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Commuting and College Student Wellbeing

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Abstract

Commuting to college is a prominent feature of student life in many countries. 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 find that living at home reduces wellbeing for female students but not for males. We also show that long commutes are independently associated with very large increases in poor wellbeing for female students. Our results challenge the theory that disutility from commuting is compensated by other factors relating to where an individual lives.

Keywords

Commuting; Living arrangements; Wellbeing; College students.

Declaration

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 (Cullinan et al. 2014; 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.

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; Jacob et al. 2019; Künn-Nelen 2016; Liu et al. 2022; Simón et al. 2020; Stuzer and Frey 2008). 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). In addition to the students themselves, this 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). Third, as measures of student satisfaction and experience are increasingly being used as inputs in well-known HEI rankings[2] and performance-based funding (PBF) schemes, the student wellbeing may have implications for 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

[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.

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.

Despite the vast literature on the general population, there are only a few commuting studies focussing specifically on college students. 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. 2010; St-Louis et al. 2014). In addition, a number of 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 have explored the relationship between college students' wellbeing or mental health and commuting directly. Using a sample of Italian university students, 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, 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 (OVB).

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 move away from 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; Thomas and Jones 2017). Empirical research on the effects of different living arrangements on student wellbeing is rare, though evidence on more academic-focused outcomes does 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.

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 start by estimating linear regression models of wellbeing, incorporating a rich set of controls, and focus initially on the 'total effect' of living at home. To get a sense of the extent to which unobserved confounders may bias these estimates, we employ sensitivity analysis tools for regression models (Cinelli and Hazlett 2020). Next, to further address potential endogeneity concerns, we use system-wide accessibility to higher education from a student's 'county of origin' (i.e. where they were living prior to entering higher education) as an instrumental variable (IV). We also test the sensitivity of our IV estimates using partial identification techniques (Nevo and Rosen 2012) and recently developed sensitivity analysis tools for IV models (Cinelli and Hazlett 2022). Finally, we also estimate the independent relationship between wellbeing and commute time for students living at and away from home. For all our models, we present results for the overall sample and by sex.

This paper makes several contributions to the literature. It provides the first comprehensive and nationally representative assessment of the effects of commuting on college student wellbeing. In doing so, it presents the first causal estimates of the effect of living at home while in higher education, as well as an in-depth analysis of the relationship between wellbeing and commute time. In addition, the paper also presents evidence of important differences between female and male students in both the effects of living at home and commute time. As a result, it adds to our understanding of the commuting paradox.

2. 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. 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.

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 but do 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. (2024) 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). 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 other countries across Europe. In terms of mode of transport, it is notable that Ireland is relatively car-centric, with a much higher proportion of students (40%) using a car as their primary means of getting to their HEI relative to other European countries.

3. Data and variables

3.1. 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). 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 Certificate route.[3] 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'.[4] 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.

3.2. 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

[3] 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.
[4] These are students who entered higher education for the first time after the age of 23.

wellbeing, was first introduced in its present form in 1998 (WHO 1998), and has been administered in a wide variety of settings. It has been found to have adequate validity in screening for depression and in measuring outcomes in clinical trials, while item response theory analyses indicate that the measure has good construct validity as a unidimensional scale measuring wellbeing in studies of younger persons (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;
- 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.).[5] Overall, almost one-half (46.2%) of our sample live at home, the vast majority with their parents, and commute daily/regularly to college, while 53.8% have moved away from home.[6]

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)".[7] 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

[5] This classification is motivated, in part, by a taxonomy of commuter students presented in Maguire and Morris (2018).
[6] We subsequently denote those living at home as *Home* students and those living away from home as *Away* students.
[7] A limitation of our data is that respondents were not asked to report the frequency of trips.

group by commute time quartile (defined on the basis of the full analysis sample).[8] 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%).

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

4. Methods

4.1. Overview of empirical approach

Figure 3 presents a representation 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

[8] 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.

excluded (Cinelli et al. 2024). 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 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 directly related to their wellbeing. However, it is not clear *a priori* what is the likely direction and magnitude of any selection bias. Thus, given such concerns, one possible identification strategy is to use an IV that provides a source of exogenous variation for $Home$.

4.2. Models and estimation

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 with 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 $\mathbf{X}$. We also test the robustness of our findings from the linear regression analysis by estimating a range of additional models – see below and Appendix C.

Nonetheless, even after undertaking such sensitivity analysis and robustness checks, 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* – see Figure 4. 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; Sá et al. 2004; Walsh et al. 2017).

In terms of the rationale for this IV, 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), and previous research has shown that this is a key determinant of where and what school leavers study (Cullinan and Duggan 2016; Flannery and Cullinan 2017). In particular, college students tend to study at HEIs that are close to where they live/come from and, as a result, there is evidence of highly localised patterns of transitions to higher education in Ireland (Cullinan and Halpin 2017). This 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. Further details on, and supporting evidence for, this IV approach are presented in Appendix 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 worth pointing out here that while our dependent variable *SWB* relates to *current* wellbeing, our instrument relates to accessibility *prior* to the student entering college i.e. one or more years previously. Thus, the exclusion implies that the only way in which accessibility *prior* to entry to higher education impacts *current* wellbeing is through the decision to remain at home or move away. Since it is possible, though we believe much less likely, that there could be other channels through which prior accessibility impacts current wellbeing, we also test our IV model estimates to violations of the identification assumptions using two different methods that are described in Appendix E.

Finally, in order to consider commute time more explicitly, we also directly model the relationship between *SWB* and commute time. Specifically, we estimate linear models of wellbeing for *Home* and *Away* students (overall and by sex). We interpret our estimates from these models as independent associations.

5. Results

5.1. Linear regression models

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 5 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.[9] With positive selection (i.e. upward bias), relatively strong bias (relative to the *Male-Children* group comparison) suggests that there could be a negative effect for *Home*. 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 5a), the point estimate for *Home* would be -0.38 (see figure in parentheses in Figure 5). 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. Thus, overall, this sensitivity analysis suggests that the total effect of *Home* is likely negative.

5.2. IV regression models

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 (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* could be biased upwards i.e. positive selection effects may dominate.[10] It also suggests that, on average, students with stronger preferences for living

[9] 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 and Hazlett (2020) for more details.
[10] Caution should be exercised when comparing the OLS and IV estimates since the former represents an average treatment effect, while the latter is a LATE i.e. the average effect for those induced into the treatment by the instrument.

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.

Appendix E assesses the sensitivity/robustness of the IV estimates to violations of the identification assumptions. To summarise the key results from this additional analysis, the partial identification approach, based on Nevo and Rosen (2012), supports the conclusion that living at home while in college has a negative effect on wellbeing for female students, though not for males. The second approach employs sensitivity analysis tools, this time for IV/2SLS regression, and is based on Cinelli and Hazlett (2022). It suggests that, even in the presence of confounding, living at home while in college reduces wellbeing on average. Thus, this conclusion is consistent with the findings presented in this section and from the partial identification analysis.

5.3. 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 those living away from home and the key results are presented in Table 6. 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 6 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 6 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 6 suggest that female students living at home but far from college are most negatively affected by commuting.

6. 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 researchers, HEIs, and policymakers, and that commuting is a common feature of everyday life for a significant proportion 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 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 (very) long commute. Our results are also consistent with gender disparities in the effect of commuting on wellbeing in the general population (Jacob et al. 2019; Künn-Nelen 2016; Roberts et al. 2011; Simón et al. 2020). An interesting avenue for future research would be to investigate the reasons for this in the context of student commuting.

In terms of mechanisms, there are several possible explanations as to why different living situations and commuting patterns may impact wellbeing, either positively or negatively. For example, the experience of commuting itself may bring about increased levels of stress if stuck in traffic or experiencing unreliable public transport. 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 (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 in part 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. 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.

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.

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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.

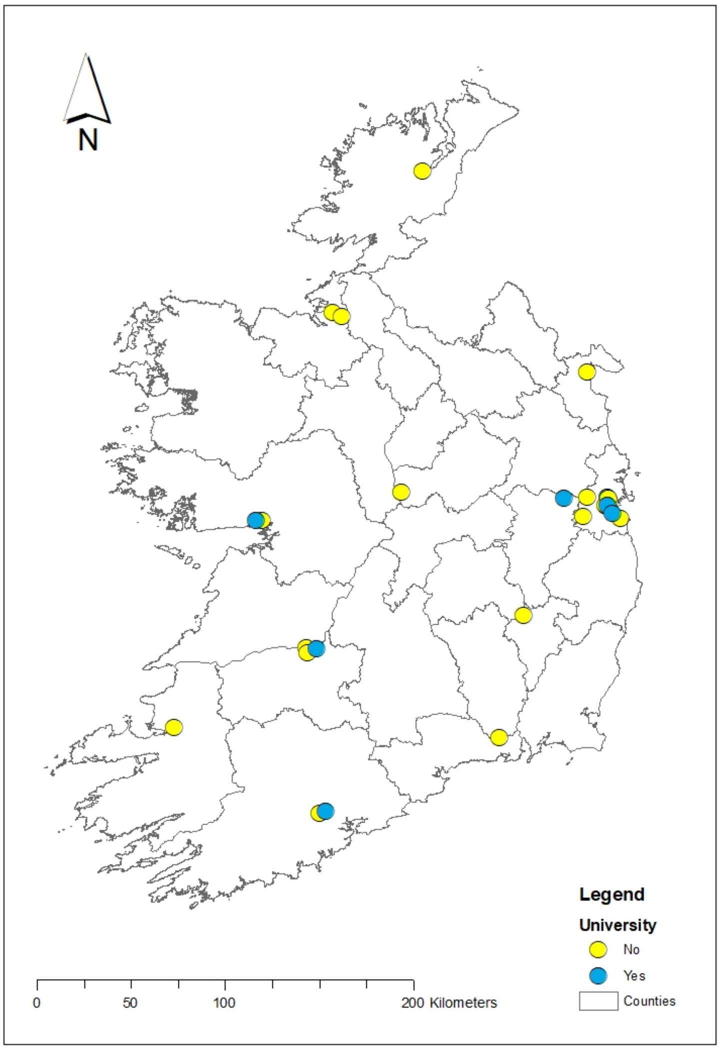
Table 6. Linear regression models of *SWB* and *Poor SWB* for *Home* and *Away* students by sex.

	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.

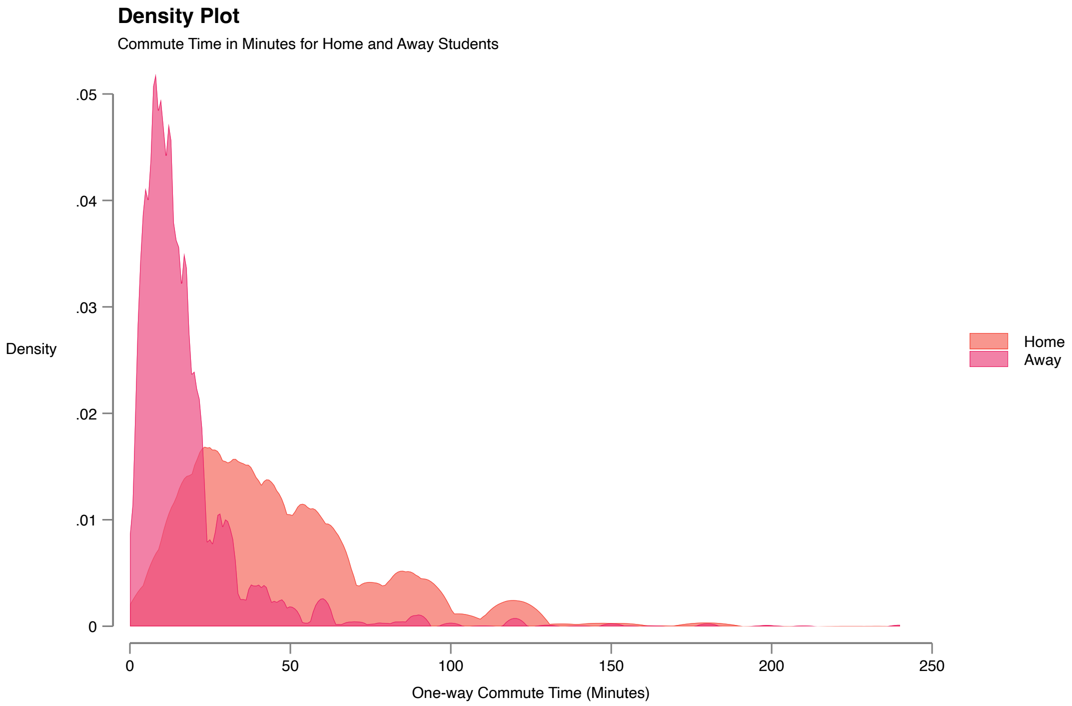
Figures

Figure 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.

Figure 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.

Figure 3. Directed paths from *Home* to *SWB*.

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

Figure 4. IV strategy.

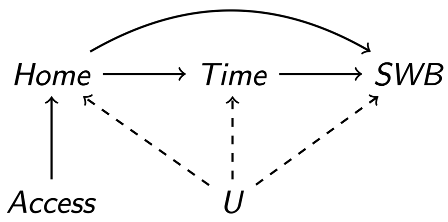
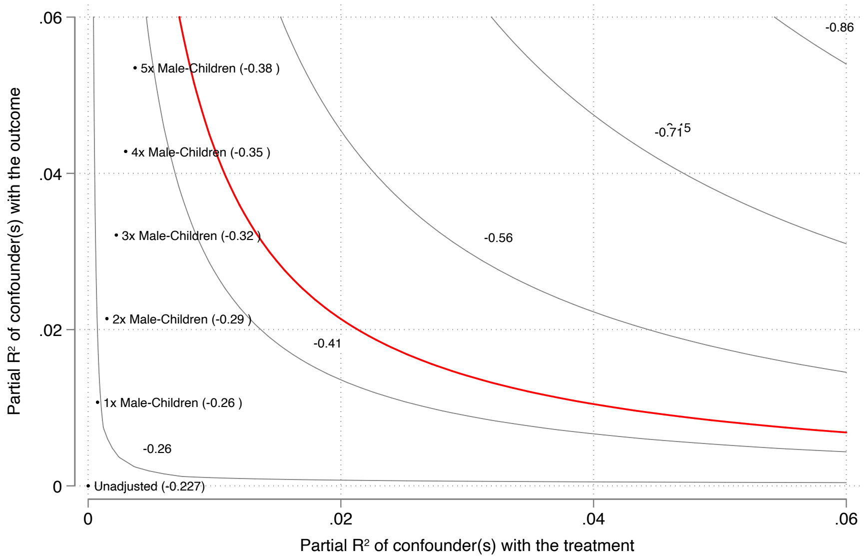
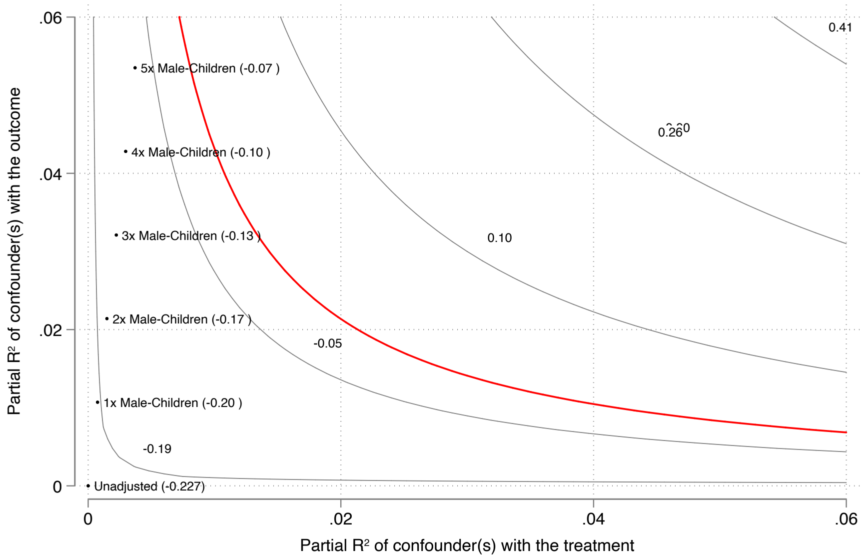


Figure 5. Sensitivity contour plots of *Home* point estimate.



(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.

Appendix A: WHO-5 Wellbeing Index

Figure A1. WHO-5 Wellbeing Index questionnaire.

Please respond to each item by marking <u>one box per row,</u> 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: Robustness Checks for Linear Regression Models

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

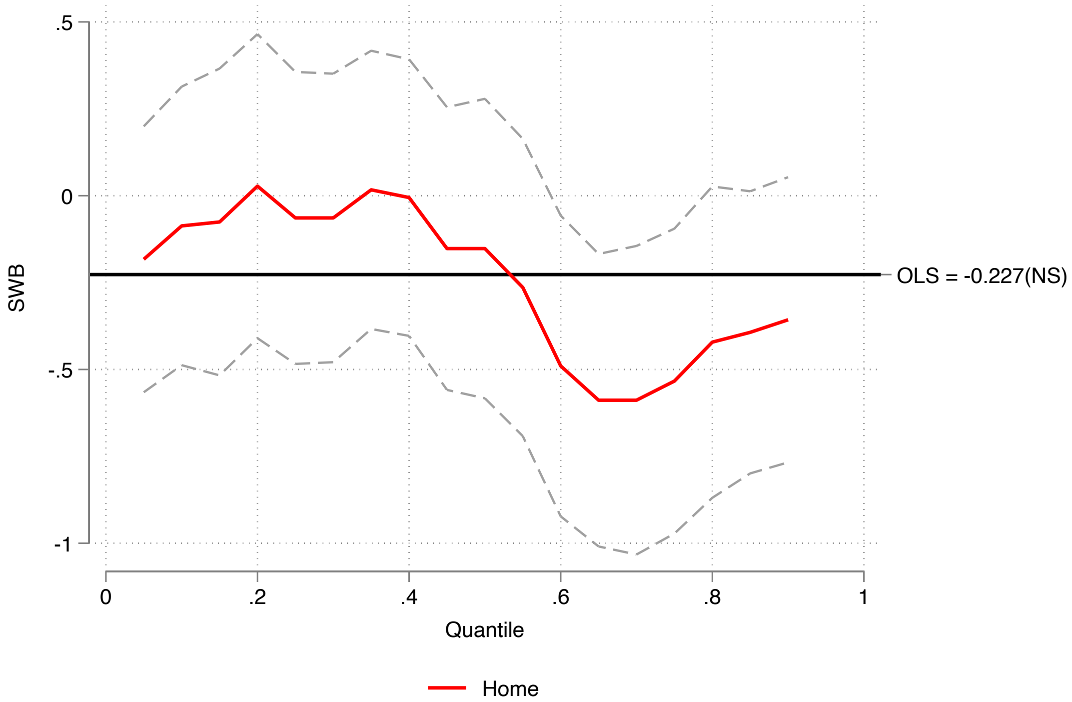
Notes: This table presents inverse probability weighting (ipw) estimates of the average treatment effect of *Home* for the full sample and by sex. All variables, including the controls, are defined in Table 1.
Source: Analysis of Eurostudent survey data for Ireland for 2013.

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.

Figure C1. Quantile regression model estimates of effect of *Home* on *SWB*.



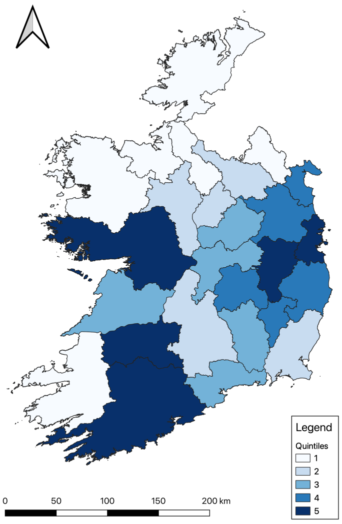
Notes: This figure presents partial effect estimates for *Home* from unconditional quantile regression models of *SWB*. The main independent variable of interest is *Home* and all variables, including the controls, are defined in Table 1.
Source: Analysis of Eurostudent survey data for Ireland for 2013.

Appendix D: Further Details on IV Approach

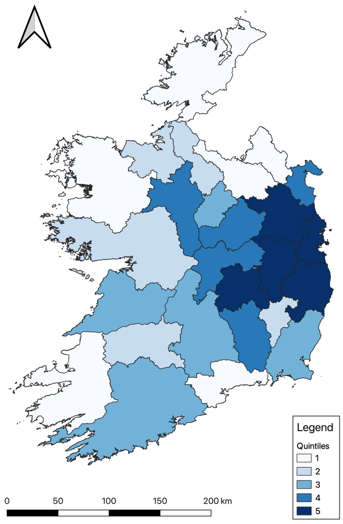
Our IV models estimate the effect of living at home on wellbeing by exploiting geographic variation in system-wide accessibility to higher education as a natural experiment. In Ireland, college students tend to study at HEIs that are close to where they live/come from and this is a result of a wide range 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, which implies shorter commutes.

Figure D1 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)).

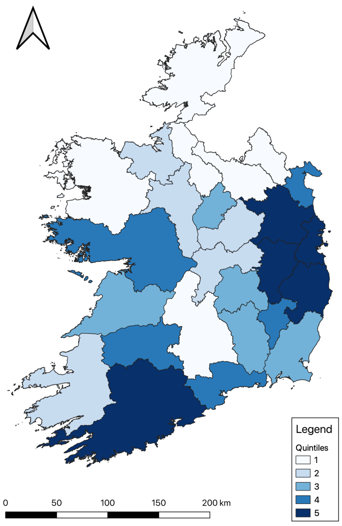
Figure D1. Accessibility, commute times, and living arrangements by county.



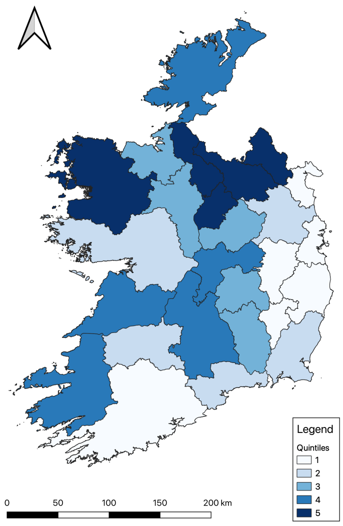
(a) System Accessibility



(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.

Appendix E: Robustness Checks for Instrumental Variables Models

In the main IV analysis, while the dependent variable relates to a student's *current* wellbeing, the instrument 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.[11] 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 $Corr(Access, \varepsilon) \neq 0$.[12] In other words, it is possible that the independence assumption might not hold and *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. 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

[11] We also estimated models excluding HEI, which showed very similar findings.

[12] 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.

assumptions. It is also possible to estimate confidence intervals (CIs) associated with these bounds.

The results are presented in Table E1 and show 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, but not for males.

Table E1 Nevo and Rosen (2012)'s Imperfect IV Bounds

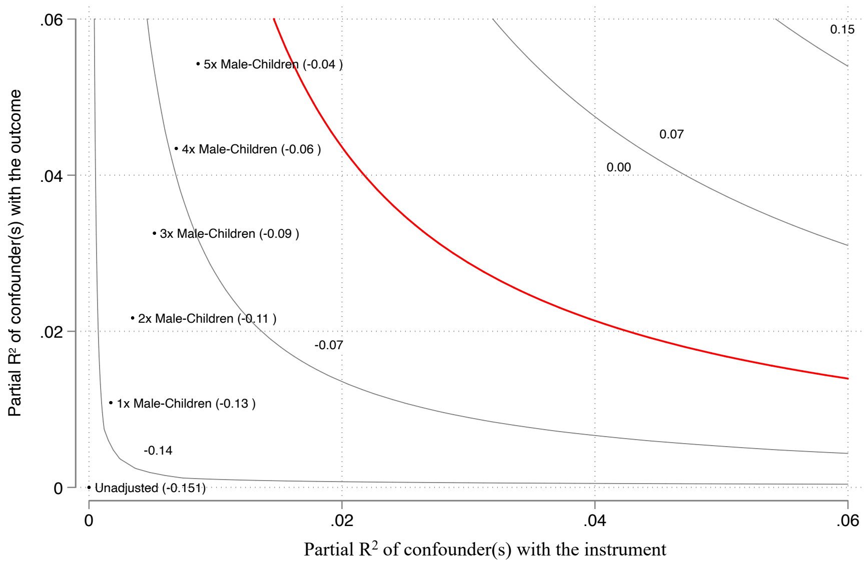
	Home			
	Lower Bound CI	Lower Bound Estimate	Upper Bound Estimate	Upper Bound CI
Total Effect				
Full Sample	-1.288	-0.684	-0.371	-0.041
Females	-1.596	-0.849	-0.433	-0.027
Males	-1.284	-0.284	-0.234	0.324

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.

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).

Results from the IV sensitivity analysis are presented in Figure E1, 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 E1 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.

Figure E1 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.