bounds.

A second approach to addressing concerns regarding instrument validity is to again employ Cinelli and Hazlett's (2020) sensitivity analysis tools, but this time for the IV/2SLS regression results. In particular, the method can be used to test how strong the association between ε and *Access* would need to be to drive the coefficient of *Home* to zero. This is because the IV estimate ($\hat{\beta}_{IV}$) can also be calculated as the ratio of the reduced-form estimate ($\hat{\beta}_{RF}$), found from regressing *SWB* on *Access* and the controls, and the first-stage estimate ($\hat{\beta}_{FS}$), found from regressing *Home* on *Access* and the controls i.e. $\hat{\beta}_{IV} = \hat{\beta}_{RF}/\hat{\beta}_{FS}$. Given this, testing how quickly $\hat{\beta}_{RF}$ vanishes to zero due to unobserved confounding can be used to do the same for $\hat{\beta}_{IV}$. For more details, see Cinelli and Hazlett (2022).

[17] This approach is similar to that adopted in Rahman (2022) who shows that their IV findings are robust to allowing for a minor relaxation of the strict exogeneity assumption using an approach set out in Conley et al. (2012). In particular, the paper shows the findings continue to hold if there is a very small correlation between the instruments and the error term in the second stage.

All of the methods so far relate to estimating the total (direct plus indirect) effect of living at home on college student wellbeing. In order to consider commute time more explicitly, the next stage of our empirical approach is to directly model the relationship between *SWB* and commute time. In particular, we estimate linear models of wellbeing for *Home* and *Away* students (overall and by sex) and interpret our estimates as independent associations. We also consider a range of potential pathways/mechanisms through which commute time might impact wellbeing. To do so we first model the relationship between commute time and the individual components of the WHO-5 wellbeing index. We then consider the relationship between commute time and students' degree of satisfaction with their general college experience, degree of satisfaction with their current study programme, work and study constraints, as well as health behaviours and general health.

6 Results

6.1 Selection on observables

Table 3 presents results from linear regression models of *SWB* for the full estimation sample. Model (1), which includes no controls, shows that wellbeing for students living at home is -0.31 lower (6.0% of a SD) compared to those living away, on average. This differential remains relatively stable across Models (2) to (4) but is not statistically significant once the full set of controls is included. Once the mediator variable *Time* (in quartiles) is added the sign switches for the CDE, though the difference remains insignificant. This is in contrast to the large estimated coefficients on the *Time* quartile dummies. For example, Model (5) shows that one-way commute times of 45 mins or more are independently associated with lower *SWB* of 1.09 (21.1% of a SD) relative to commute times of less than 10 mins.

Overall, the results in Table 3 do not suggest practically large differences in wellbeing between *Home* and *Away* students. This conclusion is supported by a range of additional models included in Appendix C, including results from models of *Poor SWB* (Table C1), models estimated by sex (Table C2), inverse probability weighting estimates (Table C3), and ordered logit models of the individual *SWB* components (Table C4). Also presented in Appendix C are results from a set of quantile regression models of *SWB* (Figure C1). These suggest that there may be some differences in effects across the *SWB* distribution. In particular, there is some evidence that the independent association is stronger for students with higher wellbeing.

However, as previously noted, the estimates in Table 3 may be biased and the direction and magnitude of any bias is unclear. To assess the potential implications of this, Figure 6 presents sensitivity contour plots of the *Home* point estimate in Model (4) assuming (a) upward bias and (b) downward bias, relative to the 'unadjusted' estimate of -0.227 (represented at the origin). To aid interpretation, a combination or 'grouping' of the variables *Male* and *Children* is used as a reference for bounds on the plausible strength of confounding[18]. With positive selection (i.e. upward bias), relatively strong bias (relative to the *Male*-*Children* group comparison) suggests that while there is a negative effect of *Home*, overall it may not be practically large. For example, if the cofounding was equivalent to omitting a variable that had five times the confoundedness of the *Male*-*Children* group (5x Male-Children in Figure 6a), the point estimate for *Home* would be -0.38 (see figure in parentheses in Figure 6). With negative selection (i.e. downward bias), even bias that was five times the confoundedness of the *Male*-*Children* group would not be enough to change the sign of the coefficient on *Home* i.e. move from a negative effect (-0.227) to a positive effect. Overall, this sensitivity analysis suggests that the effect of *Home* is likely negative.

[18] Using a group of variables for benchmarking simply involves replacing the individual partial R^2 with the group partial R^2 of those variables in the sensitivity analysis. See Cinelli et al. (2020) for more details.

6.2 Selection on unobservables

Table 4 presents results from separate IV regression models of *SWB* and *Poor SWB* estimated using 2SLS. Both models share the same first stage and the IV is a measure of system-wide accessibility to higher education at county level. The first-stage results show a strong relationship between the endogenous variable *Home* and the instrument *Access*. The estimated coefficient is practically and statistically significant and the first-stage *F* statistic easily exceeds well-known cut-offs for assessing instrument strength (Stock and Yogo 2005; Lee et al. 2022). Thus, our instrument is relevant.

In terms of the second-stage models, the 2SLS estimates suggest a negative effect of living at home on wellbeing, relative to moving, with a point estimate of -0.684 (13.3% of a SD). This is much larger (in absolute terms) than the point estimate from Model (4) in Table 3 (-0.227), implying the OLS estimates of *Home* are biased upwards i.e. positive selection effects dominate. It also suggests that, on average, students with stronger preferences for living at home tend to have better wellbeing. Table 4 also presents a model of *Poor SWB*. It shows that living at home increases the probability of experiencing poor wellbeing by 4.6 percentage points (ppts). While this is a practically large effect, it is not statistically significant for the full analysis sample.

Table 5 presents separate models of *SWB* and *Poor SWB* for female and male students. Again both models share the same first stage by sex and the reported results in Table 5 support instrument relevance. The second stage results suggest the negative effects of living at home in Table 4 are driven mainly by female students. The point estimate is -0.849 for females and statistically significant at 5%, compared to a non-significant -0.284 for males. In addition, the estimated effect of living at home on poor wellbeing is 6.9 ppts for females compared to a non-significant 0.01 for males.

But what if, as discussed, the independence assumption does not hold and *Access* is an imperfect instrument i.e. $Corr(Access, \varepsilon) \neq 0$. This would be the case if, for example, students from better accessibility areas had stronger preferences for living at home. To address such concerns, we employ Nevo and Rosen's (2012) imperfect IV partial identification approach and the results are presented in Table 6. The key assumptions here are that (i) the endogenous independent variable (*Home*) and the instrument (*Access*) have the same direction of correlation with the unobserved error term in the IV structural equation, and (ii) *Access* is less endogenous than *Home*. The implication of these assumptions, in our case, is that the IV estimates presented in Tables 4 and 5 represent lower bound estimates of the effect of *Home* on *SWB*. In other words, assuming that $Corr(Access, \varepsilon) \neq 0$, but that $Corr(Home, \varepsilon)$ and $Corr(Access, \varepsilon)$ have the same sign, implies that our IV estimates are biased downwards. However, Nevo and Rosen's (2012) approach allows us to also estimate upper bounds and, as a result, a range for the total effect.

Table 6 shows that the upper bound estimate for the effect of *Home* for the full sample is -0.371 giving an estimate range for the total effect of living at home on *SWB* of [-0.684, -0.371], which is equivalent to a reduction of 0.072 to 0.133 of a standard deviation. The associated 95% confidence interval (CI) for the range is (-1.288, -0.041), meaning the range is statistically significant at a 5% level. The equivalent range and CI for female students are [-0.849, -0.433] and (-1.596, -0.027), while for males they are [-0.284, -0.234] and (-1.284, 0.324). Thus, this partial identification analysis suggests that living at home while in college has a negative effect on wellbeing for female students, though not for males.

Results from the IV sensitivity analysis are presented in Figure 7, which shows sensitivity contour plots for the variable *Access* in the reduced-form regression of *SWB*. These contours show the reduced-form coefficients $\hat{\beta}_{RF}$ that would be obtained for different levels of residual variation of the unobservables ε with *SWB* (vertical axis) and with *Access* (horizontal axis).

The unadjusted coefficient from the regression is $\hat{\beta}_{RF} = -0.151$, represented at the origin, while the red line corresponds to $\hat{\beta}_{RF} = 0$ at different levels of confoundedness with *SWB* and $Access$. As discussed above, this would also imply that $\hat{\beta}_{IV} = 0$. Figure 8 shows that even with residual confounding five times stronger than the *Male-Children* benchmark used, the coefficient on *Access* would remain negative at $\hat{\beta}_{IV} = -0.04$. In other words, this high level of confounding would not change the qualitative conclusion. Therefore, this sensitivity analysis suggests that the coefficient on *Access* in the IV model is likely negative, even in the presence of confounding, and that living at home while in college reduces wellbeing on average. This conclusion is consistent with findings from the partial identification analysis.

6.3 The role of commute time

As discussed previously, one obvious way that students living at home might be impacted is through longer commutes – see also Figure 2. In this section, we examine the relationship between wellbeing and commute time both for students living at home (with their parents) and away from home and the key results are presented in Table 7. In particular, it includes linear regression models of *SWB* and *Poor SWB* by sex for both groups. All models are estimated using OLS and the estimates are interpreted as independent associations.

Overall Table 7 shows notable differences in the independent relationship between wellbeing and commute time both by sex and by *Home*/*Away* status. First, for female students living at home, longer commutes are independently associated with substantial decreases in *SWB* and large increases in the probability of experiencing *Poor SWB*. For example, for female students with one-way commutes of 45 mins or more, *SWB* is lower by -1.37 (31.2% of a SD) and *Poor SWB* is 13.6 ppts higher compared to a similar student with a commute of less than 10 mins. For both dependent variables, strong gradients in the associations are evident with respect to commute time. In addition, the coefficients on *Time* are much larger (in absolute terms) for female students living at home than for those living away from home, though there is still a negative relationship between wellbeing and commute time for the latter. Nonetheless, it should be noted that the number of students living away from home and undertaking long commutes is relatively small – see Table 2.

Table 7 also shows that the relationship between wellbeing and commute time is much stronger for female students than for male students and this holds for both those living at home and away from home. While there are also gradients with respect to commute time evident in the male student models, the independent associations are weaker in comparison to female students and not statistically significant. Overall, there appears to be a stronger relationship between commute time and wellbeing for female students and this seems a likely reason for the stronger negative effects of living at home for this group. In particular, the results in Table 7 suggest that female students living at home but far from college are most negatively affected by commuting.

6.4 Pathways and mechanisms

This section considers possible pathways and mechanisms through which longer commute times might impact student wellbeing. First, in terms of pathways, we consider the independent relationship between commute time and the individual components of the WHO-5 wellbeing index using ordered logistic regression models for students living at home with their parents. This descriptive analysis tells us which specific aspects of wellbeing exhibit the strongest relationship with commute time for this group. Next, a wide range of potential mechanisms relating to students' degree of satisfaction with their general college experience, degree of satisfaction with their current study programme, work and study constraints, as well as health behaviours and general health, are considered. Again, the analysis presented here is descriptive and considers the extent to which there are differences in these potential mechanisms by commute time quartiles for female and male students separately. Kruskal-Wallis tests are employed to test for statistically significant differences for ordinal variables across commute time quartiles, while one-way analysis of variance (ANOVA) is used to test for differences in the means of continuous variables.

Table 8 presents partial effect estimates for quartiles of commute time from separate ordered logit models for each of the five WHO-5 wellbeing index components for female and male students living at home with their parents[19]. These partial effects show the estimated percentage point change in the probability of reporting a given level of component wellbeing (e.g., *All of the time*) for each commute time quartile relative to the base quartile (i.e., 0-10 mins), holding all other variables in the model constant. In other words, the estimates can be interpreted as showing, for each component, the difference in the distribution across commute time quartiles relative to the base. For example, the partial effect of -0.101 for *Most of the time* for *Commute Time Quartile 4* in the *Cheerful* model for females shows that female students in the longest commute category are 10.1 ppts less likely to be cheerful most of the time when compared to a similar female student with a very short commute.

In terms of the key results, Table 8 shows distinct differences by sex and by component in terms of the independent relationships. For female students, the strongest independent association with commute time quartile is for the *Cheerful* component, with broadly similar, but less strong, associations with the *Calm*, *Fresh,* and *Interest* components. Most notably there are practically large differences in the distributions of all four of these components when comparing commute time quartile 4 to quartile 1, and also differences between quartiles 3 and 1 for *Cheerful* and *Calm*. The partial effects for *Active* are generally smaller and not statistically significant, suggesting there is less of a difference in the distribution of this component across commute time quartiles. Overall, this implies that female students with long commutes are less

[19] For comparison, Table C4 presents ordered logit model estimates of the partial effects of *Home* for each of the *SWB* components.

likely to feel cheerful and in good spirits, to feel calm and relaxed, to wake up feeling fresh and rested, or to have a daily life filled with things of interest. For male students the picture is very different. The magnitudes of the partial effects suggest the differences in distributions across quartiles for all components are much smaller than for females, while none of the partial effects are statistically significant. This difference by sex is consistent with the main analysis presented for *SWB* in Table 7.

Table 9 presents an overview of the findings from the descriptive analysis relating to potential mechanisms and full details of all the tests are presented in Appendix D Tables D1 to D4. For example, Table 9 shows there are statistically significant differences by commute time quartile in both female and male students' satisfaction with their friendships. Appendix Table D1 provides full details of the tests relating to general college experience, including a breakdown of satisfaction by commute time quartile and overall. It shows that 35.9% of female students with quartile 4 commutes are very satisfied with their friendships compared to 43.5% of female students with quartile 1 commutes, while the Kruskal-Wallis test statistic is $\chi^2(3) = 15.74$ with a p value of 0.001. Similar differences are evident for male students. Given the large amount of results associated with these tests, they are summarised in Table 9 and an overview of the main findings is presented below.

Starting with students' degree of satisfaction with their general college experience, Table 9 and Appendix Table D1 show that female students with longer commutes tend to have high levels of satisfaction with their accommodation, presumably because most are living at home. However, they are less satisfied with their financial/material wellbeing, friendships, studies, and college. For male students, there are similar patterns for accommodation, friendships, and college. Overall, this suggests that while students with longer commutes might benefit from living at home in terms of better-quality accommodation, they may be losing out on other important aspects associated with a positive college experience, which could impact wellbeing.

There are also notable differences in female students' degree of satisfaction with their current study programme – full results are available in Appendix Table D2 and summarised in Table 9. For example, there are differences by commute time quartiles with respect to quality of teaching, organisation of studies and timetable, as well as teaching staff's attitude towards students. In all cases, longer commutes tend to be correlated with lower levels of satisfaction, suggesting long commutes are associated with problems with academic engagement for female students. The same is not the case for male students, where no statistically significant differences are evident by quartile.

Table 9 also presents an overview of differences with respect to work and study constraints – full results are presented in Appendix Table D3. Interestingly, while female students with longer commutes are more likely to work during the semester, and more likely to work longer hours, there are no differences across quartiles in terms of how jobs affect academic performance or the amount of time allocated to course time or personal study time. For male students there are no differences by commute time in relation to the work and study constraint variables considered. Overall, these results do not suggest a strong relationship between commute time and work and study constraints for either female or male students.

Finally, differences in health behaviours and general health are also summarised in Table 9 with full details presented in Appendix Table D4. Both male and female students with longer commutes are less likely to consume alcohol frequently, presumably in part due to fewer opportunities for social activities when commuting. There are no significant differences in smoking or exercise frequency for female and male students by commute time quartile. In terms of general health, longer commutes are associated with more frequent headaches and higher levels of stress for female and male students, while there are no differences in terms of frequency of colds, sleeping problems, or concentration problems. Overall, these results suggest that the health of students with longer commutes could be negatively affected by more frequent headaches and increased stress, which could in part explain the lower levels of wellbeing for this group. However, given the descriptive nature of the analysis presented here, it is important not to over-interpret these findings. Instead, they should be considered as suggestive evidence and potentially used to inform future research.

7 Conclusion

To date, little research has been undertaken on the impact of commuting on the wellbeing of college students. This is despite the fact that student wellbeing is an increasing focus of many HEIs and policymakers and that commuting is a common feature of everyday life for significant proportions of students. This paper analyses the relationship between living arrangements, commute time, and wellbeing for undergraduate college students in Ireland. It finds that living at home reduces wellbeing by between 0.07 and 0.13 of a standard deviation overall, with these effects driven mainly by female students. In addition, longer commute times are found to be independently associated with substantial increases in poor wellbeing for female students living at home.

While novel in the context of college students, our results are consistent with previous findings relating to the so-called *commuter paradox*. Standard microeconomic theory suggests that any disutility from commuting should be compensated by other factors relating to where an individual chooses to live and/or work/study. The rationale is that individuals will weigh up the relative costs and benefits when choosing where to live, implying there should be no statistical relationship between commuting patterns and wellbeing. However, such a framework makes less sense in the context of college student commuting. Given the often significant costs involved in moving to attend college, the only option for many students will be to live at home and commute. As a result, while there may be benefits from residing at home while studying, these can be more than offset by a long commute.

Our results are also consistent with gender disparities in the effect of commuting on wellbeing in the general population. Previous research suggests that such differential effects may be a result of females' greater responsibility for day-to-day household tasks, including childcare and housework (Roberts et al. 2011). The reasons are likely different in our context and we present suggestive evidence that while students with longer commutes might benefit from living at home in terms of better-quality accommodation, they may be losing out on other important aspects associated with a positive college experience. For female students, this includes potential negative effects of long commutes on friendships and their studies. We also find notable differences in female students' degree of satisfaction with their current study programme, including the quality of teaching, organisation of studies and timetable, and teaching staff's attitude towards students. Previous research has shown that younger females tend to be more conscientious than males and this could be playing a role in these findings (Vecchione et al. 2012; Verbree et al. 2023). We find no relationship between commute time and work or study constraints, but do find that students with longer commutes suffer more frequent headaches and stress. In addition, while our results suggest that female commuters may be more negatively impacted in terms of social and academic engagement, it could also be the case that female students suffer a greater disutility from commute time compared to males.

In terms of addressing the issue, it is likely that a mix of short- and longer-term policy responses are required across a range of stakeholders. In the Irish context, one obvious current issue relates to a shortfall of suitable and affordable student accommodation, including on-campus accommodation. This will take time to address and it is likely that both HEIs and national policymakers have important roles to play. In terms of more short-term measures, there is no shortage of practical actions that HEIs can consider to assist commuter students. While these are likely to be context-specific, they include adjustments to timetables to include later starts, or blocked timetables to help reduce the number and/or timing of days that commuter students need to be on campus. In terms of social integration, holding more events during the day and the creation of commuter common rooms could be considered. Maguire and Morris (2017) also discuss a range of other possible measures. These include adapting welcome and induction activities, providing better advice and guidance about commuting, matching the curriculum and assessment models to commuter students' needs, as well as creating online commuter support communities with activities close to commuter students' homes.

References

Abou-Zeid M, Ben-Akiva M (2011) The effect of social comparisons on commute well-being. Transp Res Part A Policy Pract 45(4):345–361

Allen J, Farber S (2018) How time-use and transportation barriers limit on-campus participation of university students. Travel Behav Soc 13:174–182

Alonso W (1964) Location and land use: Toward a general theory of land rent. Harvard University Press, Cambridge

American Council on Education (2021) College and university presidents respond to Covid-19: 2021 spring term survey. American Council on Education, TIAA Institute

Australian Department of Education, Skills and Employment (2019) Performance-based funding for the Commonwealth Grant Scheme. Report for the Minister for Education, Commonwealth of Australia

Bergstad C, Gamble A, Gärling T, et al. (2011) Subjective well-being related to satisfaction with daily travel. Transportation 38(1):1–15

Bolotnyy V, Basilico M, Barreira P (2022) Graduate student mental health: lessons from American economics departments. J Econ Lit 60(4):1188–1222

Bruffaerts R, Mortier P, Kiekens G, et al. (2018) Mental health problems in college freshmen: prevalence and academic functioning. J Affect Disorders 225:97–103

Chatterjee K, Chng S, Clark B, et al. (2020) Commuting and wellbeing: a critical overview of the literature with implications for policy and future research. Transport Rev 40(1):5–34

Chickering A (1974) Commuting versus resident students. Jossey-Bass, San Francisco

Cinelli C, Forney A, Pearl J (2022) A crash course in good and bad controls. Sociol Method Res. https://doi.org/10.1177/00491241221099552

Cinelli C, Hazlett C (2020) Making sense of sensitivity: extending omitted variable bias. J R Stat Soc Series B 82(1):39–67

Cinelli C, Hazlett C (2022) An omitted variable bias framework for sensitivity analysis of instrumental variables. SSRN. https://ssrn.com/abstract=4217915

Clarke D, Matta B (2018) Practical considerations for questionable IVs. Stata J 18(3):663–691

Coates D, Anand P, Norris M (2021) A review essay on housing, subjective wellbeing and the capabilities approach. Economics Literature 3(2):1–33

Conley TG, Hansen CB, Rossi PE (2012) Plausibly exogenous. Rev Econ Stat 94(1): 260–272

Coutts S, Aird B, Mitra R, Siemiatycki M (2018) Does commute influence post-secondary students' social capital? A study of campus participation at four universities in Toronto, Canada. J Transp Geogr 70:172–181

Cullinan J, Duggan J (2016) A school-level gravity model of student migration flows to higher education institutions. Spat Econ Anal 11(3):294–314

Cullinan J, Flannery D (2022) Distance matters: Geographic accessibility and higher education participation decisions. In: Mendolia S, O'Brien M, Paloyo A, Yerokhin O (eds) Critical perspectives on economics of education. Routledge, London pp 213–236

Cullinan J, Flannery D, Walsh S, McCoy S (2013) Distance effects, social class and the decision to participate in higher education in Ireland. Econ Soc Rev 44(1):19–51

Cullinan J, Halpin B (2017) A spatial economic perspective on higher education choices. In: Cullinan J, Flannery D (eds) Economic insights on higher education policy in Ireland: evidence from a public system. Palgrave Macmillan, pp 53–80

Cullinan J, Hynes S, O'Donoghue C (2008) Estimating catchment area population indicators using network analysis. Ir Geogr 41(3):279–294

Cullinan J, Walsh S, Flannery D, Kennelly B (2022) A cross-sectional analysis of psychological distress among higher education students in Ireland. Ir J Psychol Med. https://doi.org/10.1017/ipm.2022.2

De Neve J-E, Oswald A (2012) Estimating the influence of life satisfaction and positive affect on later income using sibling fixed-effects. Proc Natl Acad Sci USA 109(49):19953–19958

De Vos J, Schwanen T, Van Acker V, Witlox F (2013) Travel and subjective well-being: A focus on findings, methods and future research needs. Transport Rev 33(4):42142

De Vos J, Mokhtarian P, Schwanen T, Van Acker V, Witlox F (2016) Travel mode choice and travel satisfaction: bridging the gap between decision utility and experienced utility. Transportation 43(5):771–796

Dickerson A, Hole A, Munford L (2014) The relationship between well-being and commuting revisited: does the choice of methodology matter? Reg Sci Urban Econ 49:321–329

Diener E (2009) The science of well-being: the collected works of Diener. Social Indicators Research Series, Volume 37. Springer, Dordrech

Donnelly M, Gamsu S (2018) Home and away: social, ethnic and spatial inequalities in student mobility. Sutton Trust/University of Bath. https://www.suttontrust.com/wp-content/uploads/2019/12/Home_and_away_FINAL.pdf

Eisenberg D, Golberstein E, Gollust S (2007) Help-seeking and access to mental health care in a university student population. Med Care 45(7):594–601

Eisenberg D, Golberstein E, Hunt J (2009) Mental health and academic success in college. BE J Econ Anal Poli 9(1):40

Ettema D, Gärling T, Eriksson L, Friman M, Olsson L, Fujii S (2011) Satisfaction with travel and subjective well-being: development and test of a measurement tool. Transportation Res F--Traf 14(3):167–175

Ettema D, Gärling T, Olsson L, Friman M (2010) Out-of-home activities, daily travel, and subjective well-being. Transport Res A-Pol 44(9):723–732

Evans G, Wener R, Phillips D (2002) The morning rush hour: predictability and commuter stress. Environ Behav 34(4):521–530

Flannery D, Cullinan J (2014) Where they go, what they do and why it matters: the importance of geographic accessibility and social class for decisions relating to higher education institution type, degree level and field of study. App Econ 46(24):2952–2965

Frey B, Stutzer A (2014) Economic consequences of mispredicting utility. J Happiness Stud 15:937–956

Friman M, Gärling T, Ettema D, Olsson L (2017) How does travel affect emotional well-being and life satisfaction? Transport Res A-Pol 106:170–180

Frijters P, Clark A, Krekel C, Layard R (2020) A happy choice: wellbeing as the goal of government. Behavioural Public Policy 4(2):126–165

Gatersleben B, Uzzell D (2007) Affective appraisals of the daily commute: comparing perceptions of drivers, cyclists, walkers, and users of public transport. Environ Behav 39(3):416–431

Giménez-Nadal J, Molina J, Velilla J (2023) Commuting, family, and wages. In: Zimmermann K (ed) Handbook of labor, human resources and population economics. Springer, Cham, pp 1–13

Goldman-Mellor S, Avshalom C, Harrington H, et al. (2014) Suicide attempt in young people: a signal for long-term health care and social needs. JAMA Psychiat 71(2):119–127

Gottholmseder G, Nowotny K, Pruckner G, Theurl E (2009) Stress perception and commuting. Health Econ 18(5):559–576

Gu Y, Guo N, Wu J, Zou B (2021) Home location choices and the gender commute gap. J Human Resour. https://doi.org/10.3368/jhr.1020-11263R2

Harmon D, Foubert O (2013) Eurostudent Survey V: Report on the social and living conditions of higher education students in Ireland 2013. Insight Statistical Consulting, Dublin

Hauschildt K, Gwosć G, Schirmer H, Wartenbergh-Cras F (2021) Social and economic conditions of student life in Europe: Eurostudent VII synopsis of indicators 2018-2021. https://www.eurostudent.eu/download_files/documents/EUROSTUDENT_VII_Synopsis_of_Indicators.pdf

Hauschildt K, Gwosć C, Netz N, Mishra S (2015) Social and economic conditions of student life in Europe: Eurostudent V synopsis of indicators 2012–2015. https://www.Eurostudent.eu/download_files/documents/EVSynopsisofIndicators.pdf

Henry E, Cullinan J (2021) Mental health spillovers from serious family illness: Doubly robust estimation using EQ-5D-5L population normative data. Soc Sci Med 279:113996

Huriot J-M, Thisse J-F (2000) Economics of cities: theoretical perspectives. Cambridge University Press, Cambridge

Hysenbegasi A, Hass S, Rowland C (2005) The impact of depression on the academic productivity of university students. J Ment Health Policy 8(3):145–151

Indecon (2022) Review of the student grant scheme. https://www.indecon.ie/assets/files/pdf/report_on_indecon_review_of_the_student_grant_scheme.pdf

Jacob N, Munford L, Rice N, Roberts J (2019) The disutility of commuting? The effect of gender and local labor markets. Reg Sci Urban Econ 77:264–275

Kahneman D, Krueger A, Schkade D, Schwarz N, Stone A (2004) A survey method for characterizing daily life experience: the day reconstruction method. Science 306(5702):1776–1780

Kahneman D, Wakker P, Sarin R (1997) Back to Bentham? explorations of experienced utility. Q J Econ 112(2):375–405

Kelchen R (2018) A look at college students' living arrangements. https://robertkelchen.com/2018/05/28/a-look-at-college-students-living-arrangements/#_ftn2.

Kerr D, Capaldi D (2011) Young men's intimate partner violence and relationship functioning: long-term outcomes associated with suicide attempt and aggression in adolescence. Psychol Med 41(4):759–769

Kobus M, Van Ommeren J, Rietveld P (2015) Student commute time, university presence and academic achievement. Reg Sci Urban Econ 52:129–140

Koslowsky M, Kluger A, Reich M (1995) Commuting stress: causes, effects and methods of coping. Plenum, New York

Kuh G, Kinzie J, Buckley J, Bridges B, Hayek J (2007) Piecing together the student success puzzle: research, propositions, and recommendations. ASHE Higher Education Report, v32, n5. https://eric.ed.gov/?id=EJ791634

Künn-Nelen A (2016) Does commuting affect health? Health Econ 25(8):984–1004

Larcombe W, Finch S, Sore R, et al. (2016) Prevalence and socio-demographic correlates of psychological distress among students at an Australian university. Stud High Educ 41(6):1074–1091

Le Barbanchon T, Rathelot R, Roulet A (2021) Gender differences in job search: trading off commute against wage. Q J Econ 136(1):381–426

Lee D, McCrary J, Moreira M, Porter J (2022) Valid t-ratio inference for IV. Am Econ Rev 112(10):3260–3290

Lewis J, Bolton P (2023) Student mental health in England: statistics, policy and guidance. House of Commons Research Briefing. House of Commons Library, London

Lipson S, Lattie E, Eisenberg D (2019) Increased rates of mental health service utilization by U.S. college students: 10-year population-level trends (2007–2017). Psychiatr Serv 70(1):60–63

Lipson S, Zhou S, Abelson S, et al. (2022) Trends in college student mental health and help-seeking by race/ethnicity: findings from the National Healthy Minds Study, 2013–2021. J Affect Disorders 306:138–147

Liu J, Ettema D, Helbich M (2022) Systematic review of the association between commuting, subjective wellbeing and mental health. Travel Behaviour and Society 28:59–74

Liu S, Su Y (2022) The geography of jobs and the gender wage gap. Rev Econ Stat. https://doi.org/10.1162/rest_a_01188

Lockwood-Reynolds C (2020) The effect of dormitory residence during college on student outcomes. J Hum Capital 14(2):249–289

Lorenz O (2018) Does commuting matter to subjective well-being? J Transp Geogr 66:180–199

Maguire D, Morris D (2018) Homeward bound: defining, understanding and aiding commuter students. Higher Education Policy Institute, Oxford

Matsudaira J (2016) Economic conditions and the living arrangements of young adults: 1960 to 2011. J Popul Econ 29:167–195

Muth R (1969) Cities and housing. University of Chicago Press, Chicago

National Centre for Education Statistics (2016) Full-time postsecondary students in 2011-12. US Department of Education, NCES 2016-136. https://nces.ed.gov/pubs2016/2016136.pdf

Nevo A, Rosen A (2012) Identification with imperfect instruments. Rev Econ Stat 94(3):659–671

Niederkrotenthaler T, Tinghög P, Alexanderson K, et al. (2014) Future risk of labour market marginalization in young suicide attempters – a population-based prospective cohort study. Int J Epidemiol 43(5):1520–1530

O’Donnell G, Deaton A, Durand M, Halpern D, Layard R (2014) Wellbeing and policy. Legatum Institute, London

Parker J, Yacoub A, Mughal S, Mamari F (2023) Family support and psychological distress among commuter college students. J Am Coll Health 71(2):479–488

Pearl J (2009) Causality. Cambridge University Press

Porru F, Robroek S, Bültmann U, et al. (2021) Mental health among university students: the associations of effort-reward imbalance and overcommitment with psychological distress. J Affect Disorders 282:953–961

Putnam R (2000) Bowling alone: the collapse and revival of the American community. Simon & Schuster

Rahman K (2023) International migration and the religious schooling of children in the home country: Evidence from Bangladesh. J Popul Econ 36:1963–2005

Roberts J, Hodgson R, Dolan P (2011) “It’s driving her mad”: gender differences in the effects of commuting on psychological health. J Health Econ 30(5):1064–1076

Sá C, Florax R, Rietveld P (2004) Determinants of the regional demand for higher education in the Netherlands: a gravity model approach. Reg Stud 38(4):375–392

Scott K, Lim C, Al-Hamzawi A, et al. (2016) Association of mental disorders with subsequent chronic physical conditions: World Mental Health Surveys From 17 Countries. JAMA Psychiat 73(2):150–158

Sen A (1993) Capability and wellbeing. In: Nussbaum M, Sen A (eds) The quality of life. Clarendon Press, Oxford, pp 30–53

Simón H, Casado-Díaz J, Lillo-Bañuls A (2020) Exploring the effects of commuting on workers’ satisfaction: evidence for Spain. Reg Stud 54(4):550–562

Spiess CK, Wrohlich K (2010) Does distance determine who attends a university in Germany? Econ Educ Rev 29(3):470–479

Stiglitz J, Sen A, Fitoussi J-P (2009) Report by the Commission on the measurement of economic performance and social progress. Commission on the Measurement of Economic Performance and Social Progress, Paris

St-Louis E, Manaugh K, van Lierop D, El-Geneidy A (2014) The happy commuter: a comparison of commuter satisfaction across modes. Transport Res Part F-Traf 26(Part A):160–170

Stock J, Yogo M (2005) Testing for weak instruments in linear IV regression. In: Andrews D, Stock J (eds) Identification and inference for econometric models. Cambridge University Press, New York, pp 80–108

Stutzer A, Frey B (2008) Stress that doesn't pay: the commuting paradox. Scand J Econ 110(2):339–366

Tao Y, van Ham M, Petrović A, Ta N (2023) A household perspective on the commuting paradox: longitudinal relationships between commuting time and subjective wellbeing for couples in China. Transport Res A-Pol 170:103640

Thomas L, Jones R (2017) Student engagement in the context of commuter students. The Student Engagement Partnership, UK

Tiebout C (1956) A pure theory of local expenditure. J Polit Econ 64(5):416–24

Topp C, Østergaard S, Søndergaard S, Bech P (2015) The WHO-5 well-being index: a systematic review of the literature. Psychother Psychosom 84(3):167–76

Vecchione M, Alessandri G, Barbaranelli C, Vittorio Caprara G (2012) Gender differences in the Big Five personality development: a longitudinal investigation from late adolescence to emerging adulthood. Pers Indiv Differ 53(6):740–746

Verbree A-R, Hornstra L, Maas L, Wijngaards-de Meij L (2023) Conscientiousness as a predictor of the gender gap in academic achievement. Res High Educ 64(3):451–72

Walsh S, Cullinan J (2017) Factors influencing higher education institution choice. In: Cullinan J, Flannery D (eds) Economic insights on higher education policy in Ireland: evidence from a public system. Palgrave Macmillan, pp 81–108

Walsh S, Cullinan J, Flannery D (2017) Geographic inequalities in university accessibility in Ireland – modelling the impact of proposed higher education reforms. Appl Spat Anal Polic 10(4):515–36

Walsh S, Flannery D, Cullinan J (2015) Geographic accessibility to higher education on the island of Ireland. Irish Educ Stud 34(1):5–23

Walsh S, Flannery D, Cullinan J (2018) Student preferences for the attributes of higher education institutions: a discrete choice experiment. Education Economics 26(2):161–78

Wang X, Rodríguez D, Sarmiento O, Guaje O (2019) Commute patterns and depression: evidence from eleven Latin American cities. J Transp Health 14:100607

Webb O, Turner R (2020) The association between residential arrangements and academic performance in UK university students. Journal of Further and Higher Education 44(10):1320–34

WHO (1998) Wellbeing measures in primary health care/The Depcare Project. WHO Regional Office for Europe, Copenhagen

Tables

Table 1 Variable Definitions and Sample Descriptive Statistics

Variable	Definition	Mean (SD) or %
Dependent Variables		
SWB	WHO-5 wellbeing index score	12.33 (5.14)
Poor SWB	=1 if <13 on WHO-5 index	50.70%
Independent Variables		
Home	Lives at home while in college	46.15%
Time	One-way commute time in minutes	31.22 (29.67)
Age	Age in years	20.92 (1.70)
Sex	Female	67.01%
	Male	32.99%
Nationality	Irish citizen through birth	80.31%
	Naturalised Irish citizen	14.47%
	Foreign national resident in Ireland	5.03%
	Not reported	0.18%
Children	Has children	0.77%
	Does not have children	97.50%
	Not reported	1.73%
Disability	No disability	82.06%
	Disability - no obstacle to studies	4.42%
	Disability - minor obstacle to studies	2.91%
	Disability - medium obstacle to studies	3.45%
	Disability - major obstacle to studies	5.00%
	Disability - big obstacle to studies	2.03%
	Not reported	0.13%
HEI	Higher education institution attended	See Appendix B
Course	Current main area of study	See Appendix B
Year	1st year of study	30.85%
	2nd	28.93%
	3rd	22.49%
	4th	13.48%
	5th or more	4.24%
Programme	Higher Certificate	2.30%
	Diploma	0.38%
	Ordinary Bachelor Degree	15.61%
	Honours Bachelor Degree	81.72%
Income	Total monthly disposable income (€)	455.93 (410.45)
Social Class	Student assessment of family's social standing from 1 (low) to 10 (high)	5.20 (1.47)
Instrumental Variable		
Access	System-wide accessibility measure	6.79 (1.13)
N		5,562

Notes: Breakdowns for the variables *HEI* and *Course* are presented in Appendix B Table B1 due to the relatively large numbers of categories in each.
Source: Analysis of Eurostudent survey data for Ireland for 2013.

Table 2 One-Way Commute Times for *Home* and *Away* Students

	Home		*Away*	
	N	%	N	%
Time				
<10 mins	166	6.47%	1,438	48.01%
10-20 mins	406	15.82%	975	32.55%
20-45 mins	805	31.36%	392	13.09%
45+ mins	1,190	46.36%	190	6.34%
N	2,567		2,995	

Note: This table presents a breakdown of one-way commute times by commute time quartiles for *Home* and *Away* students.
Source: Analysis of Eurostudent survey data for Ireland for 2013.

Table 3 Linear Regression Models of *SWB*

	Dependent Variable: *SWB*				
	(1)	(2)	(3)	(4)	(5)
Home	-0.308**	-0.369***	-0.239*	-0.227	0.243
	(0.138)	(0.135)	(0.144)	(0.147)	(0.178)
Time					
10-20 mins					-0.293
					(0.189)
20-45 mins					-0.671***
					(0.220)
45+ mins					-1.085***
					(0.233)
Controls					
Personal	N	Y	Y	Y	Y
Higher Education	N	N	Y	Y	Y
Socioeconomic	N	N	N	Y	Y
Mean Dep. Var.	12.33	12.33	12.33	12.33	12.33
R^2	0.001	0.050	0.071	0.089	0.093
N	5,562	5,562	5,562	5,562	5,562

Notes: This table presents results from linear regression models of *SWB* estimated using OLS. The main independent variable of interest is *Home* and all variables, including the controls, are defined in Table 1. * p<0.1, ** p<0.05, *** p<0.01.
Source: Analysis of Eurostudent survey data for Ireland for 2013.

Table 4 IV Regression Models of *SWB* and *Poor SWB*

	1st Stage *Home*	2nd Stage *SWB*	2nd Stage *Poor SWB*
Access	0.221***		
	(0.006)		
Home		-0.684**	0.046
		(0.308)	(0.030)
Controls			
Personal	Y	Y	Y
Higher Education	Y	Y	Y
Socioeconomic	Y	Y	Y
First stage *F*	1586.15		
Mean Dep. Var.	0.462	12.33	0.507
R^2	0.364	0.087	0.058
N	5,562	5,562	5,562

Note: This table presents results from separate IV regression models of *SWB* and *Poor SWB* estimated using 2SLS. Both models share the same first stage and the IV is a measure of system-wide accessibility to higher education at county level. The main independent variable of interest is *Home* and all variables, including the controls, are defined in Table 1. * p<0.1, ** p<0.05, *** p<0.01.
Source: Analysis of Eurostudent survey data for Ireland for 2013.

Table 5 IV Regression Models of *SWB* and *Poor SWB* by Sex

	Female			Male		
	1st Stage *Home*	2nd Stage *SWB*	2nd Stage *Poor SWB*	1st Stage *Home*	2nd Stage *SWB*	2nd Stage *Poor SWB*
Access	0.220***			0.228***		
	(0.007)			(0.010)		
Home		-0.849**	0.069*		-0.284	0.005
		(0.381)	(0.037)		(0.510)	(0.051)
Controls						
Personal	Y	Y	Y	Y	Y	Y
Higher Education	Y	Y	Y	Y	Y	Y
Socioeconomic	Y	Y	Y	Y	Y	Y
First stage *F*	1043.03			541.75		
Mean Dep. Var.	0.440	11.99	0.533	0.505	13.02	0.453
R^2	0.361	0.086	0.056	0.387	0.109	0.091
N	3,727	3,727	3,727	1,835	1,835	1,835

Note: This table presents results from separate IV regression models of *SWB* and *Poor SWB* for females and males estimated using 2SLS. Both models for females and males respectively share the same first stage and in all cases the IV is a measure of system-wide accessibility to higher education at NUTS3 regional level. The main independent variable of interest is *Home* and all variables, including the controls, are defined in Table 1. * p<0.1, ** p<0.05, *** p<0.01.

Source: Analysis of Eurostudent survey data for Ireland for 2013.

Table 6 Nevo and Rosen (2012)'s Imperfect IV Bounds

	Home			
	Lower Bound CI	Lower Bound Estimate	Upper Bound Estimate	Upper Bound CI
Total Effect				
Full Sample	-1.288	-0.684	-0.371	-0.041
Females	-1.596	-0.849	-0.433	-0.027
Males	-1.284	-0.284	-0.234	0.324

Note: This table presents bounds estimates of the effect of *Home* on *SWB* assuming that *Access* is an invalid instrument. In particular, it shows results using the Imperfect IV approach of Nevo and Rosen (2012) under the assumptions that: (i) the endogenous independent variable (*Home*) and the instrument (*Access*) have the same direction of correlation with the unobserved error term in the IV structural equation; and, (ii) *Access* is less endogenous than *Home*.
Source: Analysis of Eurostudent survey data for Ireland for 2013.

Table 7 Linear Regression Models of *SWB* and *Poor SWB* for *Home* and *Away* Students by Sex

	Female				Male			
	SWB		*Poor SWB*		*SWB*		*Poor SWB*	
	Home	*Away*	*Home*	*Away*	*Home*	*Away*	*Home*	*Away*
Time								
10-20 mins	-0.476	-0.283	0.035	0.021	0.379	-0.475	-0.072	0.019
	(0.582)	(0.262)	(0.057)	(0.025)	(0.902)	(0.369)	(0.089)	(0.036)
20-45 mins	-1.008*	-0.646*	0.099*	0.055*	-0.678	-0.371	0.033	0.024
	(0.538)	(0.341)	(0.053)	(0.033)	(0.856)	(0.493)	(0.085)	(0.049)
45+ mins	-1.371***	-0.960**	0.136***	0.096**	-0.966	-0.668	0.084	0.024
	(0.528)	(0.480)	(0.052)	(0.046)	(0.845)	(0.736)	(0.084)	(0.073)
Controls								
Personal	Y	Y	Y	Y	Y	Y	Y	Y
Higher Education	Y	Y	Y	Y	Y	Y	Y	Y
Socioeconomic	Y	Y	Y	Y	Y	Y	Y	Y
Mean Dep. Var.	11.79	12.09	0.553	0.523	12.86	13.06	0.459	0.453
R^2	0.115	0.104	0.094	0.072	0.133	0.137	0.124	0.129
N	1,597	2,243	1,597	2,243	901	1,058	901	1,058

Note: This table presents results from linear regression models of *SWB* and *Poor SWB* for *Home* and *Away* students, by sex, estimated using OLS. The main independent variable of interest is one-way commute time and all variables, including the controls, are defined in Table 1. * p<0.1, ** p<0.05, *** p<0.01.
Source: Analysis of Eurostudent survey data for Ireland for 2013.

Table 8 Ordered Logit Model Partial Effect Estimates of *Time* for SWB Components for *Home* Students by Sex

	Female					*Male*				
	Cheerful	Calm	Active	Fresh	Interest	Cheerful	Calm	Active	Fresh	Interest
Commute Time Quartile 2										
At no time	0.003	0.018	-0.005	0.009	0.006	0.002	0.003	-0.009	-0.044	-0.007
Some of the time	0.025	0.043	-0.008	0.006	0.021	0.008	0.013	-0.022	-0.037	-0.026
Less than half	0.018	0.018	-0.005	-0.001	0.010	0.007	0.008	-0.021	0.003	-0.014
More than half	0.010	-0.018*	0.005	-0.006	-0.005	0.004	0.001	0.002	0.029	0.002
Most of the time	-0.044	-0.052	0.011	-0.006	-0.023	-0.015	-0.019	0.036	0.040	0.029
All of the time	-0.012	-0.009	0.002	-0.002	-0.009	-0.005	-0.006	0.014	0.009	0.016
Commute Time Quartile 3										
At no time	0.005**	0.020**	0.018	0.025	0.012	0.006	0.009	0.013	-0.019	0.005
Some of the time	0.047**	0.048**	0.027	0.016	0.038	0.028	0.036	0.030	-0.014	0.016
Less than half	0.031**	0.020	0.013	-0.004	0.016	0.021	0.020	0.022	0.003	0.007
More than half	0.014	-0.021**	-0.019	-0.017	-0.011*	0.010	-0.001	-0.011	0.012	-0.003
Most of the time	-0.078**	-0.057*	-0.033	-0.017	-0.041	-0.050	-0.049	-0.041	0.015	-0.017
All of the time	-0.019*	-0.010	-0.006	-0.004	-0.015	-0.016	-0.015	-0.014	0.003	-0.008
Commute Time Quartile 4										
At no time	0.007***	0.024**	0.020	0.062**	0.017**	0.007	0.010	0.017	-0.006	0.008
Some of the time	0.063***	0.057**	0.029	0.034**	0.050**	0.034	0.041	0.039	-0.004	0.029
Less than half	0.039***	0.022*	0.014	-0.013***	0.020*	0.025	0.022	0.027	0.001	0.012
More than half	0.014	-0.026***	-0.020	-0.038**	-0.015***	0.011	-0.002	-0.015	0.004	-0.007
Most of the time	-0.101***	-0.066**	-0.036	-0.037*	-0.053*	-0.059	-0.054	-0.051	0.004	-0.029
All of the time	-0.023**	-0.012*	-0.006	-0.008*	-0.019*	-0.018	-0.017	-0.017	0.001	-0.013
Controls										
Personal	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Higher Education	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Socioeconomic	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	1,597	1,597	1,597	1,597	1,597	901	901	901	901	901

Notes: This table presents partial effect estimates for quartiles of commute time from separate ordered logit models of each of the five WHO-5 wellbeing index components. See Figure A1 for full definitions of these components and Table A1 for sample descriptive statistics. *Commute Time Quartile 1* is the base and represents a commute of 0-10 mins, while *Commute Time Quartiles 2, 3, and 4* represents commutes of 10-20 mins, 20-45 mins, and 45 mins or more respectively. All other variables, including the controls, are defined in Table 1. * p<0.1, ** p<0.05, *** p<0.01.
Source: Analysis of Eurostudent survey data for Ireland for 2013.

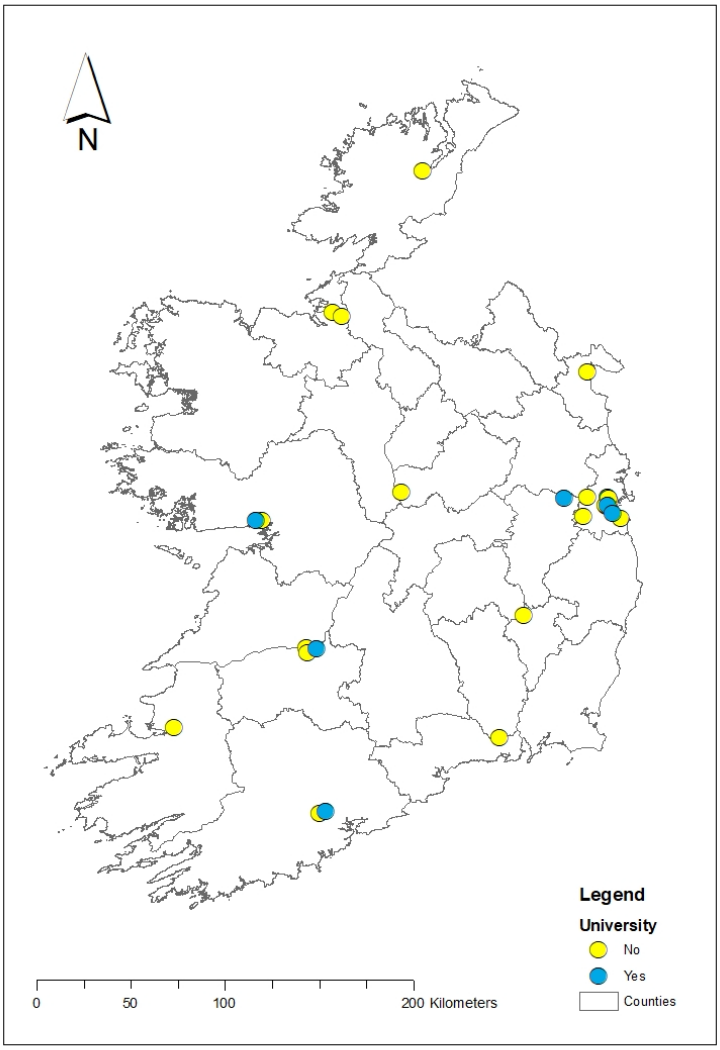
Table 9 Potential Mechanisms: Differences by Commute Time Quartiles

	Differences?	
	Female	Male
Satisfaction with General College Experience		
Your Accommodation	Yes***	Yes***
Your Financial/Material Wellbeing	Yes***	No
Your Friendships	Yes***	Yes***
Your Studies	Yes**	No
The College You Study In	Yes***	Yes***
Satisfaction with Current Study Programme		
Quality of Teaching	Yes***	No
Organisation of Studies and Timetable	Yes***	No
Possibility to Select from a Broad Variety of Courses	No	No
College Administration's Attitude Towards Students	No	No
Teaching Staff's Attitude Towards Students	Yes**	No
Study Facilities	No	No
Work and Study Constraints		
Working During the Semester	Yes*	No
Hours Worked	Yes***	No
Does Your Job Affect Your Academic Performance	No	No
Course Time per Week	No	No
Study Time per Week	No	No
Health Behaviours		
Alcohol consumption	Yes***	Yes***
Smoking	No	No
Exercise	No	No
General Health		
Colds	No	No
Headaches	Yes***	Yes**
Sleeping Problems	No	No
Concentration Problem	No	No
Stress	Yes*	Yes***
N	3,727	1,835

Note: This table presents a summary of findings from a set of Kruskal-Wallis and ANOVA tests of differences by commute time quartiles for variables relating to students' satisfaction with their general college experience, current study programme, work and study constraints, health behaviours, and general health. The full results from these tests can be found in Appendix D Tables D1-D4. * $p<0.1$, ** $p<0.05$, *** $p<0.01$.
Source: Analysis of Eurostudent survey data for Ireland for 2013.

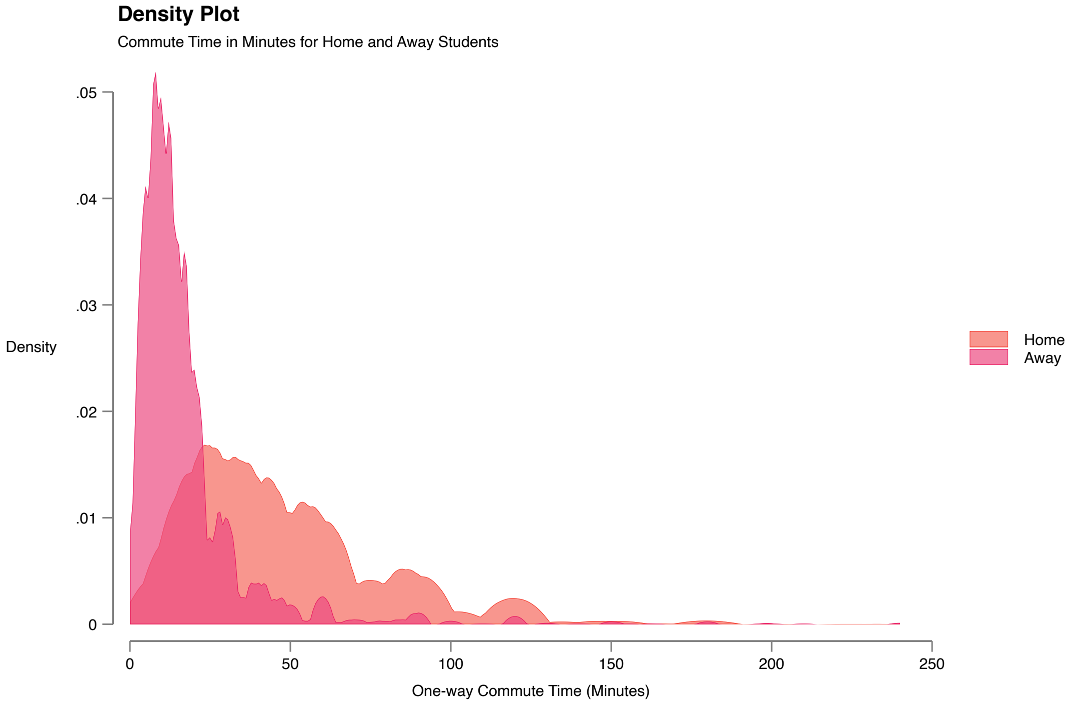
Figures

Fig. 1 The Spatial Distribution of Higher Education Institutions in Ireland in 2013



Notes: There were seven universities in Ireland in 2013, represented by the blue dots. The other HEIs, represented by the yellow dots, included ITs and CEs. Since 2019, a number of ITs have amalgamated to form TUs.

Fig. 2 Distributions of One-Way Commute Times for *Home* and *Away* Students



Notes: This figure presents the distributions of one-way commute times for *Home* (i.e. living at home) and *Away* (i.e. living away from home) students.
Source: Analysis of Eurostudent survey data for Ireland for 2013.

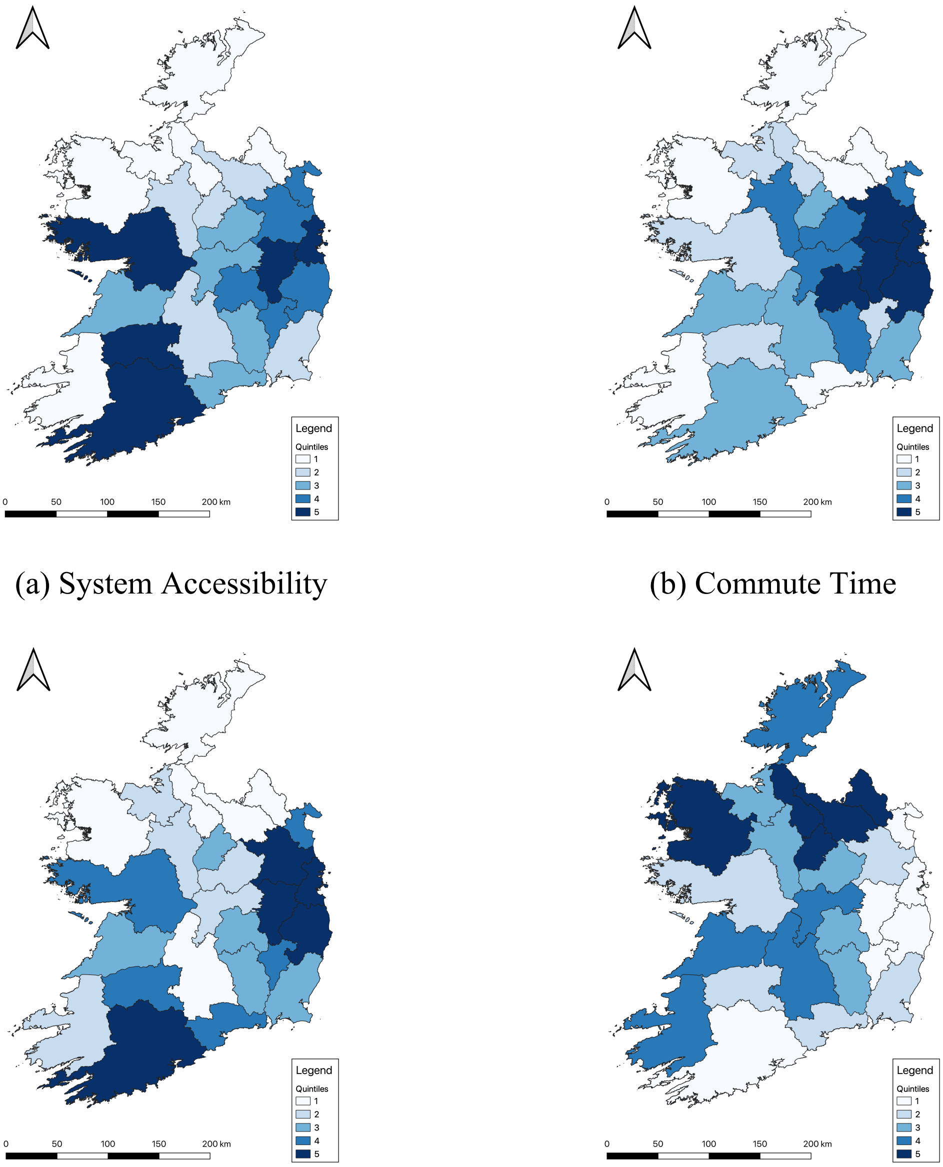
Fig. 3 Directed Paths from *Home* to *SWB*

$$\begin{tikzcd} Home \arrow[r] \arrow[rr, bend left] & Time \arrow[r] & SWB \end{tikzcd}$$

Fig. 4 IV Strategy

$$\begin{tikzcd} Home \arrow[r] \arrow[rr, bend left] & Time \arrow[r] & SWB \\ Access \arrow[u] & U \arrow[ul, dashed] \arrow[u, dashed] \arrow[ur, dashed] & \end{tikzcd}$$

Fig. 5 Accessibility, Commute Times, and Living Arrangements by County



(a) System Accessibility

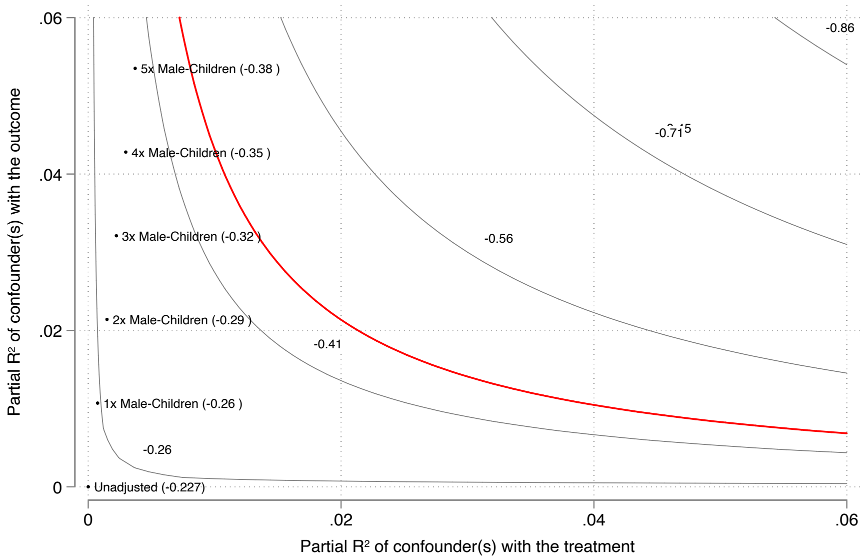
(b) Commute Time

(c) Living with Parents

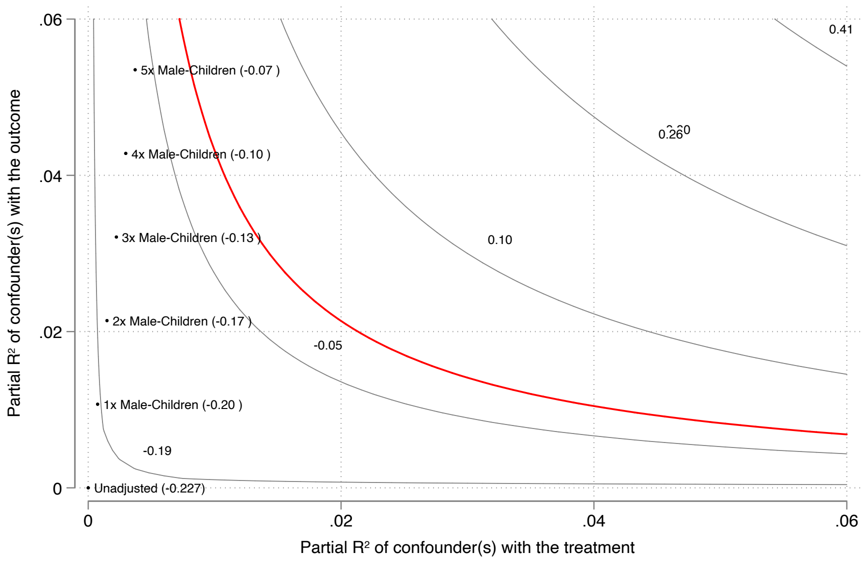
(d) Living with Students

Notes: Panel (a) presents quintiles of system-wide accessibility to higher education by county, with higher quintiles representing greater accessibility. Panel (b) presents quintiles of average student commute times by county, with higher quintiles representing longer commutes. Panel (c) presents quintiles of the proportions of students living with their parents by county, with higher quintiles representing more students living with their parents. Panel (d) presents quintiles of the proportions of students living with other students by county, with higher quintiles representing more students living with other students.
Source: Analysis of Eurostudent survey data for Ireland for 2013.

Fig. 6 Sensitivity Contour Plots of *Home* Point Estimate



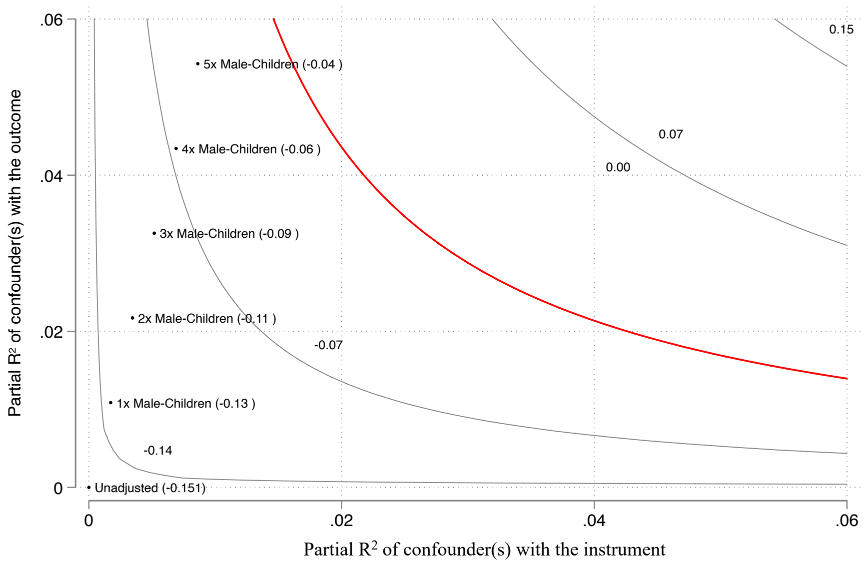
(a) Assuming Upward Bias



(b) Assuming Downward Bias

Notes: The charts present sensitivity contour plots for the variable *Home* assuming (a) upward bias and (b) downward bias. A combination of the variables *Male* and *Children* is used as a reference for bounds on the plausible strength of confounding.
Source: Analysis of Eurostudent survey data for Ireland for 2013.

Fig. 7 Sensitivity Contour Plots of *Access* Point Estimate in Reduced-Form Equation



Notes: This chart presents sensitivity contour plots assuming downward bias for the variable *Access* in the IV reduced-form regression of *SWB* on *Access* and controls. A combination of the variables *Male* and *Children* is used as a reference for bounds on the plausible strength of confounding.

Source: Analysis of Eurostudent survey data for Ireland for 2013.

Appendix A – WHO-5 Wellbeing Index

Fig. A1 WHO-5 Wellbeing Index Questionnaire

Please respond to each item by marking one box per row, regarding how you felt in the last two weeks.		All of the time	Most of the time	More than half the time	Less than half the time	Some of the time	At no time
WHO 1	I have felt cheerful in good spirits.	☐ 5	☐ 4	☐ 3	☐ 2	☐ 1	☐ 0
WHO 2	I have felt calm and relaxed.	☐ 5	☐ 4	☐ 3	☐ 2	☐ 1	☐ 0
WHO 3	I have felt active and vigorous.	☐ 5	☐ 4	☐ 3	☐ 2	☐ 1	☐ 0
WHO 4	I woke up feeling fresh and rested.	☐ 5	☐ 4	☐ 3	☐ 2	☐ 1	☐ 0
WHO 5	My daily life has been filled with things that interest me.	☐ 5	☐ 4	☐ 3	☐ 2	☐ 1	☐ 0

Source: WHO (1998).

Table A1 Sample Breakdown of WHO-5 Wellbeing Index Components (%)

	Cheerful	Calm	Active	Fresh	Interest
At no time	1.60	5.47	7.05	18.28	4.67
Some of the time	15.12	20.19	18.52	24.72	21.45
Less than half the time	15.82	22.04	26.07	25.28	19.56
More than half the time	26.07	25.12	25.75	17.26	26.61
Most of the time	36.66	23.79	19.38	12.32	21.61
All of the time	4.73	3.40	3.24	2.14	6.09
N	5,562	5,562	5,562	5,562	5,562

Source: Analysis of Eurostudent survey data for Ireland for 2013.

Appendix B – Additional Sample Descriptive Statistics

Table B1 Additional Independent Variable Definitions and Sample Descriptive Statistics

Variable	Definition	%
HEI	Athlone Institute of Technology	1.37%
	Cork Institute of Technology	5.29%
	Dublin City University	4.31%
	Dublin Institute of Technology	6.80%
	Dun Laoghaire Institute of Art, Design	0.95%
	Dundalk Institute of Technology	1.40%
	Galway-Mayo Institute of Technology	1.04%
	Institute of Technology, Blanchardstown	0.61%
	Institute of Technology, Carlow	2.48%
	Institute of Technology, Sligo	1.53%
	Institute of Technology, Tallaght	1.62%
	Institute of Technology, Tralee	0.88%
	Letterkenny Institute of Technology	0.61%
	Limerick Institute of Technology	1.04%
	Mary Immaculate College	3.29%
	Mater Dei Institute of Education	1.62%
	National College of Art & Design	0.41%
	National University of Ireland, Galway	11.83%
	National University of Ireland, Maynooth	8.41%
	St. Angela's College of Education	1.24%
	St. Patrick's College Drumcondra	1.46%
	Trinity College Dublin	11.79%
	University College Cork	8.14%
	University College Dublin	12.785
	University of Limerick	5.90%
	Waterford Institute of Technology	3.18%
Course	Education	7.91%
	Humanities & Arts	22.62%
	Social Science	5.27%
	Business	13.47%
	Law	3.29%
	Science	17.80%
	Maths/Computing/Computer Science	6.27%
	Engineering, Manufacturing and Construction	8.85%
	Agriculture/Veterinary	1.65%
	Health/Welfare	10.03%
	Sport/Leisure	1.65%
	Catering	0.76%
	Services	0.43%
N		5,562

Source: Analysis of Eurostudent survey data for Ireland for 2013.

Appendix C: Linear Regression Models – Additional Analysis

Table C1 Linear Regression Models of *Poor SWB*

	Dependent Variable: *Poor SWB*				
	(1)	(2)	(3)	(4)	(5)
Home	0.026**	0.031**	0.019	0.018	-0.028
	(0.013)	(0.013)	(0.014)	(0.015)	(0.018)
Time					
10-20 mins					0.020
					(0.019)
20-45 mins					0.055**
					(0.022)
45+ mins					0.106***
					(0.023)
Controls					
Personal	N	Y	Y	Y	Y
Higher Education	N	N	Y	Y	Y
Socioeconomic	N	N	N	Y	Y
Mean Dep. Var.	0.507	0.507	0.507	0.507	0.507
R^2	0.001	0.028	0.047	0.058	0.062
N	5,562	5,562	5,562	5,562	5,562

Notes: This table presents results from linear regression models of *Poor SWB* estimated using OLS. The main independent variable of interest is *Home* and all variables, including the controls, are defined in Table 1. * p<0.1, ** p<0.05, *** p<0.01.
Source: Analysis of Eurostudent survey data for Ireland for 2013.

Table C2 Linear Regression Models of *SWB* by Sex

	Dependent Variable: *SWB*			
	Female		Male	
	(1)	(2)	(1)	(2)
Home	-0.247	0.214	-0.211	0.277
	(0.181)	(0.217)	(0.253)	(0.314)
Time				
10-20 mins		-0.276		-0.267
		(0.233)		(0.333)
20-45 mins		-0.687**		-0.671*
		(0.270)		(0.390)
45+ mins		-1.069***		-1.065**
		(0.283)		(0.415)
Controls				
Personal	Y	Y	Y	Y
Higher Education	Y	Y	Y	Y
Socioeconomic	Y	Y	Y	Y
Mean Dep. Var.	11.99	11.99	13.02	13.02
R^2	0.089	0.093	0.109	0.112
N	3,727	3,727	1,835	1,835

Notes: This table presents results from linear regression models of *SWB* by sex estimated using OLS. The main independent variable of interest is *Home* and all variables, including the controls, are defined in Table 1. * p<0.1, ** p<0.05, *** p<0.01.
Source: Analysis of Eurostudent survey data for Ireland for 2013.

Table C3 Inverse Probability Weighting Estimates of the Effect of *Home*

	Dependent Variable: *SWB*		
	All	Female	Male
ATE	-0.192	-0.190	-0.202
Robust SE	0.151	0.188	0.245
Z	-1.27	-1.01	-0.83
p	0.204	0.312	0.409
N	5,557	3,723	1,829

Notes: This table presents inverse probability weighting (ipw) estimates of the average treatment effect of *Home* for the full sample and by sex. All variables, including the controls, are defined in Table 1.

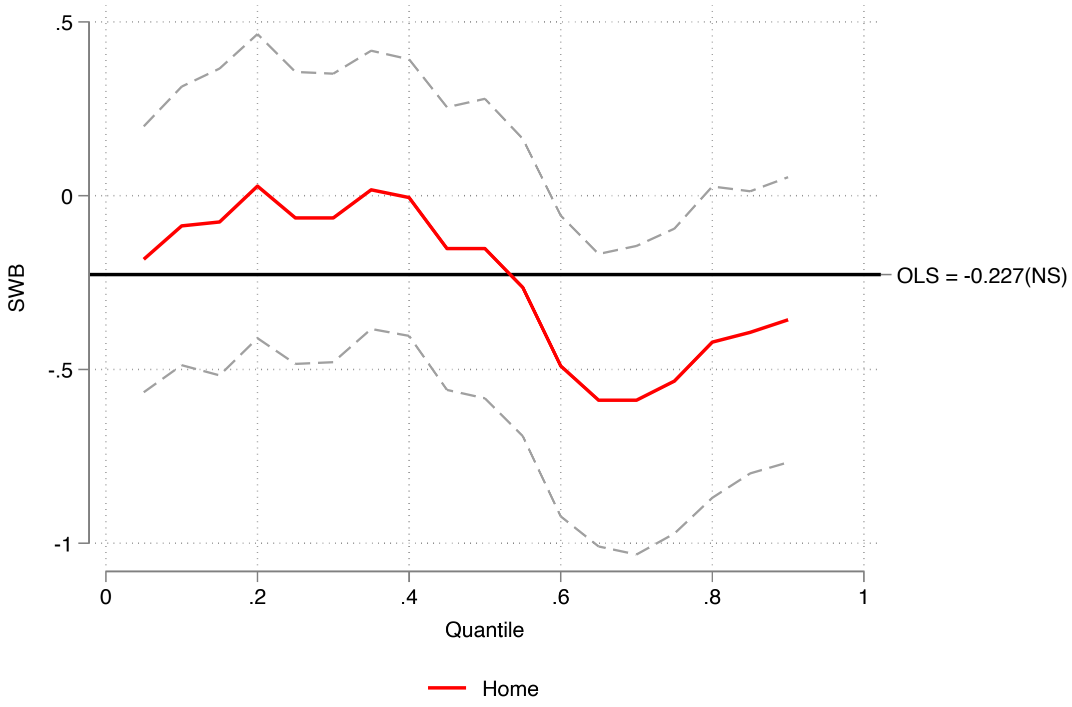
Source: Analysis of Eurostudent survey data for Ireland for 2013.

Table C4 Ordered Logit Model Estimates of Partial Effects of *Home* for SWB Components

	SWB Component				
	Cheerful	*Calm*	*Active*	*Fresh*	*Interest*
At no time	0.001	0.006**	0.002	0.013	0.001
Some of the time	0.009	0.015**	0.003	0.008	0.004
Less than half the time	0.006	0.006**	0.002	-0.002	0.002
More than half the time	0.002	-0.005**	-0.002	-0.007	-0.001
Most of the time	-0.015	-0.018**	-0.004	-0.009	-0.004
All of the time	-0.003	-0.004**	-0.001	-0.002	-0.002
Controls					
Personal	Y	Y	Y	Y	Y
Higher Education	Y	Y	Y	Y	Y
Socioeconomic	Y	Y	Y	Y	Y
N	5,562	5,562	5,562	5,562	5,562

Notes: This table presents partial effect estimates for *Home* from separate ordered logit models of each of the five WHO-5 wellbeing index components. See Figure A1 for full definitions of these components and Table A1 for sample descriptive statistics. All other variables, including the controls, are defined in Table 1. * p<0.1, ** p<0.05, *** p<0.01.
Source: Analysis of Eurostudent survey data for Ireland for 2013.

Fig. C1 Quantile Regression Model Estimates of Effect of *Home* on *SWB*



Notes: This figure presents partial effect estimates for *Home* from unconditional quantile regression models of *SWB*. The main independent variable of interest is *Home* and all variables, including the controls, are defined in Table 1.
Source: Analysis of Eurostudent survey data for Ireland for 2013.

Appendix D: Mechanisms – Full Test Results

Table D1 Satisfaction with General College Experience by Commute Time Quartile and Sex

	Female					Male				
	Q1	*Q2*	*Q3*	*Q4*	*All*	*Q1*	*Q2*	*Q3*	*Q4*	*All*
Your Accommodation										
Very Dissatisfied	4.54	4.19	3.30	2.63	3.73	4.99	2.95	3.66	2.35	3.49
Dissatisfied	11.67	11.48	7.62	8.01	9.87	11.85	9.68	6.10	5.97	8.50
Neither	8.46	10.26	8.26	7.46	8.61	12.27	9.26	9.76	10.02	10.35
Satisfied	48.35	41.94	36.21	36.22	41.27	50.31	48.63	36.34	34.75	42.78
Very Satisfied	26.98	32.01	44.60	45.66	36.49	20.37	29.47	44.15	46.91	34.82
Missing	0.00	0.11	0.00	0.00	0.03	0.21	0.00	0.00	0.00	0.05
	$\chi^2(3) = 80.84$, $p < 0.001$					$\chi^2(3) = 70.41$, $p < 0.001$				
Your Financial/Material Wellbeing										
Very Dissatisfied	9.26	11.48	11.56	12.40	11.05	8.52	11.37	11.22	11.94	10.74
Dissatisfied	28.14	29.69	27.57	31.28	29.17	25.57	23.79	26.10	26.65	25.50
Neither	18.52	19.43	19.82	20.42	19.48	19.54	19.37	16.34	18.34	18.47
Satisfied	36.69	30.79	32.40	29.42	32.57	37.63	34.95	36.10	32.62	35.31
Very Satisfied	7.03	8.39	8.64	6.37	7.54	8.52	10.53	10.24	10.45	9.92
Missing	0.36	0.22	0.00	0.11	0.19	0.21	0.00	0.00	0.00	0.05
	$\chi^2(3) = 12.09$, $p = 0.007$					$\chi^2(3) = 1.25$, $p = 0.741$				
Your Friendships										
Very Dissatisfied	0.80	1.32	1.78	1.87	1.40	1.25	2.11	2.20	1.71	1.80
Dissatisfied	6.23	6.18	6.99	6.70	6.49	7.48	5.89	7.32	7.04	6.92
Neither	7.03	7.95	7.75	11.75	8.56	7.90	8.21	11.95	11.09	9.70
Satisfied	42.21	46.25	45.36	43.69	44.22	43.87	46.53	48.78	48.61	46.87
Very Satisfied	43.54	38.08	37.99	35.89	39.17	39.50	37.26	29.51	31.56	34.66
Missing	0.18	0.22	0.13	0.11	0.16	0.00	0.00	0.24	0.00	0.05
	$\chi^2(3) = 15.74$, $p = 0.001$					$\chi^2(3) = 11.39$, $p = 0.010$				

Your Studies										
Very Dissatisfied	2.23	3.09	2.03	2.63	2.50	3.53	3.58	5.12	3.20	3.81
Dissatisfied	9.26	13.47	10.80	13.83	11.73	13.31	15.37	13.41	13.43	13.90
Neither	15.41	16.67	17.41	18.33	16.85	17.67	19.79	18.29	17.70	18.37
Satisfied	60.11	52.54	54.51	52.25	55.17	52.60	48.63	53.41	51.60	51.50
Very Satisfied	13.00	14.02	15.12	12.73	13.63	12.89	12.63	9.76	14.07	12.43
Missing	0.00	0.22	0.13	0.22	0.13	0.00	0.00	0.00	0.00	0.00
		$\chi^2(3) = 10.47$, $p = 0.015$					$\chi^2(3) = 3.01$, $p = 0.390$			
The College You Study In										
Very Dissatisfied	1.25	1.21	2.29	2.85	1.85	1.87	2.32	2.68	2.99	2.45
Dissatisfied	4.72	5.63	4.57	7.24	5.53	5.61	7.37	6.10	8.53	6.92
Neither	9.80	9.27	9.66	10.98	9.93	10.81	13.26	14.88	14.29	13.24
Satisfied	45.33	48.01	49.17	45.99	46.95	42.20	45.26	44.63	44.35	44.09
Very Satisfied	38.91	35.87	34.31	32.82	35.71	39.50	31.79	31.46	29.64	33.19
Missing	0.00	0.00	0.00	0.11	0.03	0.00	0.00	0.24	0.21	0.11
		$\chi^2(3) = 12.05$, $p = 0.007$					$\chi^2(3) = 13.00$, $p = 0.005$			
N	1,123	906	787	911	3,727	481	475	410	469	1,835

Note: This table presents a summary of findings from a set of Kruskal-Wallis tests of differences by commute time quartiles for variables relating to students' satisfaction with their general college experience.
Source: Analysis of Eurostudent survey data for Ireland for 2013.

Table D2 Satisfaction with Current Study Programme by Commute Time Quartile and Sex

	Female					Male				
	Q1	*Q2*	*Q3*	*Q4*	*All*	*Q1*	*Q2*	*Q3*	*Q4*	*All*
Quality of Teaching										
Very Dissatisfied	0.45	0.88	0.51	0.99	0.70	0.83	1.05	0.49	1.07	0.87
Dissatisfied	4.19	5.74	7.24	7.35	5.98	7.90	8.63	8.54	8.32	8.34
Neither	5.16	6.62	8.26	7.57	6.76	8.73	9.47	8.78	9.17	9.05
Satisfied	65.98	63.47	65.31	63.34	64.58	65.70	62.11	64.88	62.90	63.87
Very Satisfied	24.13	23.29	18.55	20.64	21.89	16.84	18.74	17.32	18.34	17.82
Missing	0.09	0.00	0.13	0.11	0.08	0.00	0.00	0.00	0.21	0.05
	$\chi^2(3) = 16.47$, $p < 0.001$					$\chi^2(3) = 0.01$, $p = 0.999$				
Organisation of Studies and Timetable										
Very Dissatisfied	2.23	2.32	2.41	4.06	2.74	2.70	3.16	3.66	4.05	3.38
Dissatisfied	12.20	15.23	17.15	16.47	15.03	10.81	13.26	12.68	15.14	12.97
Neither	8.46	10.71	10.42	11.64	10.20	12.89	14.11	12.68	15.78	13.90
Satisfied	57.44	53.31	54.76	48.85	53.77	59.04	55.16	55.61	51.17	55.26
Very Satisfied	19.59	18.43	14.87	18.77	18.11	14.35	14.11	15.12	13.65	14.28
Missing	0.09	0.00	0.38	0.22	0.16	0.21	0.21	0.24	0.21	0.22
	$\chi^2(3) = 15.95$, $p = 0.001$					$\chi^2(3) = 5.07$, $p = 0.167$				
Possibility to Select from a Broad Variety of Courses										
Very Dissatisfied	2.67	2.87	3.30	1.98	2.68	3.95	4.21	1.71	2.35	3.11
Dissatisfied	12.73	10.82	11.82	16.03	12.88	11.64	10.95	13.17	15.57	12.81
Neither	22.26	19.87	21.73	20.75	21.20	24.53	21.47	21.22	22.81	22.56
Satisfied	40.69	44.37	42.57	40.18	41.86	38.05	43.58	38.78	36.89	39.35
Very Satisfied	21.19	22.08	20.33	20.97	21.17	21.41	19.79	23.90	22.17	21.74
Missing	0.45	0.00	0.25	0.11	0.21	0.42	0.00	1.22	0.21	0.44
	$\chi^2(3) = 4.22$, $p = 0.239$					$\chi^2(3) = 1.95$, $p = 0.583$				

College Administration's Attitude Towards Students										
Very Dissatisfied	2.67	3.53	3.56	4.17	3.43	4.37	4.00	5.61	5.12	4.74
Dissatisfied	11.22	12.80	12.96	11.31	11.99	11.85	13.89	9.76	14.71	12.64
Neither	16.38	17.00	17.92	18.55	17.39	17.46	17.68	20.73	18.55	18.53
Satisfied	50.67	48.34	47.01	44.24	47.76	46.78	46.74	46.83	39.87	45.01
Very Satisfied	18.88	18.32	18.17	21.51	19.24	19.13	17.47	17.07	21.54	18.86
Missing	0.18	0.00	0.38	0.22	0.19	0.42	0.21	0.00	0.21	0.22
			$\chi^2(3) = 2.91, p = 0.405$					$\chi^2(3) = 0.78, p = 0.855$		
Teaching Staff's Attitude Towards Students										
Very Dissatisfied	0.71	1.32	1.65	1.76	1.31	1.25	2.11	0.98	1.71	1.53
Dissatisfied	4.10	7.40	4.83	6.26	5.58	4.99	7.58	5.12	4.90	5.67
Neither	8.46	9.38	12.07	9.88	9.79	12.89	10.74	17.07	11.09	12.81
Satisfied	53.78	52.65	52.60	50.93	52.56	50.31	52.00	50.73	52.24	51.34
Very Satisfied	32.86	29.03	28.59	31.06	30.59	30.56	27.58	26.10	29.85	28.61
Missing	0.09	0.22	0.25	0.11	0.16	0.00	0.00	0.00	0.21	0.05
			$\chi^2(3) = 10.02, p = 0.018$					$\chi^2(3) = 3.86, p = 0.277$		
Study Facilities										
Very Dissatisfied	2.76	1.77	2.8	2.09	2.36	2.70	3.37	2.44	3.20	2.94
Dissatisfied	11.93	9.82	10.29	10.43	10.71	9.56	9.89	9.27	9.81	9.65
Neither	7.93	8.94	6.73	8.56	8.08	8.52	8.63	9.02	10.23	9.10
Satisfied	44.52	46.91	44.73	44.68	45.18	48.02	45.26	42.44	46.06	45.56
Very Satisfied	32.24	32.23	35.2	33.37	33.14	30.77	32.84	36.59	29.85	32.37
Missing	0.62	0.33	0.25	0.88	0.54	0.42	0.00	0.24	0.85	0.38
			$\chi^2(3) = 2.39, p = 0.496$					$\chi^2(3) = 3.25, p = 0.354$		
N	1,123	906	787	911	3,727	481	475	410	469	1,835

Note: This table presents results from a set of Kruskal-Wallis tests of differences by commute time quartiles for variables relating to students' satisfaction with their current study programme.

Source: Analysis of Eurostudent survey data for Ireland for 2013.

Table D3 Work and Study Constraints by Commute Time Quartile and Sex

	Female					Male				
	Q1	*Q2*	*Q3*	*Q4*	*All*	*Q1*	*Q2*	*Q3*	*Q4*	*All*
Working During the Semester										
Yes, whole semester	25.82	27.81	29.10	30.30	28.09	18.71	21.89	21.46	23.03	21.25
Yes, time to time	19.95	22.41	20.20	21.51	20.98	22.45	22.11	19.76	20.26	21.20
No	53.96	49.67	50.32	48.08	50.71	58.84	55.79	58.54	56.72	57.44
Missing	0.27	0.11	0.38	0.11	0.21	0.00	0.21	0.24	0.00	0.11
			$\chi^2(3) = 6.99$, $p = 0.072$					$\chi^2(3) = 1.30$, $p = 0.729$		
Hours Worked										
Mean Hours	5.35	6.32	6.47	6.73	6.16	5.30	5.59	5.26	6.12	5.57
			$F = 4.22$, $p = 0.006$					$F = 0.73$, $p = 0.534$		
Does Your Job Affect Your Academic Performance										
Negatively	11.90	11.80	15.12	15.91	13.59	12.70	13.17	11.66	12.50	12.55
Somewhat Neg.	31.75	32.52	32.10	30.75	31.75	28.04	26.34	32.52	33.50	29.99
Neither	47.42	44.99	42.44	43.23	44.68	47.09	48.29	46.63	42.00	45.97
Somewhat Pos.	5.75	5.57	6.90	6.24	6.07	6.88	6.34	6.13	7.00	6.61
Positively	3.17	5.12	3.45	3.87	3.90	5.29	5.85	3.07	5.00	4.89
			$\chi^2(3) = 1.90$, $p = 0.593$					$\chi^2(3) = 1.13$, $p = 0.770$		
Course Time per Week										
Mean Hours	19.93	20.11	20.35	19.82	20.03	21.06	20.42	20.35	20.83	20.67
			$F = 0.64$, $p = 0.590$					$F = 0.75$, $p = 0.524$		
Study Time per Week										
Mean Hours	15.52	16.16	15.44	15.41	15.63	14.59	15.01	14.49	13.80	14.47
			$F = 0.85$, $p = 0.467$					$F = 0.89$, $p = 0.448$		
N	1,123	906	787	911	3,727	481	475	410	469	1,835

Note: This table presents a summary of findings from a set of Kruskal-Wallis and ANOVA tests of differences by commute time quartiles for variables relating to financial, work, and study constraints.
Source: Analysis of Eurostudent survey data for Ireland for 2013.

Table D4 Health Behaviours and General Health by Commute Time Quartile and Sex

	Female					Male				
	Q1	*Q2*	*Q3*	*Q4*	*All*	*Q1*	*Q2*	*Q3*	*Q4*	*All*
Alcohol Consumption Frequency										
Daily	0.18	0.22	0.00	0.00	0.11	0.62	0.84	0.73	0.21	0.60
Few times per week	10.33	6.73	6.23	5.93	7.51	14.97	13.26	9.76	9.17	11.88
Weekly	41.41	36.09	34.18	31.17	36.09	42.83	41.05	41.71	35.61	40.27
Monthly	26.09	33.77	28.97	30.95	29.76	25.16	27.79	24.15	27.93	26.32
Less than monthly	13.54	14.90	20.46	20.86	17.12	7.90	10.11	11.95	14.93	11.17
Never	8.46	8.28	10.17	10.98	9.39	8.52	6.74	11.71	12.15	9.70
Missing	0.00	0.00	0.00	0.11	0.03	0.00	0.21	0.00	0.00	0.05
	$\chi^2(3) = 51.04$, $p < 0.001$					$\chi^2(3) = 25.02$, $p < 0.001$				
Smoking Frequency										
Regularly	6.41	8.28	8.26	8.56	7.78	11.85	9.68	10.73	10.23	10.63
Occasionally	12.11	11.92	11.44	11.96	11.89	12.06	15.79	12.68	10.02	12.64
Never	80.94	79.58	79.92	78.92	79.90	75.88	73.47	76.10	79.10	76.13
Missing	0.53	0.22	0.38	0.55	0.43	0.21	1.05	0.49	0.64	0.60
	$\chi^2(3) = 0.92$, $p = 0.821$					$\chi^2(3) = 1.67$, $p = 0.644$				
Exercise Frequency										
5+ times a week	7.84	11.48	12.45	9.22	10.03	16.42	18.11	21.95	15.57	17.87
4 times a week	10.77	12.03	11.05	11.31	11.27	12.89	17.47	13.66	15.78	14.99
3 times a week	18.25	19.65	16.26	20.20	18.65	20.58	18.53	16.83	17.91	18.53
Twice a week	21.02	19.21	18.17	21.08	19.99	16.01	13.68	12.44	15.78	14.55
Once a week	14.96	11.92	15.12	12.62	13.68	12.06	11.16	12.68	11.73	11.88
Less than once	21.02	19.65	19.57	18.33	19.72	16.22	14.74	15.85	14.71	15.37
Never	5.79	6.07	7.24	7.03	6.47	5.61	5.89	6.59	8.10	6.54
Missing	0.36	0.00	0.13	0.22	0.19	0.21	0.42	0.00	0.43	0.27
	$\chi^2(3) = 6.27$, $p = 0.100$					$\chi^2(3) = 3.38$, $p = 0.336$				

Catch Colds										
< once a year	12.82	12.91	13.98	11.20	12.69	16.42	21.47	17.32	18.55	18.47
Once a year	25.91	27.92	24.40	24.92	25.84	33.26	31.37	31.46	31.13	31.83
Twice a year	44.52	45.70	48.16	47.20	46.23	39.09	37.68	43.17	39.66	39.78
Once a month	13.18	11.04	11.44	13.17	12.29	8.32	8.00	6.59	8.74	7.96
> once a month	3.12	2.43	1.78	3.29	2.71	2.29	0.84	0.98	1.49	1.42
Missing	0.45	0.00	0.25	0.22	0.24	0.62	0.63	0.49	0.43	0.54
		$\chi^2(3) = 5.53, p = 0.137$					$\chi^2(3) = 2.79, p = 0.425$			
Headaches										
< once a year	16.21	14.02	14.10	12.62	14.35	27.23	31.16	23.90	24.31	26.76
Once a year	9.80	9.49	10.29	6.48	9.02	17.46	16.63	16.59	16.42	16.78
Twice a year	21.46	20.97	21.09	18.33	20.50	25.36	22.32	23.66	24.95	24.09
Once a month	26.89	29.36	26.05	29.86	28.04	18.50	17.47	22.44	18.34	19.07
> once a month	24.93	25.83	28.21	32.16	27.61	11.02	11.37	12.68	15.14	12.53
Missing	0.71	0.33	0.25	0.55	0.48	0.42	1.05	0.73	0.85	0.76
		$\chi^2(3) = 22.23, p < 0.001$					$\chi^2(3) = 8.82, p = 0.032$			
Sleeping Problems										
< once a year	16.65	15.12	13.34	13.50	14.81	18.50	20.00	19.02	18.34	18.96
Once a year	7.84	7.40	9.28	8.23	8.13	11.23	10.74	9.27	9.38	10.19
Twice a year	16.38	16.45	16.26	13.28	15.62	20.17	18.74	18.29	13.86	17.77
Once a month	22.08	22.08	22.11	24.81	22.75	20.17	22.32	21.22	23.67	21.85
> once a month	36.51	38.52	38.88	39.63	38.26	29.52	26.74	31.71	34.12	30.46
Missing	0.53	0.44	0.13	0.55	0.43	0.42	1.47	0.49	0.64	0.76
		$\chi^2(3) = 4.82, p = 0.185$					$\chi^2(3) = 5.76, p = 0.124$			
Concentration Problems										
< once a year	8.19	7.73	7.12	6.81	7.51	13.93	14.95	12.68	13.01	13.68
Once a year	6.14	4.97	5.34	5.93	5.63	6.65	4.63	6.34	6.82	6.10
Twice a year	12.29	14.68	11.94	12.18	12.77	16.01	14.95	10.24	12.79	13.62
Once a month	27.34	26.16	26.18	25.58	26.38	26.40	26.74	30.49	27.29	27.63

> once a month	45.33	46.14	48.92	49.07	47.20	36.38	38.11	39.76	39.66	38.42
Missing	0.71	0.33	0.51	0.44	0.51	0.62	0.63	0.49	0.43	0.54
			$\chi^2(3) = 3.78$, $p = 0.287$					$\chi^2(3) = 2.62$, $p = 0.455$		
Stressed										
< once a year	3.21	2.98	2.29	2.52	2.79	10.60	7.79	6.10	7.68	8.12
Once a year	5.08	3.75	4.57	4.50	4.51	7.90	6.95	6.59	8.53	7.52
Twice a year	15.32	14.46	14.49	12.62	14.27	20.58	20.00	16.83	15.14	18.20
Once a month	25.29	24.94	22.87	23.05	24.15	29.73	28.63	25.85	25.59	27.52
> once a month	50.58	53.64	55.53	56.75	53.88	30.98	35.58	43.66	42.64	37.98
Missing	0.53	0.22	0.25	0.55	0.40	0.21	1.05	0.98	0.43	0.65
			$\chi^2(3) = 7.40$, $p = 0.060$					$\chi^2(3) = 18.30$, $p < 0.001$		
N	1,123	906	787	911	3,727	481	475	410	469	1,835

Note: This table presents a summary of findings from a set of Kruskal-Wallis tests of differences by commute time quartiles for variables relating to students' health behaviours and health.

Source: Analysis of Eurostudent survey data for Ireland for 2013.