Institut canadien des dérivés
Canadian Derivatives Institute

L'Institut bénéficie du soutien financier de l'Autorité des marchés financiers ainsi que du ministère des Finances du Québec

Document de recherche

DR 22-01

Human Capital Risk and Portfolio Choices: Evidence from University Admission Discontinuities

Publié Juillet 2022

Ce document de recherche a été rédigée par :

Philippe D'Astous, HEC Montréal
Stephen H. Shore, Robinson College of Business, GSU

L'Institut canadien des dérivés n'assume aucune responsabilité liée aux propos tenus et aux opinions exprimées dans ses publications, qui n'engagent que leurs auteurs. De plus, l'Institut ne peut, en aucun cas être tenu responsable des conséquences dommageables ou financières de toute exploitation de l'information diffusée dans ses publications.

Human Capital Risk and Portfolio Choices: Evidence from University Admission Discontinuities

Philippe d'Astous and Stephen H. Shore*

July 22, 2022

Abstract

Theory suggests that increasing idiosyncratic, uninsurable labor income risk may cause individuals to reduce the risk in their financial assets. This relationship is confounded empirically for two reasons. First, labor income and financial risks are jointly determined, and both are driven by unobservable preferences. Risk tolerant individuals tend to choose riskier careers and hold riskier portfolios, leading to an upward-biased estimate of the effect of earnings risk on risky assets holdings. Second, it may be difficult to disentangle the effect of earnings volatility (our proxy for earnings risk) on portfolio risk from the competing effects of other features of the earnings process, such as average earnings or human capital betas. We overcome these identification problems by exploiting a discontinuity built into the Danish national university admissions system, which provides quasi-random assignment of similar applicants to programs with different earnings volatility profiles. Our methodology allows us to measure the causal impact of enrolling in a high-volatility program, holding fixed the average program earnings and human capital betas. We show that entering a program whose enrollees subsequently experience volatile earnings causes students to have more volatile earnings and, ceteris paribus, to hold fewer risky assets and be less likely to participate in the stock market. Since there is no raw correlation between earnings volatility and portfolio risk, these findings imply risk-based selection into programs of study: students inclined to hold risky portfolios tend to select into programs of study with volatile earnings, even though those programs cause them to take less portfolio risk.

JEL Classification: I23, I26, J24

*d'Astous: Department of Finance, HEC Montréal, 3000 Chemin de la Côte-Sainte-Catherine, Montréal, Québec, H3T 2A7, Canada, email: philippe.dastous@hec.ca. Shore: Department of Risk Management and Insurance, Robinson College of Business, Georgia State University, 35 Broad Street, Atlanta, GA 30303, USA, email: sshore@gsu.edu. We thank the Canadian Derivatives Insitute (CDI) at HEC Montréal, the Economic Policy Research Network (EPRN) at the University of Copenhagen, and the Center for the Economic Analysis of Risk (CEAR) at Georgia State University for financial support. We thank Steffen Andersen, Sylvain Catherine, Chuck Howard, Raluca Roman, Barry Scholnick, Ellapulli Vasudevan, and seminar participants at Cavalcade 2021, the European Financial Association meetings 2021, the 2021 Colloquium for Financial Planning, the European Retail Investor Conference 2021, Risk Theory Society, Georgia State University, HEC Montréal, and Wisconsin-Madison for many useful comments, as well as Ann-Lea Falk Larsen for excellent and dedicated research assistance.

Human Capital Risk and Portfolio Choices:
Evidence from University Admission Discontinuities

Abstract

Theory suggests that increasing idiosyncratic, uninsurable labor income risk may cause individuals to reduce the risk in their financial assets. This relationship is confounded empirically for two reasons. First, labor income and financial risks are jointly determined, and both are driven by unobservable preferences. Risk tolerant individuals tend to choose riskier careers and hold riskier portfolios, leading to an upward-biased estimate of the effect of earnings risk on risky assets holdings. Second, it may be difficult to disentangle the effect of earnings volatility (our proxy for earnings risk) on portfolio risk from the competing effects of other features of the earnings process, such as average earnings or human capital betas. We overcome these identification problems by exploiting a discontinuity built into the Danish national university admissions system, which provides quasi-random assignment of similar applicants to programs with different earnings volatility profiles. Our methodology allows us to measure the causal impact of enrolling in a high-volatility program, holding fixed the average program earnings and human capital betas. We show that entering a program whose enrollees subsequently experience volatile earnings causes students to have more volatile earnings and, ceteris paribus, to hold fewer risky assets and be less likely to participate in the stock market. Since there is no raw correlation between earnings volatility and portfolio risk, these findings imply risk-based selection into programs of study: students inclined to hold risky portfolios tend to select into programs of study with volatile earnings, even though those programs cause them to take less portfolio risk.

JEL Classification: I23, I26, J24

1 Introduction

Human capital risk — specifically labor income risk — is arguably the most important risk people face. When income risk is independent of asset returns and cannot be traded away or diversified, consumers with standard preferences should optimally tilt their investment portfolio away from risky assets (Kimball, 1993, Gollier and Pratt, 1996, Viceira, 2001, Cocco et al., 2005). As a response to this "background risk", households with higher labor income risk should therefore be less likely to participate in the stock market, and conditional on participation should hold less risky assets.[1] Quantifying the effect of earnings risk on financial choices has important implications for asset pricing (Bodie et al., 1992, Danthine and Donaldson, 2002, Addoum et al., 2019), the hedging of labor income through financial markets (Massa and Simonov, 2006, Betermier et al., 2012), and for the link between stock market participation and the equity premium (Vissing-Jørgensen, 2002).

However, individuals jointly choose their careers and investment portfolios for reasons driven by common factors that are frequently unobservable to researchers, such as risk preferences. This can lead to an omitted variable bias, causing an attenuation of the effect of labor earnings risk on portfolio risk (Fagereng et al., 2018). Put simply, risk tolerant individuals tend to choose riskier careers *and* riskier portfolio holdings, so the observed correlation between earnings and portfolio risk will be larger than implied by the true causal effect of income risk on portfolio choices. Furthermore, in order to credibly isolate the impact of earnings risk, researchers must not only use variation orthogonal to unobserved preferences, but also control for other features of the earnings process (level, growth, and comovement with stock returns) that might impact stock holding.

To overcome this identification problem, we exploit an institutional feature of the Danish university admissions system that creates quasi-random variation in admission to university programs, and therefore in earnings risk profiles. Prospective university students rank up to eight programs in preferred order and compete for limited enrollment capacity in selective programs based on a composite score that reflects their grades in high school. A central agency allocates placement in the different programs in preferred order to students with the highest scores, giving

[1] More generally, when the correlation between earnings growth and stock market returns is positive, individuals should optimally tilt their portfolios away from risky assets as their labor income risk increases. However, in Section 5.4 we find that programs of study have causal effects on earnings volatility, but not substantive ones on human capital betas. The source of variation in earnings risk we explore can therefore be understood as an increase in background risk.

rise to time-varying program-level admission cutoffs. For students with a score that is close to the cutoff for their more-preferred "reach" program but well above the cutoff for their next most preferred or "safety" program, the admission process effectively randomizes them into programs with different subsequent labor income risk profiles. Students with scores just above the "reach" program cutoff are assigned to that program, while nearly identical students with scores just below this cutoff are assigned to their "safety" program.

Our empirical design exploits this exogenous variation in program enrollment for students with a reach-safety program pair, combined with the fact that different programs of study lead students to subsequently experience different amounts of earnings volatility. We build on d'Astous and Shore (2021), who use the same education discontinuities to show that enrolling in a program in which the enrollees have higher permanent earnings volatility increases an individual's subsequent permanent earnings volatility one-to-one, but with no substantive effect on human capital betas.[2] These results imply that cross-program variation in permanent earnings volatility reflects causal effects, and can be interpreted as a change in background risk. In this paper, our identification strategy compares students on each side of their admission cutoffs – who will consequently be assigned to high- or low-volatility university programs, respectively – to estimate the effect of increasing earnings volatility on investment and housing choices, holding fixed the earnings level and human capital beta of the program of study.

We find that higher earnings volatility caused by university programs of study leads *ceteris paribus* to lower stock market participation and, conditional on participation, to a smaller proportion of risky assets in the investment portfolio.[3] We show that a one-standard-deviation increase in cross-program permanent earnings volatility (i.e., an increase from 11% to 14% annually) lowers stock market participation by 23% (a 6.5 percentage-point drop from 0.28 to 0.215). Furthermore, conditional on individuals participating in the stock market, a one-standard-deviation increase in cross-program permanent earnings volatility decreases the share of risky assets in the portfolio by

[2]We model individual- and program-level attributes of the earnings process 8 to 12 years after enrollment, following Meghir and Pistaferri (2004). We decompose earnings volatility, our proxy for labor income risk, into its transitory and permanent components. Permanent earnings risk is more likely to affect portfolio choices, since portfolio rebalancing is typically infrequent (Bertaut and Haliassos, 1997), and transitory shocks are typically damped by the social safety net, thus less likely to pass through to consumption (Blundell et al., 2008, Pruitt and Turner, 2020).

[3]In Section 5.2.2, we repeat our empirical exercise using individual-level earnings volatility, again instrumented with quasi-random assignment to reach and safety programs. While individual-level earnings process attributes are less precisely measured, we find qualitatively similar results, albeit with less statistical precision.

8% (a 2 percentage-point drop from 0.25 to 0.23).

While earnings volatility – driven by variation in program of study – causes people to take less portfolio risk, there is no association between earnings volatility and portfolio risk. This divergence between correlations and causal effects can be explained by risk-based selection into programs of study. Students inclined to hold risky portfolios tend to select into programs of study with volatile earnings, even though those programs cause them to take less portfolio risk. To illustrate this, we decompose our results in terms of average earnings and permanent earnings volatility from one of the least risky broad fields (education) to one of the riskiest fields (business). Higher earnings in business, ceteris paribus, would lead to a 0.06 higher stock market participation rate than that corresponding to education, but the effect of permanent earnings volatility, ceteris paribus, would lead to a 0.08 lower stock market participation rate than that corresponding to education. The two effects combined would therefore suggest a 0.02 lower participation rate for business programs. However, in the data, the participation rate for business majors is 0.19 higher than for education majors, which means that selection and program effects completely offset or even overturn the negative effect of stock market participation. The null association found in the data could therefore be the result of an omitted variable bias, highlighting the need for an identification strategy to measure the causal effect of earnings risk.

Our identification strategy exploits the rich cross-section variation in programs' earnings process attributes and allows us to instrument for various attributes simultaneously. We can therefore measure the causal impact of enrolling in a high-volatility program, holding fixed the average program earnings or human capital betas. We also investigate other potential mechanisms that could be at play. First, the program-level share of stock market participation could be driving our results, either through program peer effects (e.g. Brunello et al., 2010, Feld and Zölitz, 2017, Booij et al., 2017) or knowledge about the stock market (e.g. Hong et al., 2004, Ouimet and Tate, 2020). We rule out this channel by simultaneously instrumenting for the share of individuals participating in the stock market in the program of study. Next, we investigate the possibility that low-risk programs of study allow students to accumulate wealth faster, causing the increase in stock market participation. We augment our specifications by simultaneously instrumenting for financial wealth and find that our conclusions are unchanged. Finally, program ranking by prospective students or other reach and safety program features could affect our results through characteris-

tics that correlate with permanent earnings volatility. To rule out this possibility, we include reach and safety program fixed effects to our estimations, in order to capture any fixed characteristics of the programs that could be affecting our results. Again, we find that this channel cannot explain our findings.

We further show that our results are robust to using alternative time periods to average individuals' earnings process attributes, as well as using raw earnings instead of excess earnings, and to different empirical specifications of the model and various bandwidths around the admission cutoffs selected for study. These sensitivity analyses suggest that our results are robust to different assumptions about the earnings process and our preferred empirical specifications. We also investigate the role of human capital betas (e.g. Guvenen et al., 2017) in explaining stock market participation, to find that the admission discontinuities we exploit do not provide substantial exogenous variation in human capital betas, and, as a result, do not affect portfolio choices in our context.

Beyond the prediction that an increase in background risk should lead to lower risky asset holdings, other economic theories make predictions on the impact of labor income risk on committed consumption. These theories predict that higher earnings risk will lead to lower homeownership rates, and conditional on homeownership, to ambiguous effects on housing size (e.g. Shore and Sinai, 2010, Chetty and Szeidl, 2007). We find evidence that an increase in permanent earnings volatility leads to a decrease in the homeownership rate, while an increase in transitory volatility leads to an increase in housing and mortgage size.

1.1 Contribution to the Literature

Similar admission discontinuities to those we exploit here have been used in other contexts, most often to measure the effect of program of study on earnings.[4] While we use these same discontinuities, our work differs by studying how individuals adjust their portfolio choices in response to features of their program of study, notably its permanent earnings volatility.

Beginning with Guiso et al. (1996), a growing literature has documented the effect of labor

[4]For example, Kirkeboen et al. (2016) study the returns to different fields of education, Andersen et al. (2020) study the cross-program dispersion in the gender earnings gap, Hastings et al. (2013) study the returns associated with different university degrees, Heinesen (2018) studies the returns relative to higher education, and Hvidberg (2020) studies the effect of enrolling in an economics or business major on financial delinquency.

income risk on household investment portfolios. Some evidence suggests that labor income risk typically has small effects in deterring stock market participation, or the fraction of risky assets held in investment portfolios (Fagereng et al., 2018).[5] Bertaut and Haliassos (1997) study long-run precautionary motives in portfolio allocations and show that it is persistent risk that affects rebalancing, rather than short-run risk. This idea is put forth more directly by Angerer and Lam (2009) who study the association between earnings risk and portfolio choices by explicitly separating permanent and transitory volatility. However, unobservable risk preferences could correlate with both career and portfolio choices; the effect of risk preferences on portfolio allocations was established some decades ago (Cass and Stiglitz, 1972, Cohn et al., 1975),[6] and research suggests that risk preferences also affect educational and career choices (e.g. Saks and Shore, 2005, Nielsen and Vissing-Jorgensen, 2006, Calvet et al., 2021). While the literature has recognized that the correlation between earnings risk and portfolio choices is likely to suffer from an omitted variable bias as a result, an issue remains because of the difficulty in finding sources of exogenous variation in earnings risk.

To address this point, Betermier et al. (2012) analyze the portfolio holdings of households who switch industries between 1999 and 2002, in order to evaluate the effect of earnings risk on portfolio choices while holding individual preferences constant. There is evidence that firms differ in the earnings volatility of their employees (e.g. as correlated with technological innovation, (Kogan et al., 2020)), and this paper tests the degree to which this association is causal. They find effects of switching across industries but no level effects, suggesting that differences in cross-sectional preferences influence both earnings volatility and portfolio choices.[7] Fagereng et al. (2018) instrument the labor income risk of individuals using financial shocks to their employers. They measure the effect of this source of variation in earnings risk on portfolio choices, which allows them to quantify the amount of wage insurance that firms provide to their employees. Jo (2020) studies

[5]Guiso et al. (1996) finds support for this prediction using survey responses on expected inflation and expected income growth to proxy for the subjective variance of income growth. A relationship between background or earnings risk has also been investigated in respect to counter-cyclical income risk (Shen, 2018, Catherine et al., 2019, Catherine, Forthcoming), the presence of liquidity constraints (Koo, 1998), the context of retirement (Viceira, 2001, Bagliano et al., 2014), the effect of sea level rise (Ilhan, 2020), and the effect of other types of income, such as entrepreneurial income (Heaton and Lucas, 2000). Guvenen et al. (2017) further document the heterogeneity that exists in the effect of aggregate risk exposure using worker betas.

[6]For example, Ranish (2013) shows that although risk tolerant individuals tend to hold riskier portfolios, conditioning on measures of risk aversion could explain this sorting pattern.

[7]Familiarity, such as holding stocks closely related to one's work industry, can also play an important role in the relationship between portfolio holdings and preferences (Massa and Simonov, 2006).

the effect of state-level changes in employment protection laws using the Survey of Income and Program Participation, and finds an increase in stock market participation and the share of their financial wealth held in risky assets. Finally, Calvet and Sodini (2014) find a smaller role for labor income risk in the portfolio holdings of identical twins using twin fixed effect regressions as identification strategy, under the assumption that twins have the same risk preferences.[8]

We contribute to this literature by showing that students use education to sort into occupations that differ in their earnings risk, based on their risk aversion. The literature has identified that a welfare cost may exist due to the imperfect matching between prospective students' risk preferences and the earnings risk associated with their program of study (Jensen and Shore, 2015, Barth et al., 2017). Our results suggest that exogenous variation in the accumulation of human capital passes through from earnings risk into portfolio choices. We therefore provide evidence that individuals adjust other aspects of their financial choices in response to the effect of earnings volatility stemming from their program of study.

Furthermore, compared to previous studies, the rich cross-sectional variation in program earnings allows us to credibly study the causal effect on financial decision-making of several features of the earnings process simultaneously. This is an important feature of our empirical design because programs may differ along other dimensions in addition to earning volatility, such as their level, growth, and human capital betas. Our results show that these other earnings process features do not mediate the causal impact of earnings volatility on portfolio choices. To our knowledge, this paper is unique in cleanly estimating the causal impact on portfolio choices of all of these earnings process features simultaneously.

2 Institutional Setting

2.1 Danish National University Application

Our study design is based on the institutional details of university admissions in Denmark. Prospective students apply to university through a central agency that allocates students to programs with limited enrollment capacity, which creates plausibly exogenous variation in the probability of acceptance into different programs. As described in Andersen et al. (2020) and Heinesen (2018),

[8] Barnea et al. (2010) also study the portfolio holdings of twins, decomposing the total variance in risk aversion.

university admission in Denmark is based on prospective students' high school performance. A standardized score ranging from 0 to 13 in 0.1 increments is calculated based on students' grades in their senior years of high school, taking into account the level and difficulty of the classes. Students can list up to eight programs (that is, university-major pairs such as International Finance at Copenhagen Business School) in order of preference. Admission is granted to programs in preferred order to students with the highest scores until all seats are filled. For competitive programs, this generates an admission cutoff, according to which students with a score above the cutoff are admitted, while those with a score below it are not.

Admission to most programs depends only on the prospective student's high school score, with two exceptions. First, admissions can be made through two different "Quota" systems. The Quota 1 admission system, with applications in June, is intended for students applying directly after completion of high school. These prospective students are evaluated for admission into their chosen programs solely based on their composite high school score. The Quota 2 admission system, with applications in March, also evaluates prospective students based on their composite score, but allocates additional bonus points for extra-curricular activities. This system is usually chosen by students with relevant work experience for the programs to which they are applying. In our data we cannot observe these bonus points, thus the admission rule for Quota 2 partially depends on unobservable factors. In the sample we analyze, 54.4% of applications are made through the Quota 1 admission system and the remainder through Quota 2.

Second, when applying to different programs, students have the option to be included on a standby list in case they are very close to the cutoff for their preferred program but are not accepted (typically, in such cases they are 0.1 to 0.2 points below the admission cutoff). If any students drop out of the program in the first few weeks of the semester, applicants on the standby list will be offered places in the program. If no students drop out of the program, applicants on the standby list are guaranteed admission to the program in the following year. In our sample, about 40% of students choose this option when applying. Because these applications are conceptually different and allow students to be admitted to programs despite having a lower score than the admission cutoff, we rule them out in our analysis.

The institutional setting of university admission in Denmark is ideal for studying the effect of education on individuals. Because the system credibly leads to exogenous variation in admission

to different programs, it *de facto* randomizes students who are close to the admission cutoffs into programs with different earnings processes. The fact that randomness dictates admission to different programs for students close to the admission cutoff allows us to control for the potentially endogenous self-selection into university programs. If risk-averse students tend to enroll in programs for which earnings are less volatile, studying the relationship between earnings volatility and stock market participation could lead to erroneous conclusions regarding its effect. Instead, as described below, we focus on marginal students who are either slightly under or slightly above the cutoff for their preferred program, such that a small change in the admission cutoff would lead to admission to different programs.

2.2 Admission Discontinuities

We restrict our focus to the sample of students who choose a viable pair of "reach" and "safety" programs. The students included in this sample are those for whom the admission system generates quasi-random assignment to different programs. To be eligible for our sample, students had to be within 0.5 points over or under the admission cutoff for their preferred reach program and at least 0.5 points above the admission cutoff for their less-preferred safety program. This ensures that small changes in admission cutoffs due to annual supply and demand will generate discontinuous variation in the enrollment program of these students. When the admission system is implemented strictly based on a student's high school score, admission to either their reach or safety program is determined according to the following equation:

$$p_i = \begin{cases} r_i & \text{if } D_i \geq 0 \\ s_i & \text{if } D_i < 0, \end{cases} \tag{1}$$

where p_i denotes the enrollment program of student i, r_i and s_i denote their reach and safety programs, respectively, and D_i represents the distance between the student's score and the admission cutoff for their reach program. However, as detailed in Section 2.1, a number of complications arise such that the admission system does not operate exactly as detailed in equation (1). First, Quota 2 applications are noisier than Quota 1 applications because we are not able to observe the bonus points assigned to students based on their extra-curricular activity. This means that some

students could effectively be closer to (over or under) the admission cutoff of their reach program than what we observe. Second, because some programs require the completion of specific classes for admission, another factor we are unable to observe, admission could be denied despite the student having a score that exceeds the admission threshold. Third, for students whose scores fall exactly at the admission cutoff for their reach program, an algorithm breaks ties. We do not have details on these tie-breakers, but we verified that exclusion of such students does not alter the conclusions of our study.

Figure 1 shows the empirical admission discontinuities for students applying via the Quota 1 and 2 admission systems. Panel (a) shows that for Quota 1 applications, as students cross the admission cutoff for their reach program from below, their admission probability jumps discontinuously to quickly reach about 90%. At the same time, their admission probability for the safety program drops from about 75% to less than 10%. This shows that students slightly to the right of the admission cutoff for their reach program are discontinuously more likely to enroll in their reach program, while students slightly to the left of the same admission cutoff are discontinuously more likely to enroll in their safety program. This provides the source of variation we exploit in our analysis.[9]. Panel (b) shows the same information for students who apply via Quota 2. We can again see discontinuous differences in the probabilities of enrolling in reach or safety programs around the admission cutoff of the reach program, although the discontinuity is smaller than in Quota 1. This additional noise comes from the fact that students in the Quota 2 admission system may get additional bonus points, which we do not observe. For analysis, we pool applications from both admission systems but include Quota fixed effects and measure the probability of acceptance in the reach program separately to effectively treat both types of application independently.

2.2.1 Validity of the Admission Discontinuities

The Danish National University admission system closely relates to serial dictatorship, which is both Pareto efficient and strategy-proof (Svensson, 1999), subject to limits on the number of programs that can be ranked. This generates credible variation in admission to different university

[9]In Figure 1, we omit students who were accepted to a program other than their reach or safety and those not accepted by any programs, however for completeness we include all of these students in our main analysis

programs (Kirkeboen et al., 2016). However, a potential problem could arise if prospective students were able to guess the cutoff of their preferred programs based on public information about past cutoffs and manipulate their rankings to increase their chances of entering their preferred program. In this section, we present year-to-year variation in cutoffs, as well as formal density manipulation tests.

Panels (a) and (b) of Figure A1 show how cutoffs move from year to year, both unconditionally and based on the distance between the student's current score and the previous year's admission cutoff.[10] This figure shows that there is significant year-to-year variation +/- 1 point around admission cutoffs, which also justifies our choice of estimation bandwidth around the cutoffs. In our main results, we also control for the previous year's admission cutoffs, so that the results are identified from changes in the admission cutoff. Panel (c) presents the density of applications around the cutoffs. There is no evidence of bunching around the cutoffs, however we formally test this in the next section.

Table A1 presents the p-values for density manipulation tests developed by Cattaneo et al. (2019) under different assumptions. The estimation details are presented in the table's notes. Only 1 of these 12 cases (less than 10%), fails to reject manipulation of the assignment variable at the 5% significance level. This provides evidence that the admission system works and that individuals are quasi-randomly assigned to different university programs based on their scores. We further show that average individual characteristics are also smooth around the cutoffs, and present the results of the first-stage estimations for our main model in Sections 4.6 and 5.2, respectively.

3 Models and Estimation

3.1 Earnings Process Model

We follow Meghir and Pistaferri (2004) in specifying the earnings process as

$$w_{it} = c_t + \beta' X_{it}^w + u_{it}, \tag{2}$$

[10] For ease of exposition, this figure omits 12% of observations with cutoff variations larger than 1 in absolute value.

where w_{it} is the logarithm of real annual earnings,[11] c_t is a calendar year effect, and X_{it}^w is a vector of observable characteristics.[12] u_{it} represents the unexplained (or excess) component of earnings which can be decomposed into a transitory innovation and a martingale permanent component such that

$$u_{it} = \tau_{it} + \pi_{it}, \text{ and,} \tag{3a}$$

$$\pi_{it} = g_i + \pi_{it-1} + \zeta_{it}, \tag{3b}$$

with τ_{it} representing the transitory shocks to earnings, and π_{it} the permanent components of earnings.[13] The excess component of earnings growth is defined as Δu_{it} and total volatility is defined as $(\Delta u_{it})^2 \equiv \sigma^2$. We define the variance of the transitory shock τ as σ_τ^2, and normalize it by presenting its additive inverse. We define the variance of the permanent shock as σ_π^2.

3.2 Earnings Process Estimation

The moment conditions that identify the permanent and transitory shocks are

$$\mathbb{E}\left[\Delta u_{it}\Delta u_{it-1}\right] = \mathbb{E}\left(\tau_{it}^2\right) \equiv \sigma_\tau^2, \text{ and} \tag{4a}$$

$$\mathbb{E}\left[\Delta u_{it}\left(\sum_{j=-(1+q)}^{(1+q)} \Delta u_{it+j}\right)\right] = \mathbb{E}\left(\zeta_{it}^2\right) \equiv \sigma_\pi^2. \tag{4b}$$

In the analysis, we replace u_{it} with the residuals of the regression in equation (2). We replace the theoretical moments with their sample analog and denote them with hats, such as $\hat{\sigma}_{\pi,i}^2$ and $\hat{\sigma}_{\tau,i}^2$ for the estimated individual-level permanent and transitory volatility, respectively. We then average the various attributes of the earnings process by program of study p to create program-level averages. We denote these averages with overlines such as $\overline{\sigma}_{\pi,p_i}^2$ and $\overline{\sigma}_{\tau,p_i}^2$ for the average permanent and transitory volatility of the student's enrollment program p_i, respectively. We set

[11] We bottom code earnings at 100,000DKK and top code earnings at the 1 percent level.

[12] These characteristics include a constant, marital status, number of children, three levels of education (less than high school, high school, and college or more), a dummy for bottom-coded earnings, a quadratic in age, as well as gender, and gender interacted with all other observable characteristics.

[13] Note that the transitory component of earnings includes both transitory shocks and a potential measurement error term. Although measurement error is an important aspect to model when using survey responses for income, our usage of administrative income data in the analysis makes this distinction less relevant in our setting.

$q = 1$, in which case the transitory shock follows an MA(1) process, and the permanent shock is a composite MA(2) process.[14]

3.3 Effect of Earnings Volatility on Individuals' Financial Holdings

Our main equation of interest relates stock holdings to earnings process attributes:

$$SH_i = \Gamma(y_i \text{ or } \overline{y}_{p_i}) + \beta X_i + \mu_i, \tag{5}$$

where SH_i represents measures of stock holdings such as a binary variable indicating stock market participation, and a continuous variable indicating the fraction of risky assets held in the investment portfolio, $\overline{y}_{p_i}$ and y_i represent vectors of earnings process attributes, measured either at the program- or individual-level, and defined in Section 3.1 (e.g., excess earnings u, earnings growth Δu, total volatility σ^2, transitory volatility σ^2_τ, or permanent volatility σ^2_π), X_i represents a vector of control variables, and μ_i is the error term.[15] In our main findings, when $\overline{y}_{p_i}$ represents the permanent volatility of earnings, Γ measures the extent to which program-level permanent earnings volatility affects stock market participation or the share of risky assets in the individual's portfolio.[16] In Section 5.2.2, we investigate the effect of individual-level earnings process attributes and find qualitatively similar, albeit less precise, results.

3.4 Effect of Program of Study on Individuals' Earnings Process

As a first step in our analysis, we investigate the extent to which average earnings from programs of study affect individuals' earnings processes. We build on the results in d'Astous and Shore

[14] This follows Meghir and Pistaferri (2004). In unreported results, we also test a simpler model with $q = 0$ and our conclusions are unchanged.

[15] Equation (5) is written as a linear model for simplification, but in the analysis, we estimate probit models for stock market participation and report the marginal effects of participation, and we estimate tobit models for the share of risky assets in the portfolio, and report marginal effects for the share of risky assets, conditional on participation.

[16] In our baseline specification, we average the values of the earnings process attributes over the 8 to 12 year period following initial enrollment in order to smooth out the estimates. We allow this average to consist of less than 5 years of observations to maximize our sample size. The average number of observations used to construct these averages ranges from 4.35 for levels to 4.24 for permanent volatility, due to the number of years needed to construct these measures, as detailed in Section 3.1. Because programs include a relatively large number of individuals enrolled over many years, including or excluding y_i from the calculation of $\overline{y}_{p_i}$ has virtually no effect on the value of $\overline{y}_{p_i}$ or the results that follow from it. For individuals not admitted to any program of study, we calculate the average earnings of their enrollment cohort as the sample average of students not admitted to any program in the reach-safety program pair sample used in our main analysis.

(2021) who use the same econometric model to predict the various individual-level outcomes y_i based on the average attributes $\overline{y}_{p_i}$ of the program of enrollment:

$$y_i = \delta \overline{y}_{p_i} + \beta X_i + \epsilon_i, \tag{6}$$

where, again, y_i represents a vector of possible outcomes from the various attributes of the earnings process, $\overline{y}_{p_i}$ denotes the analogous program-level average outcome of the individuals who enroll in the same program p_i as individual i, X_i denotes individual covariates, and ϵ_i is the error term. When $\overline{y}_{p_i}$ represents the permanent volatility of earnings, δ measures the extent to which the permanent volatility of program earnings affect an individual's own permanent earnings volatility.

3.5 Fuzzy Regression Discontinuity Design

Directly estimating equations (5) and (6) may not reveal an unbiased estimate of Γ and δ in the presence of selection problems, that is, if $\text{cov}(y_i, \mu_i) \neq 0$ or $\text{cov}(y_i, \epsilon_i) \neq 0$. For example, if risk-averse individuals tend to select both fields of study in which earnings are less volatile and less risky investment portfolios, a classic omitted variable problem will plague the estimation of the causal effect of earnings risk on financial holdings, causing an attenuation bias. To overcome this identification problem, our analysis uses the admission discontinuity presented in Section 2.2 as a source of exogenous variation in admission to programs of study.

In both equations (5) and (6), we obtain causal estimates of Γ and δ by restricting our estimation sample to students near the admission cutoff of their preferred reach program, and using admission discontinuities to estimate a fuzzy regression discontinuity IV design. The first-stage regression used in our fuzzy regression discontinuity design is given by:

$$y_i \text{ or } \overline{y}_{p_i} = \phi X_i + \chi Z_i + \xi_i, \tag{7}$$

and the following variables are included as instruments in Z_i:

$$\mathbb{P}(p_i = r_i | D_i) \times \overline{y}_{r_i}; \text{ and } \mathbb{P}(p_i = s_i | D_i) \times \overline{y}_{s_i}, \tag{8}$$

where $\overline{y}_{r_i}$ and $\overline{y}_{s_i}$ denote the various attributes of the earnings process, averaged for the reach and safety programs, respectively. For example, we instrument permanent volatility using $\mathbb{P}(p_i = r_i|D_i) \times \overline{\sigma}^2_{\pi,r_i}$ and $\mathbb{P}(p_i = s_i|D_i) \times \overline{\sigma}^2_{\pi,s_i}$. The first-stage equation uses the source of variation in our instruments Z_i to identify the effect of changes in admissions on the future earnings processes of admitted students. These instruments are good candidates to use in a regression discontinuity design because they capture the variation in the earnings process attributes across reach and safety programs and account for selection in the admission process by interacting these with the probability of being admitted to the reach and safety programs. This is a valid identification strategy because, when comparing scores just below and just above the reach program cutoff, the probability of being admitted to the reach and safety programs discontinuously increases and decreases, respectively.

To test the validity of our instruments, Figure A2 provides a graphical representation of the first-stage equations (7), by replacing the continuous measure of the probability of enrollment in the reach program with a sequence of dummy variables reflecting distance from the admission cutoff. Each student has exactly one such dummy variable, equal to 1, representing their own distance from the admission cutoff, while all other dummies are equal to 0. This figure shows that all first-stage outcomes have large discontinuous jumps around the admission cutoff, confirming that as students cross the admission discontinuity from below, they are exposed to the earnings process of their reach program instead of the safety. These jumps are large, discontinuous and are estimated very precisely, such that concerns about weak instruments are absent in our context.[17] To further verify the validity of these instruments, we present bunching and other density manipulation tests in Section 2.2.1. The results show no evidence of manipulation around the admission cutoff.

In the analysis, we use the predicted values from equation (7) in two-stage estimation models, for which the second stage equations are represented by equations (6) and (5). When using more than one attribute of the earnings process in our estimation, we instrument each attribute using its analogous set of equations (8). We use reach and safety averages to instrument both individual- and program-level attributes of the earnings process. Because our analysis shows that permanent

[17] d'Astous and Shore (2021) presents the reduced form and detail estimation of the reduced form results, including the breakdown between Quota 1 and Quota 2 applications.

earnings volatility is determined one-for-one by program-level earnings volatility, our main results use program-level earnings volatility in equation (5), and we demonstrate that our results hold using individual-level earnings volatility, although they are less precisely estimated.

4 Data and Descriptive Statistics

Our study uses administrative data available through various Danish agencies, as detailed below. We start by constructing the population data, which consists of the universe of individuals that apply to university for the first time between 1993 and 2006.[18] We retain only individuals for whom we have access to the complete set of variables used in our analysis and obtain a total of 321,091 valid student application-year observations. We use this population data to construct program-level averages. We then construct our main sample, consisting of the subset of these applicants who have a reach-safety program pair. From this sample, we obtain 10,567 observations, which we use in our main tests described in Section 3.5.

Table 1 presents individual-level descriptive statistics for the main variables used in the analysis. We present averages for the entire population of students applying to university for the first time (all applications; left), as well as the subsample of these students who have a reach-safety program pair (used sample; right). This allows us to show how individuals in our reach-safety sample differ from the population in general, and to present the average of program-level attributes as calculated in the population of first-time applicants.

4.1 Demographics

First, we obtain the demographic characteristics of individuals up to 2016 through the Danish Civil Registration System. From these data, we obtain a unique identification number for each individual, allowing us to match their records from other registries. Panel I. of Table 1 shows that students in both samples are about 21 years old when initially applying, and close to 40% are male. Individuals in our main sample are somewhat positively selected based on the wealth and

[18] We keep the first time a student applied to university programs and entered into a program that year. If an individual applied once or more but was not accepted into a university program, we retain only their initial application. We select admission years 1993 to 2006 for two reasons: 1) because the admission data starts in 1993, and 2) because the earnings data end in 2016, and we require at least 10 years of observations to estimate the earnings process.

education characteristics of their parents.

4.2 Educational Data

Second, we use admission data from the Ministry of Education on the universe of prospective students applying to university programs. For each individual, these data include their high school score, their program application rankings, the program to which they were admitted (if any), whether their application was submitted via Quota 1 or 2, and whether they opted to be placed on a standby list. The data also include the official cutoff figures for each program. Panel II. of Table 1 shows that students in our main sample have higher scores (8.8 vs 8.2) and rank one more program than those in the population. Typically, the rank of their reach program is first and that of their safety is second. We also show that students are on average 0.1 below the admission cutoff for their reach program, and that 60% of them rank reach and safety programs in the same fields, and 30% at the same institution.

4.3 Earnings Data

We obtain earnings information for the period of 1993 to 2016 through the Danish Tax Authority. These data are directly reported by employers to the fiscal authority. We bottom code earnings at 100,000 DKK and top code them at the 99% level in the population of first-time university applicants.[19] From these data, we estimate the attributes of the earning process for individuals and programs, as described in Section 3.1. We estimate this model in the population data by pooling all individuals between the ages of 25 and 55 during the period of 1993 to 2016.

Panel III. of Table 1 presents the earnings characteristics of these prospective students. While they all start out with similar initial earnings, students in our main sample take about one more year to complete their program and find a job than students in the general population. The attributes of the earnings process are averaged 8 to 12 years after enrollment. They are similar across both groups, although excess earnings growth and earnings risk are larger in our main sample, while the correlation between earnings and stock market returns is smaller.

[19] The January 2019 exchange rate for USD to DKK was 6.5.

4.4 Financial Wealth Data

Lastly, we obtain financial wealth data for the period of 1993 to 2016 through the Danish Tax Authority. These include the amount of savings in bank deposits and the amount invested in stocks and bonds, all of which are directly reported to the fiscal authority by the financial institutions. We categorize as investments in "stocks" any investments in the stock market, which could include exchange traded funds or mutual funds in different asset classes. We winsorize financial data at the 1% and 99% levels in the population of first-time university applicants. From these data, we create a measure of stock market participation as a dummy variable indicating whether the individual holds stocks in any of the years studied, as well as the ratio of total stocks held to total financial wealth as a measure of the riskiness of the investment portfolio. Panel IV. of Table 1 shows the financial wealth of both samples. In both cases, 28% of individuals hold stocks and 8% hold bonds. The reach-safety sample is somewhat positively selected, with individuals holding on average 42,000 DKK in stocks (vs 37,000 DKK in the general population), and 38,000 DKK in bonds (vs 35,000 DKK), conditional on holding these financial instruments. Virtually every individual in our main sample holds bank deposits with an average value of 73,000 DKK in our main sample (vs 67,000 DKK). Lastly, the unconditional ratio of stocks to total financial wealth (i.e., stocks + bonds + bank deposits) is 7% for both samples, reflecting low individual participation in the stock market. Conditional on participation, this ratio increases to 25%.

4.5 Program-Level Descriptive Statistics

Table 2 shows average values for the attributes of the earnings process and financial wealth at the individual and cohort-level for the population, and at the reach-, safety- and gap-levels for the reach-safety sample. This illustrates the source of variation used in our analysis to identify our main results. When relevant, the program-level standard deviation of each variable is presented in parentheses, while the standard deviation across programs is presented in brackets. We present descriptive statistics for the main variables used in our analysis conditional on fields of study in Appendix Table A2. Although our analysis is based on discontinuities in the admission process at the *program level*, this table facilitates an understanding of the variation in the data. The table reveals variation in all dimensions of the earnings process across fields. For example, humanities

and science majors take the longest to complete their studies, law and engineering have the highest initial earnings, humanities have the highest total volatility, and business and law have the highest permanent volatility. In terms of financial wealth, business programs have the highest rate of stock ownership, and the highest value of stocks held, whereas education has the lowest analogous values. This provides evidence that there is substantial variation in stock market participation across fields, which we exploit in the main analysis. The table also indicates the average number of students per program-year, the number of programs per field, and the distribution of reach and safety programs per field.

4.6 Average Characteristics Across the Admission Cutoffs

Plotting the distribution of prospective student characteristics across the admission cutoff for their reach program allows us to verify whether there are differences in candidates on either side of the cutoff. Figure A3 illustrates that the high school score, number of programs ranked, parental wealth, future earnings, and the ranking of reach and safety fields are continuous around the admission discontinuity. Combined with our results in Section 2.2.1 showing no manipulation in admissions around the cutoffs, this confirms the validity of using admission cutoff discontinuities as a source of exogenous variation.

5 Main Results

In this section, we present our main results using the identification strategy detailed in Section 3.5, as well as the analogous non-instrumented results. For interpretation of the results, it is useful to compare the estimates for the IV and OLS equations. The OLS equations, by construction, include causal effects of the earnings process but also self-selection and program effects, whereas the IV results are identified from the exogenous variation in program admission and therefore isolate the causal effect of program-level attributes on individual outcomes. In all our results, we report heteroscedasticity-consistent standard errors.

5.1 Effect of Program Earnings Process on Individual Earnings Process

As the first step in our analysis, we demonstrate how the program-level earnings process affects the individual's earnings process. Table 3 presents the baseline results, and d'Astous and Shore (2021) present a battery of robustness tests to validate these effects.[20] Panel A shows the instrumental variable estimation. For each attribute of the earnings process, we estimate equation (6) by two-stage least-squares using equation (7) as the first stage. We instrument each component of the earnings process using the analogous instruments presented in equation (8).[21] Panel B shows the results estimated with OLS regressions. In both panels, the dependent variables are individual-level outcomes of the earnings process (e.g., excess earnings growth and volatilities) and the main explanatory variables are the various attributes of the earnings process, measured at the program level.

The earnings results presented in Table 3 show how individual-level earnings process attributes depend on program-level earnings process attributes. First, we demonstrate that excess earnings are caused by programs of study: an additional $1 in excess program-level earnings is estimated to increase individual earnings by $0.53. A contrario, earnings growth is largely driven by self-selection. This can be seen by comparing the IV and OLS estimates; for excess earnings, both estimates are similar and statistically significant, whereas for earnings growth, the OLS estimate of 0.84 is highly significant, while the IV estimate is not. Although the OLS results for excess earnings growth suggest a strong effect of the program studied, the IV counterpart is insignificant, suggesting that most of the OLS effect is driven by the self-selection of students in the program.

In terms of earnings volatility, Panel A shows that total volatility is partly due to the program of study (an estimated coefficient of 0.52 compared to 0.88 for its OLS counterpart). This result can be better understood by decomposing total volatility into transitory and permanent components. Transitory volatility is only partly due to programs of study (an estimated coefficient of 0.55 compared to 1.03 for its OLS counterpart), a result similar to that of total volatility. However, permanent volatility is highly significant with a coefficient of 1, suggesting that the permanent earn-

[20] Among other tests, they show that these results are robust to various econometric specifications and the inclusion of reach and safety program fixed effects.

[21] d'Astous and Shore (2021) present the first-stage results and show that the regression F-tests range from 450 to 1,598, a statistic well large enough to rule out any concern about weak instruments. Figure A2 graphically illustrates the first-stage estimations and confirms that the reach-safety design strongly predicts enrollment-program outcomes.

ings volatility of the program of study is causal, and carried on to students about one-for-one.[22] This justifies the use of program-level variation in permanent and transitory earnings volatility to investigate the role of earnings risk in financial choices.

5.2 Effect of Earnings Volatility on Individual Portfolio Choices

Having presented evidence that programs of study cause permanent earnings volatility literally one-for-one, we turn to the effect of earnings risk on individual financial holdings. Table 4 presents the results for stock market participation and the share of risky assets in the portfolio. The left and right panels use program- and individual-level risk measures, respectively. Panel A shows the instrumental variable estimation. Specifically, we instrument both the program-level and individual-level measures using the same reach and safety instruments presented in Section 3.5. For stock market participation, we estimate equation (5) by two-stage probit least-squares using equation (7) as the first stage and report the marginal effect on the probability of holding stocks. For the share of risky assets, we estimate the model by two-stage tobit least-squares and report the marginal effects on the share of risky assets, conditional on stock market participation.[23] Panel B shows the analogous results estimated using probit and tobit models, but without using the admission discontinuity instruments and instead presenting the raw association in the data.

5.2.1 Program-Level Earnings Volatility Effects

The left panel of Table 4 shows that program-level permanent earnings volatility strongly influences stock ownership and the ratio of risky assets to total financial wealth. The marginal effect of permanent earnings risk on stock market participation is -6.36, which implies that a one percentage-point increase in permanent earnings risk (roughly one standard deviation of the enrollment cohort average, as documented in Table 2), reduces stock market participation by 23% (a 6.5 percentage-point decrease from a baseline of 28 percent). The marginal effect of permanent earnings risk on the share of risky assets held, conditional on participation, is -1.88, which im-

[22] d'Astous and Shore (2021) show that this effect is robust to many different econometric specifications and assumptions about the earnings process.

[23] The first-stage results are presented in Table A3, and show the high predictive power of reach and safety program earnings process attributes. Note that the first-stage results are identical for all our main results, in which we always instrument for program- or individual-level earnings process attributes using the same reach and safety program-level instruments. The F-tests range from 56 to 319, which is large enough to rule out any weak instrument concerns.

plies that a one percentage-point increase reduces the risky asset share by 8% (a 2 percentage-point decrease from a baseline of 25 percent). Table A6 shows that these results are robust to different econometric specifications.

Importantly, the non-instrumented analogous results of these equations do not detect any relationship between the volatility of program-level earnings and individual investment behavior. This shows that there is likely to be an important attenuation bias in the non-instrumented estimation of these effects.[24] To better understand this null result in raw association, appendix Table A4 presents further evidence of financial holding by prospective student who rank riskier programs in their university application. In that table, we reproduce our main findings from Table 4, but additionally present the coefficients on the control variables for the reach and safety earnings volatility controls used in our main specification. Although these variable enter our specification solely as controls, they are informative about the effect of program rankings by prospective students on financial holdings. Specifically, the results show that students who rank programs with higher permanent earnings volatility also are more likely to hold stocks, and conditional on participation, they hold a larger share of their portfolios in risky assets. These effects are as large as the instrumented results we present, which explains why there is a perfect offset of earnings risk characteristics in the raw associations presented in Table 4.

5.2.2 Individual-Level Earnings Volatility Effects

An alternative identification strategy uses the same admission discontinuities, as well as reach and safety program attributes, to instrument for *individual-level* earnings risk. Because of the limited time series of data available, individual-level earnings attributes are noisier, which could lead to less precise estimation results. In the right panel of Table 4, we replace the program-level earnings process attributes used in our main results with their individual-level analogs, using the same reach and safety program instruments as used previously. The results are qualitatively similar to the results using program-level attributes. For stock market participation, permanent earnings volatility is still significant at the 1% level, with a marginal effect of -3.56. Its effect on the

[24] Angerer and Lam (2009) also quantify the effect of permanent earnings risk on the share of risky assets in a comparable setting to ours, but without instrumenting for earnings risk. In their setting, the effects are smaller than ours; they show that a one percentage-point increase in permanent income risk leads to a 1.084% decrease in the share of risky assets. This is consistent with at least some selection effect when analyzing the association between financial holdings and earnings risk.

share of risky assets is significant at the 10% level, with a similar marginal effect of -2.05. This lower statistical significance and attenuation bias (compared to program-level estimates) is to be expected when measuring noisy individual-level earnings processes, due to limited time series income data. Nonetheless, the evidence shows that our main conclusions hold for both the program- and individual-level estimations.

5.2.3 Quantifying the Effect of Earnings Volatility on Individual Financial Holdings

To further illustrate the implications of our findings, we show how our results can be used to explain the gap in stock market participation between business and education majors. In terms of field-specific averages, Table A2 shows that, compared to education, business has higher excess log earnings (0.091 vs -0.025), higher permanent volatility (0.018 vs 0.006) and a higher stock market participation rate (0.40 vs 0.21). We make use of the marginal effects of excess earnings and permanent earnings volatility to decompose the participation gap between business and education majors into the causal effects of earnings and earnings risk, and residual selection. First, given that permanent earnings volatility is $0.018 - 0.006 = 0.012$ higher in business than in education, this would lead to a rate of stock market participation that is 7.8 percentage points lower (i.e., $(0.018 - 0.006) \times -6.50$) in business than it is in education, attributable to permanent earnings risk, ceteris paribus.

Second, given that excess earnings are $0.091 - (-0.025) = 0.116$ higher in business, this would lead to a rate of stock market participation that is 6 percentage points higher (i.e., $0.116 \times 0.51 = 0.06$) in business than in education, attributable to excess earnings, ceteris paribus. Therefore, based only on the effects of earnings and their volatility, the stock market participation rate should be $0.078 - 0.06 = 0.018$ lower in business. However, Table A2 shows that stock market participation is $0.40 - 0.21 = 0.19$ higher in business than in education. Out of this gap, -0.078 comes from differences in permanent earnings volatility and 0.06 comes from excess earnings. The excess gap between these two majors is therefore 0.208, and is due to a mix of self-selection and the effect of the program of study. This illustrates the fact that using the association between earnings risk and stock market participation will miss large offsetting effects of the program of study. This is consistent with Panel B of Table 4 which shows no association between permanent earnings risk

and financial holdings.

Another way of scaling our results is in terms of the share of the variation in portfolio holdings that can be explained by education-induced permanent earnings volatility. First, note that Table 2 shows that the cross-sectional standard deviations of individuals' and programs' stock shares are 0.17 and 0.033, respectively. This implies that $(0.033/0.17)^2 \simeq 3.8\%$ of the variation in an individual's stock shares can be explained by their program of study. Table 2 shows that the cross-sectional standard deviation of programs' permanent volatility is 0.008, and Table 4 shows that the coefficient on the causal impact of permanent volatility on stock share is -2. Therefore, 1% of the variation in individuals' stock shares (i.e., $(2^2 \times 0.008^2)/0.17^2$) — and 24% of the variation in programs' stock shares (i.e., $(2^2 \times 0.008^2)/0.033^2 \simeq$) — can be explained by the causal effect of the program of study's permanent earnings risk on stock shares, respectively.

5.3 Effect of Earnings Volatility on Housing and Committed Consumption

In this section, we investigate the effect of earnings risk on financial choices related to committed consumption in the form of housing (Chetty and Szeidl, 2007, Shore and Sinai, 2010). When households face low or uncertain future earnings, or when they are faced with negative income shocks, they may delay purchasing their first home (Attanasio et al., 2012, Ortalo-Magne and Rady, 2006).[25] To test whether earnings risk impacts the decision to become a homeowner, we create a variable indicating whether individuals in our sample own a house in the 8 to 12 years following their application to university. Furthermore, housing consumption is illiquid, and its adjustment is costly, so that adjustments in housing consumption will only be optimal following large earnings losses. Shore and Sinai (2010) show, both in theory and in practice, that this can lead households with higher earnings volatility to buy bigger houses. We therefore test whether the earnings process affects the size of the house purchased and its mortgage, conditional on being a homeowner.

The left and right panels of Table 5 present our results using program- and individual-level earnings risk measure, respectively. We report average partial effects from estimating probit models on the binary variable representing home ownership, and instrumental least squares for home

[25]Stock market participation can also interact with the decision to own or rent a home, through individuals' savings motives (Vestman, 2019).

and mortgage values following equation (6). For both program- and individual-level measure, we find that individuals faced with higher permanent earnings risk are less likely to become homeowners, but this result is only statistically significant when using individual-level measures. This result is consistent with findings that households with uncertain earnings or facing negative income shocks delay becoming homeowners (Attanasio et al., 2012, Ortalo-Magne and Rady, 2006). Our results also show evidence that home ownership increases with the level of excess earnings when measured at the program level. Although our point estimate using individual-level excess earnings is similar, the standard errors are larger. Since home ownership commits the household to future housing consumption, it is not surprising that earnings drive the decision to become a homeowner.

Although are results are less conclusive for home and mortgage values, conditional on being a home owner, there is still suggestive evidence that an increase in transitory earning risk causes individuals to buy larger houses, financed with larger mortgages. This effect is only significant when using program-level measures. It echoes the finding in the literature on committed consumption that households with higher earnings volatility to buy bigger houses Shore and Sinai (2010). Taken together, our results show that the effect of earnings risk passes through housing decisions of individuals.

5.4 Human Capital Betas

When earnings comove with stock market returns, human capital betas can be created to measure the relationship (e.g., Guvenen et al., 2017, Addoum et al., 2019). If individuals consider the comovement of their earnings and stock market returns when making portfolio choices, they will tend to shy away from risky assets when their returns comove with their own earnings. We test for this relationship in our data, but find no evidence that programs of study have a causal effect on human capital betas. As such, the admission discontinuities we study do not provide convincing variation in program-level variation in human capital beta, and therefore we do not find that they affect portfolio choices in our sample.

We nonetheless present our results in Appendix Table A5. We first calculate annual program-level comovement between real earnings growth (Δu_{it}) and stock market returns and investigate

its effect on individuals' own human capital beta. We use both the Danish OMX C20 and the S&P 500 indices in percentage and log returns, and measure the average correlation 8 to 12 years after application. In Panel I, we show that cross-program variation in human capital betas does not explain individual-level human capital betas.[26] In Panel II, we show that instrument program-level human capital betas do not affect stock market participation or the portfolio share of risky assets. Finally, in Section 6, we also investigate the impact of controlling for human capital beta when measuring the effect of permanent earnings volatility and find that it does not affect our main findings.

6 Alternative Mechanisms and Robustness

In this section, we investigate alternative mechanisms and econometric specifications for our main results.

Alternative specifications. Our identification strategy allows us to instrument for different attributes of the earning process simultaneously, as well as to control for different observable characteristics. We first show robustness to using different specifications for our main results using program- and individual-level earnings risk measures in Tables A6 and A7, respectively. We focus our presentation on the results in Table A6, but all our results are qualitatively similar using individual-level measures, although our statistical power is reduced in certain instances. Each table presents different econometric specifications of our baseline findings in Table 4, reproduced and bolded in columns (3) and (9).

In Panel A, we instrument each explanatory variable using their analogous set of equations (8) and in Panel B, we present the non-instrumented results. In columns (1) to (4) and (7) to (10), we vary the set of simultaneous instruments from the program-level earnings process used to estimate our main results on stock market participation and the portfolio share of risky assets. This allows us to verify that other attributes of the earnings process are not driving our results. In columns (5) and (11), we include in the instrumental estimations the same set of controls included in our baseline non-instrumented estimations from Panel B, namely parents' wealth, income, and

[26] It is important to note that we are restricted to using yearly stock market returns to match the yearly earnings growth of individuals. Because stock market returns vary in the same way for all individuals, the effective variation we can exploit is much smaller, which could explain our lack of findings across these dimensions.

education, as well as students' grade, age, and gender. This allows to compare the IV and non-IV results with the same control variables. Finally, in columns (6) and (12) we omit the admission probabilities from the previous year from our identification strategy. In all instances, our main findings are not altered by such specification changes.

Program-level stock market participation. Next, we investigate potential alternative mechanisms that could explain our findings. We focus our presentation on the results using program-level measures in Table A8, and Table A9 presents the individual-level equivalent. Our baseline findings of Table 4 are reproduced and bolded in columns (1) and (6). We first explicitly consider the probability that the share of individuals participating in the stock market in the program of study could influence our results through peer effects or knowledge of the stock market. To rule out this possibility, we instrument the share of individuals in the student's program that invest in the stock market using our same identification strategy and instruments. Columns (2) and (7) both show that, although the program-level share of individuals that participate in the stock market has an effect on participation and the share of risky assets held, this effect is not sufficient to significantly change our results, which are both still significant at the 1% level.

Program-level human capital betas. In Section 5.4, we show that the human capital beta is not strongly caused by programs of study, nor does it predict stock market participation or the share of risky assets in our estimation strategy. Nonetheless, in columns (3) and (8) of Tables A8 and A9 present econometric specifications that simultaneously instrument for human capital beta, demonstrating that our main findings are still unaffected by such inclusion. This provides novel evidence of the role of earnings risk in portfolio choices, even when holding fix human capital betas.

Program-level financial wealth. Next, we consider the possibility that graduates from low-risk programs might accumulate financial wealth faster than their peers in riskier programs, which could drive the rise in their equity share. To rule out this possibility, we instrument financial wealth of individuals in the student's program using our same identification strategy and instruments. Columns (4) and (9) of Table A8 shows that the inclusion of this variable does not alter our findings, so that the level of financial wealth cannot be driving our findings.

Other program characteristics. Another potential mechanism that could explain our findings relates to unobserved program characteristics. This would be a potential concern in our analysis

if program rankings by prospective students or other aspects of the reach and safety programs correlate with permanent earnings volatility to drive the results. In columns (5) and (10) of Table A8 we therefore include fixed effects for each prospective student's reach and safety programs, effectively controlling for all constant effects of both programs.[27] The effects are 12% to 15% smaller, but are both statistically significant when testing at the 5% level. This provides evidence that other program characteristics cannot explain our main findings. Together, these results therefore suggest that variation of permanent earnings volatility across programs of study is driving the main effect documented here.[28]

Alternative Earnings Process Assumptions. Next, we investigate the robustness of our findings to assumptions about the earnings process. Our main results are based on excess earnings measured as the residuals from equation (2), averaged 8 to 12 years after enrollment. In table A10 we show the results for program- and individual-level earnings measures, using raw and excess earnings, and alternatively averaging the attributes of the earnings process 8 to 15 years after enrollment. Panels A to D, and Panels E to H show robustness to these alternative assumptions as they relate to our findings in Table 4. Our main conclusions remain unchanged with these different assumptions.

Alternative Estimation Bandwidths. Lastly, we demonstrate the robustness of our estimates for stock market participation and the share of risky assets presented in Table 4 to different bandwidths around admission cutoffs in Figure 2. The results show that our estimates remain similar as we narrow the bandwidth of our estimation sample around the admission cutoff of the reach program.

7 Conclusion

In this paper, we study the effect of earnings volatility on portfolio choices. Because career and investment choices are jointly determined, we use an identification strategy to isolate exogenous variation in earnings risk. We exploit an institutional feature of the Danish National University

[27] Although there are a moderate number of competitive programs, and therefore a limited number of reach programs, there are many non-competitive programs and therefore many more safety programs. In our Tobit specifications, convergence is not achieved when controlling for both reach and safety program fixed effects, therefore we replace the fixed effects for safety programs with their broad field of study, as presented in Table A2.

[28] We also include reach and safety fixed effects in Table A9, with the same caveat that for the Tobit model, due to convergence issues, we use safety program fields of study fixed effects.

system which allows us to study a sample of students who are quasi-randomly assigned to different programs of study that vary in the subsequent earnings profiles of their enrollees. d'Astous and Shore (2021) show that permanent earnings volatility passes through from programs of study to individuals one-for-one. We use this source of variation in earnings volatility to study its effect on financial decisions.

We show that individuals with exogenously higher earnings volatility are less likely to hold risky financial assets. This is consistent with the theory of background risk that an exogenous increase in idiosyncratic, uninsurable labor income risk should lead individuals to reduce the risk in their financial portfolios (Kimball, 1993). The effects that we estimate are large. A one-standard-deviation increase in permanent volatility due to the program of study decreases an individual's stock market participation by 23% and, conditional on participation, decreases the share of risky assets held by 8%. However, offsetting effects of excess earnings, self-selection and program of study obscure this relationship in raw correlations. We present evidence that this finding is robust to considering human capital betas, and also has implications for committed consumption. Our results show that individuals manage their overall risk exposure by adjusting their financial risks in response to variation in their human capital risk.

References

ADDOUM, J. M., S. DELIKOURAS, G. M. KORNIOTIS, AND A. KUMAR (2019): "Income Hedging, Dynamic Style Preferences, and Return Predictability," *The Journal of Finance*, 74, 2055–2106.

ANDERSEN, S., P. D'ASTOUS, J. MARTÍNEZ-CORREA, AND S. H. SHORE (2020): "Cross-program Differences in Returns to Education and the Gender Earnings Gap," *Working Paper*.

ANGERER, X. AND P.-S. LAM (2009): "Income risk and portfolio choice: An empirical study," *The Journal of Finance*, 64, 1037–1055.

ATTANASIO, O. P., R. BOTTAZZI, H. W. LOW, L. NESHEIM, AND M. WAKEFIELD (2012): "Modelling the demand for housing over the life cycle," *Review of Economic Dynamics*, 15, 1–18.

BAGLIANO, F. C., C. FUGAZZA, AND G. NICODANO (2014): "Optimal life-cycle portfolios for heterogeneous workers," *Review of Finance*, 18, 2283–2323.

BARNEA, A., H. CRONQVIST, AND S. SIEGEL (2010): "Nature or nurture: What determines investor behavior?" *Journal of Financial Economics*, 98, 583–604.

BARTH, D., S. H. SHORE, AND S. T. JENSEN (2017): "Identifying idiosyncratic career taste and skill with income risk," *Quantitative Economics*, 8, 553–587.

BERTAUT, C. C. AND M. HALIASSOS (1997): "Precautionary portfolio behavior from a life-cycle perspective," *Journal of Economic Dynamics and Control*, 21, 1511–1542.

BETERMIER, S., T. JANSSON, C. PARLOUR, AND J. WALDEN (2012): "Hedging labor income risk," *Journal of Financial Economics*, 105, 622–639.

BLUNDELL, R., L. PISTAFERRI, AND I. PRESTON (2008): "Consumption inequality and partial insurance," *American Economic Review*, 98, 1887–1921.

BODIE, Z., R. C. MERTON, AND W. F. SAMUELSON (1992): "Labor supply flexibility and portfolio choice in a life cycle model," *Journal of economic dynamics and control*, 16, 427–449.

BOOIJ, A. S., E. LEUVEN, AND H. OOSTERBEEK (2017): "Ability peer effects in university: Evidence from a randomized experiment," *The review of economic studies*, 84, 547–578.

BRUNELLO, G., M. DE PAOLA, AND V. SCOPPA (2010): "Peer effects in higher education: Does the field of study matter?" *Economic Inquiry*, 48, 621–634.

CALVET, L. E., J. Y. CAMPBELL, F. GOMES, AND P. SODINI (2021): "The cross-section of household preferences," *NBER Working Paper 28788*.

CALVET, L. E. AND P. SODINI (2014): "Twin picks: Disentangling the determinants of risk-taking in household portfolios," *The Journal of Finance*, 69, 867–906.

CASS, D. AND J. E. STIGLITZ (1972): "Risk aversion and wealth effects on portfolios with many assets," *The Review of Economic Studies*, 39, 331–354.

CATHERINE, S. (Forthcoming): "Countercyclical labor income risk and portfolio choices over the life-cycle," *Review of Financial Studies*.

CATHERINE, S., P. SODINI, AND Y. ZHANG (2019): "Countercyclical Income Risk and Portfolio Choices: Evidence from Sweden," *Working paper*.

CATTANEO, M. D., M. JANSSON, AND X. MA (2019): "Simple local polynomial density estimators," *Journal of the American Statistical Association*, 1–7.

CHETTY, R. AND A. SZEIDL (2007): "Consumption commitments and risk preferences," *The Quarterly Journal of Economics*, 122, 831–877.

COCCO, J. F., F. J. GOMES, AND P. J. MAENHOUT (2005): "Consumption and portfolio choice over the life cycle," *The Review of Financial Studies*, 18, 491–533.

COHN, R. A., W. G. LEWELLEN, R. C. LEASE, AND G. G. SCHLARBAUM (1975): "Individual investor risk aversion and investment portfolio composition," *The Journal of Finance*, 30, 605–620.

DANTHINE, J.-P. AND J. B. DONALDSON (2002): "Labour relations and asset returns," *The Review of Economic Studies*, 69, 41–64.

D'ASTOUS, P. AND S. H. SHORE (2021): "Programs of Study and Earnings Dynamics," *Working paper*.

FAGERENG, A., L. GUISO, AND L. PISTAFERRI (2018): "Portfolio choices, firm shocks, and uninsurable wage risk," *The Review of Economic Studies*, 85, 437–474.

FELD, J. AND U. ZÖLITZ (2017): "Understanding peer effects: On the nature, estimation, and channels of peer effects," *Journal of Labor Economics*, 35, 387–428.

GOLLIER, C. AND J. W. PRATT (1996): "Risk vulnerability and the tempering effect of background risk," *Econometrica*, 1109–1123.

GUISO, L., T. JAPPELLI, AND D. TERLIZZESE (1996): "Income risk, borrowing constraints, and portfolio choice," *The American Economic Review*, 158–172.

GUVENEN, F., S. SCHULHOFER-WOHL, J. SONG, AND M. YOGO (2017): "Worker betas: Five facts about systematic earnings risk," *American Economic Review*, 107, 398–403.

HASTINGS, J. S., C. A. NEILSON, AND S. D. ZIMMERMAN (2013): "Are Some Degrees Worth More Than Others? Evidence From College Admission Cutoffs in Chile," *NBER Working Paper No. 19241*.

HEATON, J. AND D. LUCAS (2000): "Portfolio choice in the presence of background risk," *The Economic Journal*, 110, 1–26.

HEINESEN, E. (2018): "Admission to Higher Education Programmes and Student Educational Outcomes and Earnings – Evidence from Denmark," *Economics of Education Review*, 63, 1–19.

HONG, H., J. D. KUBIK, AND J. C. STEIN (2004): "Social interaction and stock-market participation," *The journal of finance*, 59, 137–163.

HVIDBERG, K. B. (2020): "Field of Study and Financial Problems: How Economics Reduces the Risk of Default," *Working paper*.

ILHAN, E. (2020): "Sea Level Rise and Portfolio Choice," *Working paper*.

JENSEN, S. T. AND S. H. SHORE (2015): "Changes in the distribution of earnings volatility," *Journal of Human Resources*, 50, 811–836.

JO, C. (2020): "Unintended Benefits of Employment Protection Laws: Households Increased Risk-Taking Behavior," *Working Paper*.

KIMBALL, M. S. (1993): "Standard risk aversion," *Econometrica*, 589–611.

KIRKEBOEN, L. J., E. LEUVEN, AND M. MOGSTAD (2016): "Field of Study, Earnings, and Self-selection," *The Quarterly Journal of Economics*, 131, 1057–1111.

KOGAN, L., D. PAPANIKOLAOU, L. D. SCHMIDT, AND J. SONG (2020): "Technological innovation and labor income risk," *National Bureau of Economic Research*.

KOO, H. K. (1998): "Consumption and portfolio selection with labor income: a continuous time approach," *Mathematical Finance*, 8, 49–65.

MASSA, M. AND A. SIMONOV (2006): "Hedging, familiarity and portfolio choice," *The Review of Financial Studies*, 19, 633–685.

MEGHIR, C. AND L. PISTAFERRI (2004): "Income variance dynamics and heterogeneity," *Econometrica*, 72, 1–32.

NIELSEN, H. S. AND A. VISSING-JORGENSEN (2006): "The impact of labor income risk on educational choices: Estimates and implied risk aversion," *Unpublished Manuscript, Department of Economics, University of Aarhus*.

ORTALO-MAGNE, F. AND S. RADY (2006): "Housing market dynamics: On the contribution of income shocks and credit constraints," *The Review of Economic Studies*, 73, 459–485.

OUIMET, P. AND G. TATE (2020): "Learning from coworkers: Peer effects on individual investment decisions," *The Journal of Finance*, 75, 133–172.

PRUITT, S. AND N. TURNER (2020): "Earnings risk in the household: Evidence from millions of US tax returns," *American Economic Review: Insights*, 2, 237–54.

RANISH, B. (2013): "Why Do Households with Risky Labor Income Take Greater Financial Risks?" *Working paper*.

SAKS, R. E. AND S. H. SHORE (2005): "Risk and career choice," *The BE Journal of Economic Analysis & Policy*, 5.

SHEN, J. (2018): "Countercyclical Risks and Portfolio Choice over the Life Cycle: Evidence and Theory," in *9th Miami Behavioral Finance Conference*.

SHORE, S. H. AND T. SINAI (2010): "Commitment, risk, and consumption: do birds of a feather have bigger nests?" *The Review of Economics and Statistics*, 92, 408–424.

SVENSSON, L.-G. (1999): "Strategy-proof Allocation of Indivisible Goods," *Social Choice and Welfare*, 16, 557–567.

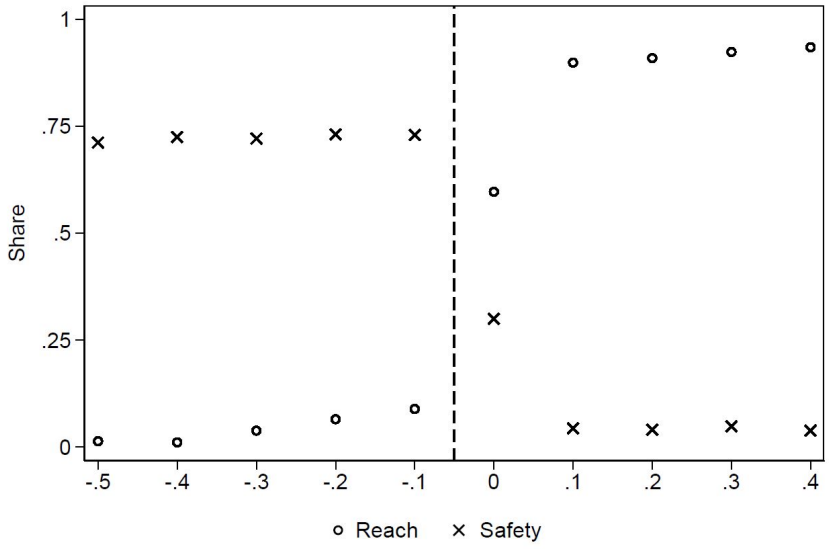
VESTMAN, R. (2019): "Limited stock market participation among renters and homeowners," *The Review of Financial Studies*, 32, 1494–1535.

VICEIRA, L. M. (2001): "Optimal portfolio choice for long-horizon investors with nontradable labor income," *The Journal of Finance*, 56, 433–470.

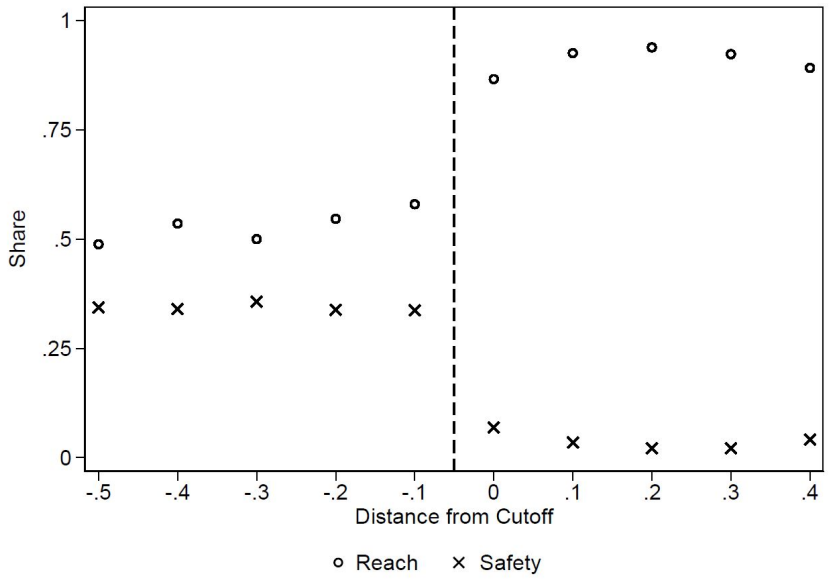
VISSING-JØRGENSEN, A. (2002): "Limited asset market participation and the elasticity of intertemporal substitution," *Journal of political Economy*, 110, 825–853.

Figures

Figure 1: Outcome of Applications



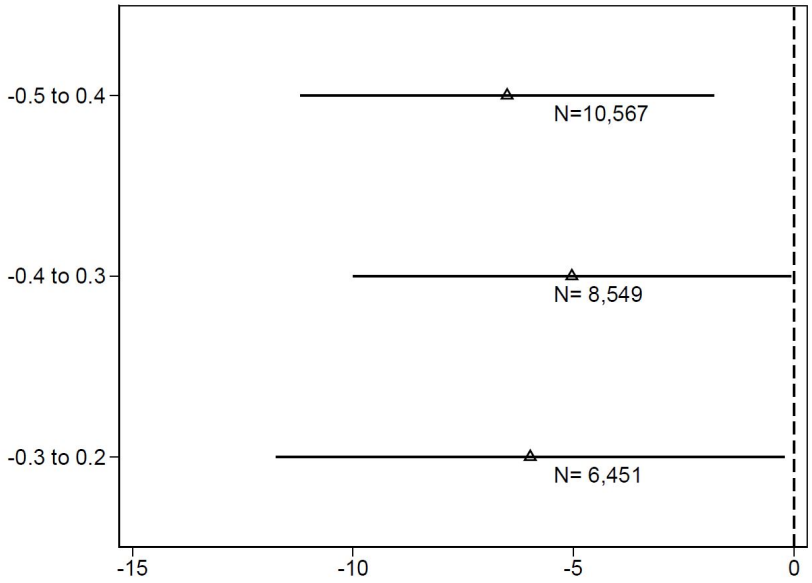
(a) Quota 1 Applications



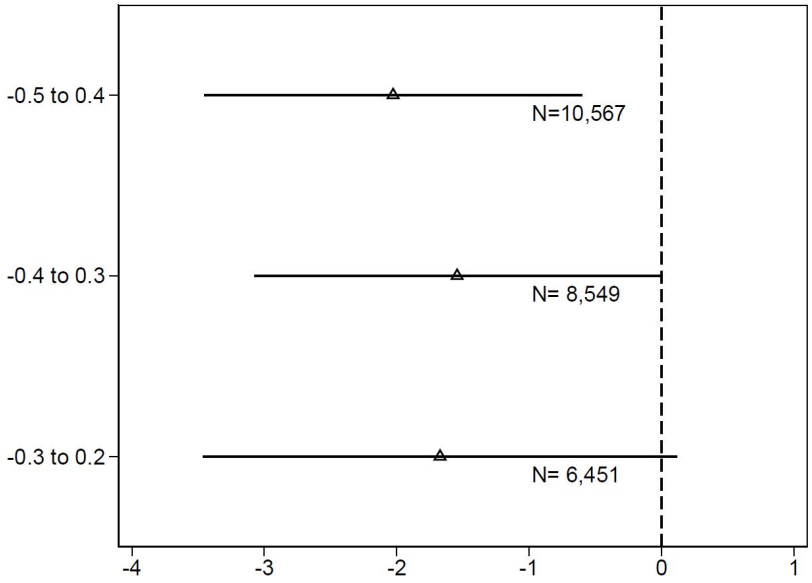
(b) Quota 2 Applications

Note: This figure shows the share of students admitted to their reach or safety program. We pool all programs and years and present the distance between the application score and the admission cutoff for the reach program on the x-axis. We use the sample of 10,567 students who have a reach–safety programs pair in application years 1994 to 2006. Panel (a) shows the subsample of applications made through the Quota 1 system of admission (6,339 observations) and Panel (b) shows Quota 2 applications (4,228 observations).

Figure 2: Alternative Bandwidths



(a) Stock Market Participation



(b) Risky asset share

Note: This figure presents the robustness of our main IV results (columns 2 and 4 of Table 4) to the selection of different bandwidths. We use the sample of 10,567 students who have a reach–safety programs pair in application years 1994 to 2006. For stock market participation, we estimate equation (5) by two-stage probit least-squares using equation (7) as first stage and report the marginal effect on the probability of holding stocks. For the share of risky assets, we estimate the model by two-stage tobit least squares and report the marginal effects on the share of risky assets, conditional on stock market participation. Point estimates and 95% confidence intervals are shown, along with the number of observations included in the different bandwidth ranges.

Tables

Table 1: Descriptive Statistics

	All applications (321,091 obs.)		Used sample (10,567 obs.)	
	Mean	Std. dev	Mean	Std. dev
I. Demographics				
Age	21.5	3.9	21.1	3.0
Male share	37.2	-	38.8	-
Parental income (000's DKK)	297.4	157.3	329.3	173.3
Parental wealth (000's DKK)	353.6	751.7	442.1	860.1
Parental education (years)	12.7	3.2	13.4	3.2
II. Education				
Score	8.2	1.0	8.8	0.7
Nbr priorities ranked	2.2	1.4	3.1	1.4
Share got in reach	-	-	0.6	0.5
Rank of reach	-	-	1.2	0.6
Rank of safety	-	-	2.3	0.7
Rank of enrollment prog.	-	-	1.6	0.9
Distance from cutoff	-	-	-0.1	0.3
Share same field	-	-	0.3	0.5
Share same institution	-	-	0.6	0.5
III. Earnings				
Years until initial earnings	6.5	3.2	7.7	3.1
Initial earnings (000's DKK)	249.3	44.5	256.1	47.0
Excess earnings: u	0.001	0.232	0.001	0.239
Excess earnings growth: Δu	0.007	0.078	0.016	0.085
Total vol.: σ^2	0.073	0.095	0.080	0.100
Trans. vol.: σ^2_τ	0.029	0.059	0.032	0.063
Perm. vol.: σ^2_π	0.012	0.063	0.015	0.069
Stock corr.: $\rho_{\Delta u,m}$	0.062	0.256	0.008	0.279
IV. Financial wealth				
Share own stocks	0.28	-	0.28	-
Stocks (000's DKK) | owns stocks	37.23	65.10	42.42	70.93
Share own bonds	0.08	-	0.08	-
Bonds (000's DKK) | owns bonds	35.48	36.32	37.93	37.74
Share own bank deposits	1.00	-	1.00	-
Bank dep. (000's DKK) | owns b. d.	65.69	88.71	72.80	93.84
Stocks/Fin. wealth: RS	0.07	0.17	0.07	0.17
Stocks/Fin wealth | owns stocks	0.25	0.24	0.25	0.24
Share own house	0.59	-	0.51	-
House value (000's DKK) | owns house	450.07	525.65	425.46	555.69
Mortgage (000's DKK) | owns house	379.92	440.03	350.18	458.11

Note: This table presents descriptive statistics for the population of students applying to university for the first time in application years 1994 to 2006 (all applications; left), as well as the sample of 10,567 students who have a reach–safety programs pair in these application years (used sample; right). Panel I presents the demographics, measured at the time of application. Parental income, wealth, and education represent the average values of both parents (or the values for a single parent). Panel II presents information typically found in a student's application. The student's score summarizes their high school grades. The number of priorities ranked refers to the number of programs to which the student applied. For the sample of students with a reach–safety pair, we present the average rankings of the reach, safety, and enrollment programs, as well as the distance from the admission cutoff of the reach program, and the share of students for which both the reach and safety programs are in the same field or institution. Panel III presents information on earnings, which are assumed to follow the process described in equation (2). The definitions of the different attributes of the earnings process follow from this equation and are averaged over the period 8 to 12 years after enrollment. Panel IV presents information on financial wealth, averaged over the period 8 to 12 years after enrollment.

Table 2: Cohort Averages

	All applications (321,091 obs.)		Used sample (10,567 obs.)				
	Own	Enroll. cohort	Own	Enroll. cohort	Reach	Safety	Gap
A. Earnings process							
Years until init. earn.	6.53	6.52	7.68	7.16	7.30	6.97	0.33
	(3.20)	[2.97]; (1.23)	(3.09)	[3.04]; (1.20)	[3.01]; (1.13)	[3.06]; (1.29)	(1.11)
Init. earn. (000's DKK)	249.28	250.28	256.06	257.63	260.90	253.74	7.17
	(44.54)	[41.12]; (18.01)	(46.63)	[45.77]; (17.49)	[47.58]; (19.18)	[43.88]; (14.87)	(17.93)
Excess earn.: u	0.001	-0.002	0.019	0.010	0.017	-0.003	0.020
	(0.232)	[0.212]; (0.092)	(0.238)	[0.223]; (0.098)	[0.226]; (0.103)	[0.220]; (0.091)	(0.093)
Excess earn. grow.: Δu	0.007	0.007	0.022	0.013	0.016	0.009	0.006
	(0.078)	[0.083]; (0.015)	(0.083)	[0.090]; (0.017)	[0.093]; (0.018)	[0.088]; (0.015)	(0.017)
Total vol.: σ^2	0.073	0.072	0.083	0.080	0.083	0.076	0.007
	(0.095)	[0.095]; (0.018)	(0.099)	[0.103]; (0.017)	[0.105]; (0.018)	[0.100]; (0.016)	(0.018)
Trans. vol.: σ^2_τ	0.029	0.029	0.033	0.031	0.033	0.030	0.003
	(0.059)	[0.058]; (0.008)	(0.063)	[0.064]; (0.008)	[0.066]; (0.009)	[0.062]; (0.008)	(0.009)
Perm. vol.: σ^2_π	0.012	0.012	0.016	0.015	0.016	0.014	0.003
	(0.063)	[0.059]; (0.008)	(0.069)	[0.066]; (0.009)	[0.068]; (0.009)	[0.062]; (0.008)	(0.009)
Stock corr.: $\rho_{\Delta u,m}$	0.062	0.041	0.007	0.043	0.039	0.048	-0.009
	(0.256)	[N.A.]; (0.249)	(0.277)	[N.A.]; (0.240)	[N.A.]; (0.234)	[N.A.]; (0.244)	(0.296)
B. Financial wealth							
Share own stocks	0.282	0.279	0.284	0.280	0.280	0.279	0.0005
	(N.A.)	[0.437]; (N.A.)	(N.A.)	[0.439]; (N.A.)	[0.441]; (N.A.)	[0.437]; (N.A.)	(0.082)
Stocks (000's DKK)	10.49	10.84	12.06	12.03	12.40	11.57	0.83
	(38.40)	[36.70]; (6.60)	(42.39)	[40.06]; (6.69)	[41.39]; (6.33)	[38.47]; (7.05)	(6.40)
Bonds (000's DKK)	2.65	2.81	3.04	3.08	3.16	2.96	0.20
	(13.63)	[12.84]; (1.68)	(14.84)	[13.84]; (1.58)	[14.23]; (1.49)	[13.31]; (1.72)	(1.47)
Bank dep. (000's DKK)	65.64	65.94	72.74	71.80	75.01	68.19	6.83
	(88.69)	[87.97]; (16.83)	(93.82)	[93.85]; (16.44)	[96.36]; (16.30)	[91.03]; (16.22)	(15.55)
Stocks/Fin. wealth	0.071	0.072	0.072	0.073	0.073	0.074	-0.0009
	(0.169)	[0.164]; (0.033)	(0.171)	[0.168]; (0.031)	[0.169]; (0.027)	[0.167]; (0.034)	(0.030)
Share own house	0.587	0.572	0.511	0.523	0.519	0.526	-0.007
	(N.A.)	[0.48]; (N.A.)	(N.A.)	[0.487]; (N.A.)	[0.488]; (N.A.)	[0.488]; (N.A.)	(0.104)
House value (000's DKK)	450.07	446.07	425.46	433.18	439.23	425.00	14.22
	(525.65)	[519.08]; (103.00)	(555.69)	[545.94]; (111.13)	[557.20]; (110.24)	[557.20]; (112.29)	(110.88)
Mortgage (000's DKK)	379.92	370.91	350.18	352.76	356.21	347.59	8.68
	(440.03)	[428.23]; (90.57)	(458.11)	[444.10]; (98.64)	[452.90]; (98.43)	[452.90]; (98.90)	(97.74)

Note: This table presents descriptive statistics for the population of students applying to university for the first time in application years 1994 to 2006 (all applications; left), as well as the sample of students who have a reach–safety programs pair in these application years (used sample; right). Earnings are assumed to follow the process described in equation (2). The definitions of the different attributes of the earnings process follow from this equation and are averaged over the period 8 to 12 years after enrollment. Financial wealth is averaged over the period 8 to 12 years after enrollment. For the population data, we present the averages over the individual's own outcomes as well as the average of their enrollment cohort, while for the reach-safety sample we present the averages over the individual's own outcomes as well as the average of their enrollment cohort, their reach and safety programs, and the average gap between the two programs. We present the standard deviation of each variable in parenthesis, and, when relevant, we present the between-program standard deviation in brackets.

Table 3: Effects of Program-Level Earnings Processes on Individuals' Earnings Process

	Individual-level outcomes				
	Excess earnings: u	Excess earn. growth: Δu	Total vol.: σ^2	Trans. vol.: σ^2_τ	Perm. vol.: σ^2_π
A. IV estimation					
Prog.-lvl expl. variable	0.53***	0.26	0.52**	0.55*	1.00***
	(0.09)	(0.21)	(0.26)	(0.30)	(0.38)
B. OLS estimation					
Prog.-lvl expl. variable	0.78***	0.84***	0.88***	1.03***	0.88***
	(0.02)	(0.06)	(0.07)	(0.10)	(0.11)

Note: This table presents the results of estimating equation (6) by IVs (Panel A) and by OLS (Panel B). Each cell presents the result from either a second stage of an IV regression or from an OLS regression. The outcome variable for each regression is the student's own estimate of the variable studied, while the explanatory variables are program-level average outcomes. In Panel A., each program-level explanatory variable is instrumented using the reach and safety program-level instruments in equation (8). In both panels, we use the sample of 10,567 students who have a reach–safety programs pair in application years 1994 to 2006 and present the results for a bandwidth of +/− 0.5 around the admission cutoff for the reach program. Earnings are assumed to follow the process described in equation (2). The definitions of the different attributes of the earnings process follow from this equation and are averaged over the period 8 to 12 years after enrollment. The IV estimation controls for the reach and safety averages of the program-level variables being instrumented, admission system (quota 1 or 2) fixed effects, distance from the admission cutoff fixed effects and their interaction with admission quota fixed effects, the probability of being accepted given last year's admission cutoff and its interaction with quota fixed effects, and calendar year FE. The OLS results control for parents' wealth, income, and education, students' grade, age, and gender, and calendar year FE. Standard errors corrected for heteroscedasticity are presented in parentheses. ***, **, and * represent significance at the 1, 5 and 10 percent level, respectively.

Table 4: Effects of Earnings Processes on Individual Financial Holding

	Program-level explanatory variables		Individual-level expanatory variables	
	Owns stocks	Stocks/Fin. wealth	Owns stocks	Stocks/Fin. wealth
	(1)	(2)	(3)	(4)
A. IV estimation				
Excess earnings: u	0.51***	0.15**	0.33	0.15
	(0.19)	(0.06)	(0.29)	(0.17)
Trans. vol.: σ_τ^2	0.08	-0.037	0.089	0.043
	(1.74)	(0.54)	(2.31)	(1.49)
Perm. vol.: σ_π^2	-6.36***	-1.88***	-3.56***	-2.05*
	(2.21)	(0.67)	(0.82)	(1.17)
B. Non-IV estimation				
Excess earnings: u				
	0.37***	0.11***	0.20***	0.049***
Trans. vol.: σ_τ^2	-0.057	-0.015	-0.02	-0.0054
	(0.35)	(0.04)	(0.01)	(0.00)
Perm. vol.: σ_π^2	-0.52	-0.14	-0.072	-0.021
	0.69	0.14	0.09	0.02

Note: This table presents the results of estimating equation (5). Each column presents the result from either the second stage of an IV regression (Panel A) or from a non-instrumented regression (Panel B). We use program- and individual-level explanatory variables in the left and right panels, respectively. The outcome variable for each regression is the student's own estimate of the variable studied, while the explanatory variables are instrumented using the reach and safety program-level instruments in equation (8). Stock market participation is estimated with a probit model, from which we report the marginal effects of participation, while the share of risky assets in the portfolio is estimated with a tobit model, from which we report marginal effects for the share of risky assets, conditional on participation. In both panels, we use the sample of 10,567 students who have a reach–safety programs pair in application years 1994 to 2006 and present the results for a bandwidth of +/− 0.5 around the admission cutoff for the reach program. Earnings are assumed to follow the process described in equation (2). The definitions of the different attributes of the earnings process follow from this equation and are averaged over the period 8 to 12 years after enrollment. Financial wealth measures are also averaged over the period 8 to 12 years after enrollment. The IV estimation controls for the reach and safety averages of the program-level variables being instrumented, admission system (quota 1 or 2) fixed effects, distance from the admission cutoff fixed effects and their interaction with admission quota fixed effects, the probability of being accepted given last year's admission cutoff and its interaction with quota fixed effects, and calendar year FE. The OLS results control for parents' wealth, income, and education, students' grade, age, and gender, and calendar year FE. Standard errors corrected for heteroscedasticity are presented in parentheses. ***, **, and * represent significance at the 1, 5 and 10 percent level, respectively.

Table 5: Effects of Earnings Processes on Housing Decisions

	Program-level explanatory variables			Individual-level expanatory variables		
	Home Owner?	Home value | Owner	Mortgage |Owner	Home Owner?	Home value | Owner	Mortgage |Owner
	(1)	(2)	(3)	(4)	(5)	(6)
A. IV estimation						
Excess earnings: u	0.40*	96.7	112.5	0.55	255.3	387.5
	(0.22)	(275.8)	(249.0)	(0.43)	(393.5)	(336.9)
Trans. vol.: σ_τ^2	2.23	5012.8*	4148.2**	-0.43	2,606.0	1,552.20
	(1.94)	(2,255.0)	(2,081.2)	(3.85)	(1,913.1)	(1,637.9)
Perm. vol.: σ_π^2	-3.32	-984.0	666.6	-3.09**	-301.0	748.7
	(2.60)	(3,637.4)	(3,416.8)	(1.35)	(3,467.3)	(3,052.8)
B. Non-IV estimation						
Excess earnings: u	-0.10***	-95.5***	11.7	-0.082***	-52.4***	8.8
	(0.03)	(18.1)	(31.3)	(0.01)	(7.3)	(11.4)
Trans. vol.: σ_τ^2	0.29	355.1**	-367.2	0.062**	-27.0	-9.0
	(0.26)	(174.2)	(285.7)	(0.03)	(27.0)	(35.3)
Perm. vol.: σ_π^2	0.29	-179.6	-947.1**	0.002	-33.7	-89.8**
	(0.28)	(204.6)	(372.3)	(0.024)	(23.8)	(41.0)

Note: This table presents the results of estimating equation (5). Each column presents the result from either the second stage of an IV regression (Panel A) or from a non-instrumented regression (Panel B). We use program- and individual-level explanatory variables in the left and right panels, respectively. The outcome variable for each regression is the student's own estimate of the variable studied, while the explanatory variables are instrumented using the reach and safety program-level instruments in equation (8). Home ownership is defined as a dummy variable indicating whether the individual is a home owner 8 to 12 years after application. The effect on home ownership is estimated with a probit model, from which we report the marginal effects of participation. House and mortgage values are defined are their average values 8 to 12 years after application, for individuals identified as home owners. In both panels, we present the results for a bandwidth of $+/-$ 0.5 around the admission cutoff for the reach program. Earnings are assumed to follow the process described in equation (2). The definitions of the different attributes of the earnings process follow from this equation and are averaged over the period 8 to 12 years after enrollment. The IV estimation controls for the reach and safety averages of the program-level variables being instrumented, admission system (quota 1 or 2) fixed effects, distance from the admission cutoff fixed effects and their interaction with admission quota fixed effects, the probability of being accepted given last year's admission cutoff and its interaction with quota fixed effects, and calendar year FE. The OLS results control for parents' wealth, income, and education, students' grade, age, and gender, and calendar year FE. Standard errors corrected for heteroscedasticity are presented in parentheses. ***, **, and * represent significance at the 1, 5 and 10 percent level, respectively.

Appendix Tables

Table A1: Density Tests

	Restricted model		Unrestricted model	
	Conventional s.e.	Jacknife s.e.	Conventional s.e.	Jacknife s.e.
Bandwitdh				
A. -0.5 to 0.4	0.796	0.785	0.339	0.353
B. -0.4 to 0.3	0.368	0.332	0.093	0.108
C. -0.3 to 0.2	0.214	0.165	0.043	0.064

Note: This table presents the p-values for density tests of $H_0 : \lim_{d\uparrow 0} f(d) = \lim_{d\downarrow 0} f(d)$ developed by Cattaneo et al. (2019). We report the results for the test statistic constructed using a local polynomial density estimator based on the c.d.f. of the observed sample, which takes the form: $T_p(h) = \frac{\hat{f}_{+,p}(h)-\hat{f}_{-,p}(h)}{\hat{V}_p(h)} \sim N(0,1)$, where $\hat{V}_p^2(h) = \left\{\hat{f}_{+,p}(h) - \hat{f}_{-,p}(h)\right\}$, $\hat{f}_{+,p}(h)$ and $\hat{f}_{-,p}(h)$ represent the local polynomial density estimators, $\hat{V}_p(h)$ presents the standard error estimator, h denotes the bandwidth used around the cutoff point, and p denotes the choice of polynomial order. We use both conventional and jackknife standard errors, as well as restricted and unrestricted models, based on both estimators $\hat{f}_{+,p}(h)$ and $\hat{f}_{-,p}(h)$ being related or not. We use local linear regressions for varying bandwidths around the cutoffs to test the robustness of the estimation to a more or less narrow estimation around admission cutoffs using the sample of 10,567 students who have a reach–safety programs pair in application years 1994 to 2006.

Table A2: Descriptive Statistics by Field of Study

	Business	Education	Engineering	Health	Humanities	Law	Other	Science	Social Science	Technology	All
I. All applications (321,091 obs.)											
A. Earnings process											
Years until initial earnings	5.85	5.76	6.04	5.91	7.87	6.64	6.67	7.81	7.35	6.10	6.52
	[2.81]; (0.89)	[2.63]; (0.70)	[2.56]; (0.95)	[2.83]; (0.96)	[3.50]; (1.17)	[3.13]; (0.32)	[3.31]; (0.43)	[3.03]; (0.70)	[3.01]; (0.79)	[2.88]; (1.49)	[2.97]; (1.23)
Initial earnings (000's DKK)	256.95	243.99	261.71	244.52	246.92	270.45	241.84	258.50	258.81	258.69	250.28
	[48.84]; (13.46)	[30.47]; (5.50)	[45.19]; (17.86)	[36.40]; (27.02)	[40.66]; (6.82)	[55.06]; (3.17)	[40.50]; (4.63)	[48.90]; (8.51)	[47.10]; (10.54)	[45.34]; (10.08)	[41.12]; (18.01)
Excess earnings: u	0.091	-0.025	0.061	-0.047	-0.065	0.151	0.039	0.015	0.016	0.026	-0.002
	[0.26]; (0.078)	[0.18]; (0.035)	[0.22]; (0.077)	[0.18]; (0.101)	[0.21]; (0.048)	[0.28]; (0.022)	[0.22]; (0.038)	[0.23]; (0.076)	[0.24]; (0.068)	[0.23]; (0.067)	[0.212]; (0.092)
Excess earnings growth: Δu	0.014	0.0002	0.010	0.004	0.002	0.029	0.001	0.015	0.022	0.005	0.007
	[0.097]; (0.013)	[0.066]; (0.004)	[0.083]; (0.013)	[0.074]; (0.018)	[0.087]; (0.009)	[0.094]; (0.002)	[0.082]; (0.005)	[0.094]; (0.010)	[0.095]; (0.015)	[0.084]; (0.011)	[0.083]; (0.015)
Total vol.: σ^2	0.071	0.055	0.060	0.071	0.082	0.074	0.075	0.082	0.079	0.068	0.072
	[0.105]; (0.012)	[0.079]; (0.007)	[0.093]; (0.013)	[0.086]; (0.024)	[0.102]; (0.011)	[0.102]; (0.003)	[0.096]; (0.007)	[0.107]; (0.011)	[0.104]; (0.010)	[0.100]; (0.017)	[0.095]; (0.018)
Trans. vol.: σ^2_τ	0.025	0.023	0.023	0.031	0.033	0.025	0.030	0.032	0.030	0.026	0.029
	[0.061]; (0.006)	[0.048]; (0.003)	[0.056]; (0.006)	[0.055]; (0.011)	[0.064]; (0.006)	[0.060]; (0.001)	[0.059]; (0.004)	[0.066]; (0.007)	[0.064]; (0.005)	[0.059]; (0.008)	[0.058]; (0.008)
Perm. vol.: σ^2_π	0.018	0.006	0.012	0.009	0.012	0.022	0.012	0.016	0.018	0.012	0.012
	[0.069]; (0.009)	[0.045]; (0.003)	[0.055]; (0.007)	[0.055]; (0.010)	[0.062]; (0.005)	[0.072]; (0.002)	[0.055]; (0.004)	[0.064]; (0.007)	[0.068]; (0.007)	[0.058]; (0.006)	[0.059]; (0.008)
Stock corr.: $\rho_{\Delta u,m}$	-0.125	0.016	-0.075	0.100	0.100	-0.135	0.097	0.086	0.066	-0.055	0.041
	[N.A.]; (0.270)	[N.A.]; (0.271)	[N.A.]; (0.227)	[N.A.]; (0.221)	[N.A.]; (0.249)	[N.A.]; (0.125)	[N.A.]; (0.261)	[N.A.]; (0.191)	[N.A.]; (0.202)	[N.A.]; (0.236)	[N.A.]; (0.249)
B. Financial wealth											
Share own stocks	0.40	0.21	0.37	0.22	0.23	0.34	0.35	0.32	0.30	0.33	0.28
	[0.48]; (N.A.)	[0.41]; (N.A.)	[0.48]; (N.A.)	[0.41]; (N.A.)	[0.41]; (N.A.)	[0.47]; (N.A.)	[0.47]; (N.A.)	[0.47]; (N.A.)	[0.45]; (N.A.)	[0.46]; (N.A.)	[0.437]; (N.A.)
Stocks (000's DKK)	19.95	5.99	18.05	6.99	8.08	16.20	11.56	13.81	13.31	13.95	10.84
	[50.70]; (8.11)	[27.95]; (1.55)	[47.41]; (8.12)	[29.81]; (3.67)	[33.28]; (3.45)	[50.09]; (1.15)	[35.73]; (3.05)	[42.56]; (4.38)	[42.63]; (6.66)	[42.51]; (6.18)	[36.70]; (6.60)
Bonds (000's DKK)	3.24	2.16	2.84	2.35	2.86	3.74	3.24	3.64	2.94	3.17	2.81
	[12.64]; (2.34)	[11.67]; (1.12)	[11.48]; (1.97)	[11.93]; (1.45)	[13.41]; (1.70)	[15.73]; (1.25)	[13.84]; (1.21)	[15.18]; (1.51)	[13.22]; (1.55)	[13.11]; (2.00)	[12.84]; (1.68)
Bank deposits (000's DKK)	81.13	56.39	80.09	60.05	57.95	85.32	58.46	74.47	73.04	76.89	65.94
	[102.93]; (16.47)	[79.26]; (7.92)	[98.03]; (20.33)	[81.13]; (16.56)	[82.79]; (11.25)	[110.37]; (6.06)	[79.19]; (7.67)	[94.28]; (14.23)	[95.43]; (12.43)	[100.25]; (15.36)	[87.97]; (16.83)
Stocks/Fin. wealth	0.12	0.05	0.11	0.05	0.06	0.09	0.09	0.09	0.08	0.09	0.07
	[0.21]; (0.033)	[0.13]; (0.008)	[0.20]; (0.030)	[0.14]; (0.016)	[0.15]; (0.016)	[0.19]; (0.008)	[0.19]; (0.016)	[0.19]; (0.017)	[0.18]; (0.036)	[0.18]; (0.027)	[0.164]; (0.033)
Share own house	0.61	0.63	0.62	0.61	0.44	0.61	0.60	0.52	0.50	0.59	0.57
	[0.48]; (N.A.)	[0.47]; (N.A.)	[0.47]; (N.A.)	[0.48]; (N.A.)	[0.49]; (N.A.)	[0.49]; (N.A.)	[0.49]; (N.A.)	[0.49]; (N.A.)	[0.49]; (N.A.)	[0.48]; (N.A.)	[0.48]; (N.A.)
House value (000's DKK)	539.31	468.22	486.72	459.29	325.50	596.65	446.83	387.16	404.52	492.13	446.07
	[593.30]; (87.54)	[500.33]; (58.98)	[509.48]; (109.60)	[494.60]; (78.72)	[491.02]; (79.85)	[674.60]; (39.19)	[504.82]; (59.50)	[496.34]; (79.84)	[536.51]; (79.04)	[556.49]; (113.01)	[519.08]; (103.00)
Mortgage (000's DKK)	458.99	388.30	409.31	389.44	255.87	485.78	380.52	312.57	329.77	402.98	370.91
	[505.26]; (69.69)	[409.05]; (46.48)	[429.34]; (91.55)	[414.04]; (67.66)	[385.32]; (70.74)	[555.30]; (15.72)	[425.36]; (44.29)	[402.18]; (72.46)	[438.95]; (68.80)	[453.98]; (98.00)	[428.23]; (90.57)
C. Nb of programs and students											
Nb students per program-year	21	52	12	36	20	126	29	34	47	14	26
	(31)	(54)	(16)	(34)	(28)	(112)	(26)	(39)	(64)	(17)	(35)
Nb programs per field	259	82	197	334	323	4	108	67	89	277	1,740
II. Used sample (10,567 obs.)											
Program rankings											
Share listed as reach (%)	9.86	8.66	0.8	19.43	20.52	5.59	0	6.2	22.97	5.97	100
Share listed as safety (%)	10.97	9.75	1.85	16.69	25.62	2.22	1.65	10.15	15.41	5.7	100

Note: This table presents descriptive statistics by fields of study for the population of students applying to university for the first time in application years 1994 to 2006. Panel I shows population-level averages while Panel II shows the ranking of reach and safety fields by the sample of students who have a reach–safety programs pair. Earnings are assumed to follow the process described in equation (2). The definitions of the different attributes of the earnings process follow from this equation and are averaged over the period 8 to 12 years after enrollment. Financial wealth is averaged over the period 8 to 12 years after enrollment. We present the standard deviation of each variable in parenthesis, and, when relevant, we present the between-program standard deviation in brackets.

Table A3: Validity of Instruments: First Stage Estimations of Table 4

Reach and safety prog.-level expl. variables	Enrollment program-level outcomes		
	Excess earnings: u	Trans. vol.: σ^2_τ	Perm. vol.: σ^2_π
$\mathbb{P}(p_i = r_i \mid D_i) \times u_{r_i}$	0.94***	0.0037	0.0062**
	(0.03)	(0.002)	(0.003)
$\mathbb{P}(p_i = s_i \mid D_i) \times u_{s_i}$	1.03***	-0.0075**	0.003
	(0.03)	(0.004)	(0.004)
$\mathbb{P}(p_i = r_i \mid D_i) \times \sigma^2_{\tau,r_i}$	-0.16	0.98***	0.0021
	(0.24)	(0.03)	(0.03)
$\mathbb{P}(p_i = s_i \mid D_i) \times \sigma^2_{\tau,s_i}$	-0.30	0.95***	-0.018
	(0.28)	(0.06)	(0.04)
$\mathbb{P}(p_i = r_i \mid D_i) \times \sigma^2_{\pi,r_i}$	-0.35	-0.090***	0.76***
	(0.27)	(0.03)	(0.06)
$\mathbb{P}(p_i = s_i \mid D_i) \times \sigma^2_{\pi,s_i}$	0.015	0.00021	0.94***
	(0.26)	(0.05)	(0.07)
F-test	319	197	56

Note: This table presents the first stage estimation results from equation (7). Each column presents the result from the first stage of an IV regression. We use the sample of 10,567 students who have a reach–safety programs pair in application years 1994 to 2006 and present the results for a bandwidth of +/− 0.5 around the admission cutoff for the reach program. Earnings are assumed to follow the process described in equation (2). The definitions of the different attributes of the earnings process follow from this equation and are averaged over the period 8 to 12 years after enrollment. The outcome variable for each regression is the student's own estimate of the variable studied, while the explanatory variable is the analogous program-level average outcome. We vary the included controls as shown in the table. The IV estimation controls for the reach and safety averages of the program-level variables being instrumented, admission system (quota 1 or 2) fixed effects, distance from the admission cutoff fixed effects and their interaction with admission quota fixed effects, the probability of being accepted given last year's admission cutoff and its interaction with quota fixed effects, and calendar year FE. The OLS results control for parents' wealth, income, and education, students' grade, age, and gender, and calendar year FE. Standard errors corrected for heteroscedasticity are presented in parentheses. ***, **, and * represent significance at the 1, 5 and 10 percent level, respectively.

Table A4: Effects of Earnings Processes on Individual Financial Holding

		Program-level explanatory variables		Individual-level expanatory variables	
		Owns stocks	Stocks/Fin. wealth	Owns stocks	Stocks/Fin. wealth
		(1)	(2)	(3)	(4)
IV estimates	Excess earnings: u	0.51***	0.15**	0.33	0.15
		(0.19)	(0.06)	-0.29	-0.17
	Trans. vol.: σ_τ^2	0.08	-0.037	0.089	0.043
		(1.74)	(0.54)	-2.31	-1.49
	Perm. vol.: σ_π^2	-6.36***	-1.88***	-3.56***	-2.05*
		(2.21)	(0.67)	-0.82	-1.17
Reach controls	Excess earnings: u	-0.002	0.003	0.049	0.043
		-0.13	(0.04)	-0.19	-0.11
	Trans. vol.: σ_τ^2	-1.03	(0.20)	-1.31	-0.62
		-1.13	(0.36)	-1.93	-1.13
	Perm. vol.: σ_π^2	5.10***	1.38***	2.80***	1.42**
		-1.43	(0.44)	-0.67	-0.72
Safety controls	Excess earnings: u	0.044	0.023	-0.0032	0.018
		-0.095	(0.03)	-0.14	-0.077
	Trans. vol.: σ_τ^2	-0.39	(0.14)	-0.31	-0.23
		-0.86	(0.25)	-1.11	-0.66
	Perm. vol.: σ_π^2	4.61***	1.57***	3.37***	2.09***
		-1.01	(0.25)	-0.65	-0.66
	Distrance from cutoff FE	✓	✓	✓	✓
	Quota FE	✓	✓	✓	✓
	Distrance from cutoff FE × Quota FE	✓	✓	✓	✓
	Previous year admin. prob.	✓	✓	✓	✓
	Previous year admin. prob. × reach and safety controls	✓	✓	✓	✓
	Year FE	✓	✓	✓	✓

Note: This table reproduces the results from Table 4 but additionally shows the coefficients on the reach and safety program control variables. Specifically, it presents the results of estimating equation (5). Each column presents the result from either the second stage of an IV regression (Panel A) or from a non-instrumented regression (Panel B). We use program- and individual-level explanatory variables in the left and right panels, respectively. The outcome variable for each regression is the student's own estimate of the variable studied, while the explanatory variables are instrumented using the reach and safety program-level instruments in equation (8). Stock market participation is estimated with a probit model, from which we report the marginal effects of participation, while the share of risky assets in the portfolio is estimated with a tobit model, from which we report marginal effects for the share of risky assets, conditional on participation. In both panels, we use the sample of 10,567 students who have a reach–safety programs pair in application years 1994 to 2006 and present the results for a bandwidth of +/− 0.5 around the admission cutoff for the reach program. Earnings are assumed to follow the process described in equation (2). The definitions of the different attributes of the earnings process follow from this equation and are averaged over the period 8 to 12 years after enrollment. Financial wealth measures are also averaged over the period 8 to 12 years after enrollment. The IV estimation controls for the reach and safety averages of the program-level variables being instrumented, admission system (quota 1 or 2) fixed effects, distance from the admission cutoff fixed effects and their interaction with admission quota fixed effects, the probability of being accepted given last year's admission cutoff and its interaction with quota fixed effects, and calendar year FE. The OLS results control for parents' wealth, income, and education, students' grade, age, and gender, and calendar year FE. Standard errors corrected for heteroscedasticity are presented in parentheses. ***, **, and * represent significance at the 1, 5 and 10 percent level, respectively.

Table A5: Effects of Human Capital Beta

Program-level explanatory variables	Individual-level outcomes			
	$\rho[\Delta u, \log(\Delta \text{OMX 20})]$	$\rho[\Delta u, \text{OMX 20 returns}]$	$\rho[\Delta u, \log(\Delta \text{S\&P 500})]$	$\rho[\Delta u, \text{S\&P 500 returns}]$
	(1)	(2)	(3)	(4)
I. Human capital betas				
A. IV estimation				
$\rho[\Delta u, \log(\Delta \text{OMX 20})]$	0.073*			
	(0.040)			
$\rho[\Delta u, \text{OMX 20 returns}]$		0.077**		
		(0.037)		
$\rho[\Delta u, \log(\Delta \text{S\&P 500})]$			0.065	
			(0.041)	
$\rho[\Delta u, \text{S\&P 500 returns}]$				0.063
				(0.041)
B. Non-IV estimation				
$\rho[\Delta u, \log(\Delta \text{OMX 20})]$	0.006			
	(0.012)			
$\rho[\Delta u, \text{OMX 20 returns}]$		0.005		
		(0.012)		
$\rho[\Delta u, \log(\Delta \text{S\&P 500})]$			0.006	
			(0.014)	
$\rho[\Delta u, \text{S\&P 500 returns}]$				0.002
				(0.014)

Prog.-level expl. var.	Individual-level outcomes			
	Owns stocks		Stocks/Fin. wealth	
	(1)	(2)	(3)	(4)
II. Portfolio choices				
A. IV estimation				
$\rho[\Delta u, \log(\Delta \text{OMX 20})]$	-0.008		0.001	
	(0.061)		(0.018)	
$\rho[\Delta u, \text{OMX 20 returns}]$		-0.021		0.003
		(0.056)		(0.020)
B. Non-IV estimation				
$\rho[\Delta u, \log(\Delta \text{OMX 20})]$	-0.068***		-0.020***	
	(0.019)		(0.005)	
$\rho[\Delta u, \text{OMX 20 returns}]$		-0.066***		-0.020***
		(0.018)		(0.006)

Note: This table presents the results of estimating equation (6) by IVs (Panels A) and by OLS (Panels B). Each cell presents the result from either a second stage of an IV regression or from an OLS regression. The outcome variable for each regression is the student's own estimate of the variable studied, while the explanatory variables are program-level average outcomes. In Panels A., each program-level explanatory variable is instrumented using the reach and safety program-level instruments in equation (8). In all panels, we present the results for a bandwidth of +/− 0.5 around the admission cutoff for the reach program. We measure the comovement as the average correlation 8 to 12 years after application of excess earnings growth and both the percentage growth in real stock market returns and their log returns for each index. The IV estimation controls for the reach and safety averages of the program-level variables being instrumented, admission system (quota 1 or 2) fixed effects, distance from the admission cutoff fixed effects and their interaction with admission quota fixed effects, the probability of being accepted given last year's admission cutoff and its interaction with quota fixed effects, and calendar year FE. The OLS results control for parents' wealth, income, and education, students' grade, age, and gender, and calendar year FE. Standard errors corrected for heteroscedasticity are presented in parentheses. ***, **, and * represent significance at the 1, 5 and 10 percent level, respectively.

Table A6: Effects of Program-Level Earnings Processes on Individuals' Financial Holding
Robustness to specifications

	Individual-level outcomes											
	Owns stocks						Stocks/Financial wealth					
	(1)	(2)	**(3)**	(4)	(5)	(6)	(7)	(8)	**(9)**	(10)	(11)	(12)
A. IV estimation												
Program-level explanatory variables: Excess earnings: u		0.54***	**0.51*** **	0.52**	0.48**	0.42***		0.16***	**0.15** **	0.14**	0.14**	0.11**
		(0.19)	**(0.19)**	(0.21)	(0.18)	(0.16)		(0.06)	**(0.06)**	(0.06)	(0.06)	(0.05)
Trans. vol.: σ^2_τ			**0.08**	0.16	-0.59	0.048			**-0.037**	-0.041	-0.26	0.13
			(1.74)	(1.76)	(1.65)	(1.47)			**(0.54)**	(0.54)	(0.51)	(0.44)
Perm. vol.: σ^2_π	-3.47*	-6.21***	**-6.36*** **	-6.50***	-5.73***	-4.18**	-1.04*	-1.83***	**-1.88*** **	-2.03***	-1.73***	-1.31**
	(2.07)	(2.21)	**(2.21)**	(2.39)	(2.11)	(1.74)	(0.63)	(0.67)	**(0.67)**	(0.73)	(0.63)	(0.53)
Excess earn. growth: Δu				-0.036						0.14		
				(1.31)						(0.40)		
Previous year admin. prob.	YES	YES	YES	YES	YES	NO	YES	YES	YES	YES	YES	NO
Previous year admin. prob. × reach and safety controls	YES	YES	YES	YES	YES	NO	YES	YES	YES	YES	YES	NO
OLS Controls	NO	NO	NO	NO	YES	NO	NO	NO	NO	NO	YES	NO
B. Non-IV estimation												
Excess earnings: u		0.37***	**0.37*** **	0.35***	0.37***	0.37***		0.11***	**0.11*** **	0.10**	0.11***	0.11***
		(0.06)	**(0.06)**	(0.06)	(0.06)	(0.06)		(0.02)	**(0.02)**	(0.02)	(0.02)	(0.02)
Trans. vol.: σ^2_τ			**-0.35**	-0.41	-0.35	-0.35			**-0.037**	-0.042	-0.037	-0.037
			(0.52)	(0.53)	(0.52)	(0.52)			**(0.14)**	(0.14)	(0.14)	(0.14)
Perm. vol.: σ^2_π	3.01***	0.59	**0.69**	0.41	0.69	0.69	0.82***	0.13	**0.14**	0.12	0.14	0.14
	(0.51)	(0.62)	**(0.64)**	(0.74)	(0.64)	(0.64)	(0.14)	(0.17)	**(0.17)**	(0.20)	(0.17)	(0.17)
Excess earn. growth: Δu				0.31						0.025		
				(0.41)						(0.11)		

Note: This table presents the robustness to different specifications for our main results presented in the left panel of Table 4. Specfically, it presents the results of estimating equation (5) by IVs (Panel A) and directly, without any instruments (Panel B). Each column presents the result from either a second stage of an IV regression or from a non-instrumented regression.The outcome variable for each regression is the student's own estimate of the variable studied, while the explanatory variables are program-level average outcomes. Stock market participation is estimated with a probit model, from which we report the marginal effects of participation, while the share of risky assets in the portfolio is estimated with a tobit model, from which we report marginal effects for the share of risky assets, conditional on participation. In Panel A., each program-level explanatory variable is instrumented using the reach and safety program-level instruments in equation (8). In both panels, we use the sample of 10,567 students who have a reach–safety programs pair in application years 1994 to 2006 and present the results for a bandwidth of +/− 0.5 around the admission cutoff for the reach program. Earnings are assumed to follow the process described in equation (2). The definitions of the different attributes of the earnings process follow from this equation and are averaged over the period 8 to 12 years after enrollment. Financial wealth is averaged over the period 8 to 12 years after enrollment. A part from the variations presented, the IV estimation always controls for the reach and safety averages of the program-level variables being instrumented, admission system (quota 1 or 2) fixed effects, distance from the admission cutoff fixed effects and their interaction with admission quota fixed effects, and calendar year FE. The OLS results control for parents' wealth, income, and education, students' grade, age, and gender, and calendar year FE. Standard errors corrected for heteroscedasticity are presented in parentheses. ***, **, and * represent significance at the 1, 5 and 10 percent level, respectively.

Table A7: Effects of Individuals' Earnings Processes on Individuals' Financial Holding
Robustness to specifications

Individual-level explanatory variables	Individual-level outcomes											
	Owns stocks						Stocks/Financial wealth					
	(1)	(2)	**(3)**	(4)	(5)	(6)	(7)	(8)	**(9)**	(10)	(11)	(12)
A. IV estimation												
Excess earnings: u		0.37	**0.33**	0.19	0.37	0.33		0.18	**0.15**	0.12	0.17	0.13
		(0.27)	**(0.29)**	(0.27)	(0.31)	(0.28)		(0.17)	**(0.17)**	(0.27)	(0.18)	(0.32)
Trans. vol.: σ_τ^2			**0.089**	0.83	-0.088	-0.0092			**0.043**	0.96	-0.061	0.57
			(2.31)	(1.88)	(2.16)	(3.77)			**(1.49)**	(1.94)	(1.34)	(3.49)
Perm. vol.: σ_π^2	-2.78***	-3.59***	**-3.56*** **	-3.37***	-3.38***	-3.93***	-1.34*	-2.12**	**-2.05***	-3.23	-1.91*	-2.64
	(1.07)	(0.69)	**(0.82)**	(0.98)	(0.87)	(1.31)	(0.74)	(0.95)	**(1.17)**	(2.35)	(1.09)	(4.25)
Excess earn. growth: Δu				1.97*						2.34		
				(1.17)						(2.36)		
Previous year admin. prob.	YES	YES	YES	YES	YES	NO	YES	YES	YES	YES	YES	NO
Previous year admin. prob. × reach and safety controls	YES	YES	YES	YES	YES	NO	YES	YES	YES	YES	YES	NO
OLS Controls	NO	NO	NO	NO	YES	NO	NO	NO	NO	NO	YES	NO
B. Non-IV estimation												
Excess earnings: u		0.20***	**0.20*** **	0.20***	0.20***	0.20***		0.049***	**0.049*** **	0.049***	0.049***	0.049***
		(0.02)	**(0.02)**	(0.02)	(0.02)	(0.02)		(0.01)	**(0.01)**	(0.01)	(0.01)	(0.01)
Trans. vol.: σ_τ^2			**-0.011**	-0.018	-0.011	-0.011			**-0.0047**	-0.0042	-0.0047	-0.0047
			(0.07)	(0.08)	(0.07)	(0.07)			**(0.02)**	(0.02)	(0.02)	(0.02)
Perm. vol.: σ_π^2	0.15**	0.087	**0.088**	0.085	0.088	0.088	0.037**	0.02	**0.02**	0.02	0.02	0.02
	(0.06)	(0.06)	**(0.06)**	(0.06)	(0.06)	(0.06)	(0.02)	(0.02)	**(0.02)**	(0.02)	(0.02)	(0.02)
Excess earn. growth: Δu				0.026						-0.0019		
				(0.06)						(0.02)		

Note: This table presents the robustness to different specifications for our main results presented in the right panel of Table 4. Specfically, it presents the results of estimating equation (5) by IVs (Panel A) and directly, without any instruments (Panel B). Each column presents the result from either a second stage of an IV regression or from a non-instrumented regression. The outcome variable for each regression is the student's own estimate of the variable studied, while the explanatory variables are individual-level average outcomes. Stock market participation is estimated with a probit model, from which we report the marginal effects of participation, while the share of risky assets in the portfolio is estimated with a tobit model, from which we report marginal effects for the share of risky assets, conditional on participation. In Panel A., each individual-level explanatory variable is instrumented using the reach and safety program-level instruments in equation (8). In both panels, we use the sample of 10,567 students who have a reach–safety programs pair in application years 1994 to 2006 and present the results for a bandwidth of +/− 0.5 around the admission cutoff for the reach program. Earnings are assumed to follow the process described in equation (2). The definitions of the different attributes of the earnings process follow from this equation and are averaged over the period 8 to 12 years after enrollment. Financial wealth is averaged over the period 8 to 12 years after enrollment. A part from the variations presented, the IV estimation always controls for the reach and safety averages of the program-level variables being instrumented, admission system (quota 1 or 2) fixed effects, distance from the admission cutoff fixed effects and their interaction with admission quota fixed effects, and calendar year FE. The OLS results control for parents' wealth, income, and education, students' grade, age, and gender, and calendar year FE. Standard errors corrected for heteroscedasticity are presented in parentheses. ***, **, and * represent significance at the 1, 5 and 10 percent level, respectively.

Table A8: Effects of Program-Level Earnings Processes on Individuals' Financial Holding
Alternative Mechanisms

	Individual-level outcomes									
	Owns stocks					Stocks/Financial wealth				
	(1)	(2)	(3)	(4)	(5)	**(6)**	(7)	(8)	(9)	(10)
A. IV estimation										
Program-level explanatory variables: Excess earnings: u	**0.51*****	0.26	0.53***	0.38	0.46**	**0.15****	0.06	0.15**	0.098	0.14**
	(0.19)	(0.23)	(0.20)	(0.23)	(0.21)	**(0.06)**	(0.07)	(0.06)	(0.07)	(0.06)
Trans. vol.: σ^2_τ	**0.08**	0.88	0.059	0.48	0.93	**-0.037**	0.25	-0.042	0.13	0.32
	(1.74)	(1.81)	(1.73)	(1.81)	(1.96)	**(0.54)**	(0.55)	(0.53)	(0.55)	(0.54)
Perm. vol.: σ^2_π	**-6.36*****	-5.90***	-6.49***	-7.02***	-5.34**	**-1.88*****	-1.80***	-1.93***	-2.12***	-1.63**
	(2.21)	(2.24)	(2.25)	(2.23)	(2.53)	**(0.67)**	(0.68)	(0.69)	(0.68)	(0.75)
Share owns stocks		0.48*					0.17**			
		(0.25)					(0.08)			
$\rho[\Delta u, \log(\Delta \text{OMX } 20)]$			0.019					0.0075		
			(0.06)					(0.02)		
Financial wealth				0.095					0.039	
				(0.11)					(0.04)	
Reach-Safety FE?	NO	NO	NO	NO	YES	NO	NO	NO	NO	YES
B. Non-IV estimation										
Excess earnings: u	**0.37*****	0.0084	0.35***	0.24***	0.37***	**0.11*****	0.0064	0.11***	0.060***	0.11***
	(0.06)	(0.07)	(0.06)	(0.07)	(0.06)	**(0.02)**	(0.02)	(0.02)	(0.02)	(0.02)
Trans. vol.: σ^2_τ	**-0.35**	1.48***	-0.36	0.059	-0.35	**-0.037**	0.47***	-0.036	0.11	-0.037
	(0.52)	(0.55)	(0.53)	(0.54)	(0.52)	**(0.14)**	(0.15)	(0.14)	(0.14)	(0.14)
Perm. vol.: σ^2_π	**0.69**	-1.01	0.68	-0.09	0.69	**0.14**	-0.31*	0.14	-0.13	0.14
	(0.64)	(0.66)	(0.64)	(0.68)	(0.64)	**(0.17)**	(0.18)	(0.18)	(0.19)	(0.17)
Share owns stocks		0.75***					0.21***			
		(0.07)					(0.02)			
$\rho[\Delta u, \log(\Delta \text{OMX } 20)]$			0.0046					0.0001		
			(0.02)					(0.01)		
Financial wealth				0.11 ***					0.038 ***	
				(0.03)					(0.01)	

Note: This table presents the robustness to different specifications for our main results presented in the left panel of Table 4. Specfically, it presents the results of estimating equation (5) by IVs (Panel A) and directly, without any instruments (Panel B). Each column presents the result from either a second stage of an IV regression or from a non-instrumented regression.The outcome variable for each regression is the student's own estimate of the variable studied, while the explanatory variables are program-level average outcomes. Stock market participation is estimated with a probit model, from which we report the marginal effects of participation, while the share of risky assets in the portfolio is estimated with a tobit model, from which we report marginal effects for the share of risky assets, conditional on participation. In Panel A., each program-level explanatory variable is instrumented using the reach and safety program-level instruments in equation (8). In both panels, we use the sample of 10,567 students who have a reach–safety programs pair in application years 1994 to 2006 and present the results for a bandwidth of +/− 0.5 around the admission cutoff for the reach program. Earnings are assumed to follow the process described in equation (2). The definitions of the different attributes of the earnings process follow from this equation and are averaged over the period 8 to 12 years after enrollment. Financial wealth is averaged over the period 8 to 12 years after enrollment. A part from the variations presented, the IV estimation always controls for the reach and safety averages of the program-level variables being instrumented, admission system (quota 1 or 2) fixed effects, distance from the admission cutoff fixed effects and their interaction with admission quota fixed effects, and calendar year FE. The OLS results control for parents' wealth, income, and education, students' grade, age, and gender, and calendar year FE. Standard errors corrected for heteroscedasticity are presented in parentheses. ***, **, and * represent significance at the 1, 5 and 10 percent level, respectively.

Table A9: Effects of Individual-Level Earnings Processes on Individuals' Financial Holding
Alternative Mechanisms

Individual-level earnings process	Individual-level outcomes									
	Owns stocks					Stocks/Financial wealth				
	(1)	(2)	(3)	(4)	(5)	**(6)**	(7)	(8)	(9)	(10)
A. IV estimation										
Excess earnings: u	**0.33**	0.15	0.42	0.025	0.35	**0.15**	0.0028	0.22	-0.051	0.18
	(0.29)	(0.36)	(0.29)	(0.36)	(0.42)	**(0.17)**	(0.17)	(0.21)	(0.20)	(0.13)
Trans. vol.: σ^2_τ	**0.089**	0.33	-0.0041	0.75	2.64	**0.043**	0.4	-0.1	0.61	0.38
	(2.31)	(2.38)	(2.38)	(2.05)	(2.33)	**(1.49)**	(1.07)	(1.72)	(1.16)	(0.79)
Perm. vol.: σ^2_π	**-3.56*****	-3.31***	-3.66***	-3.44***	-4.16*	**-2.05***	-1.44	-2.34	-1.82*	-1.05
	(0.82)	(1.08)	(0.81)	(0.90)	(2.14)	**(1.17)**	(0.91)	(1.52)	(0.93)	(0.67)
Share owns stocks		0.27					0.17*			
		(0.22)					(0.10)			
$\rho[\Delta u, \log(\Delta \text{OMX } 20)]$			0.063					0.042		
			(0.06)					(0.05)		
Financial wealth				0.012					0.078	
				(0.08)					(0.05)	
Reach-Safety FE?	NO	NO	NO	NO	YES	NO	NO	NO	NO	YES
B. Non-IV estimation										
Excess earnings: u	**0.20*****	0.15***	0.19***	0.17***	0.20***	**0.049*****	0.035***	0.047***	0.039***	0.049***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	**(0.01)**	(0.01)	(0.01)	(0.01)	(0.01)
Trans. vol.: σ^2_τ	**-0.011**	-0.022	-0.013	-0.03	-0.011	**-0.0047**	-0.0077	-0.0052	-0.011	-0.0047
	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	**(0.02)**	(0.02)	(0.02)	(0.02)	(0.02)
Perm. vol.: σ^2_π	**0.088**	0.075	0.09	0.074	0.088	**0.02**	0.016	0.021	0.015	0.02
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	**(0.02)**	(0.02)	(0.02)	(0.02)	(0.02)
Share owns stocks		0.57***					0.16***			
		(0.05)					(0.01)			
$\rho[\Delta u, \log(\Delta \text{OMX } 20)]$			-0.043**					-0.014**		
			(0.02)					(0.01)		
Financial wealth				0.13					0.042 ***	
				(0.02)					0.000	

Note: This table presents the robustness to different specifications for our main results presented in the left panel of Table 4. Specfically, it presents the results of estimating equation (5) by IVs (Panel A) and directly, without any instruments (Panel B). Each column presents the result from either a second stage of an IV regression or from a non-instrumented regression.The outcome variable for each regression is the student's own estimate of the variable studied, while the explanatory variables are program-level average outcomes. Stock market participation is estimated with a probit model, from which we report the marginal effects of participation, while the share of risky assets in the portfolio is estimated with a tobit model, from which we report marginal effects for the share of risky assets, conditional on participation. In Panel A., each program-level explanatory variable is instrumented using the reach and safety program-level instruments in equation (8). In both panels, we use the sample of 10,567 students who have a reach–safety programs pair in application years 1994 to 2006 and present the results for a bandwidth of +/− 0.5 around the admission cutoff for the reach program. Earnings are assumed to follow the process described in equation (2). The definitions of the different attributes of the earnings process follow from this equation and are averaged over the period 8 to 12 years after enrollment. Financial wealth is averaged over the period 8 to 12 years after enrollment. A part from the variations presented, the IV estimation always controls for the reach and safety averages of the program-level variables being instrumented, admission system (quota 1 or 2) fixed effects, distance from the admission cutoff fixed effects and their interaction with admission quota fixed effects, and calendar year FE. The OLS results control for parents' wealth, income, and education, students' grade, age, and gender, and calendar year FE. Standard errors corrected for heteroscedasticity are presented in parentheses. ***, **, and * represent significance at the 1, 5 and 10 percent level, respectively.

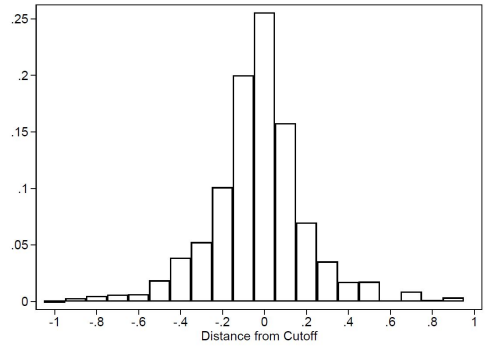
Table A10: Robustness to Earnings Process Assumptions

		Individual-level outcomes			
		Owns stocks		Stocks/Fin. wealth	
		IV Probit	Probit	IV Tobit	Tobit
Program-level expl. variables	*A. 8 to 12 years after enrol., excess earnings*				
	Perm. vol.: σ_π^2	-6.36***	0.69	-1.88***	0.14
		(2.21)	(0.64)	(0.67)	(0.17)
	B. 8 to 12 years after enrol., raw earnings				
	Perm. vol.: σ_π^2	-4.84***	0.38	-1.31**	0.017
		(1.77)	(0.54)	(0.54)	(0.15)
	C. 8 to 15 years after enrol., excess earnings				
	Perm. vol.: σ_π^2	-6.64***	0.30	-1.89***	0.031
		(2.49)	(0.72)	(0.72)	(0.19)
	D. 8 to 15 years after enrol., raw earnings				
	Perm. vol.: σ_π^2	-5.37***	0.0069	-1.33**	-0.07
		(1.99)	(0.59)	(0.58)	(0.16)
Individual-level expl. variables	*E. 8 to 12 years after enrol., excess earnings*				
	Perm. vol.: σ_π^2	-3.56***	0.088	-2.05*	0.02
		(0.82)	(0.06)	(1.17)	(0.02)
	F. 8 to 12 years after enrol., raw earnings				
	Perm. vol.: σ_π^2	-2.67**	0.056	-1.40	0.0077
		(1.05)	(0.06)	(0.89)	(0.02)
	G. 8 to 15 years after enrol., excess earnings				
	Perm. vol.: σ_π^2	-3.76***	0.068	-2.02	0.013
		(0.76)	(0.07)	(1.36)	(0.02)
	H. 8 to 15 years after enrol., raw earnings				
	Perm. vol.: σ_π^2	-3.25***	0.027	-1.45	-0.00002
		(1.08)	(0.06)	(0.98)	(0.02)

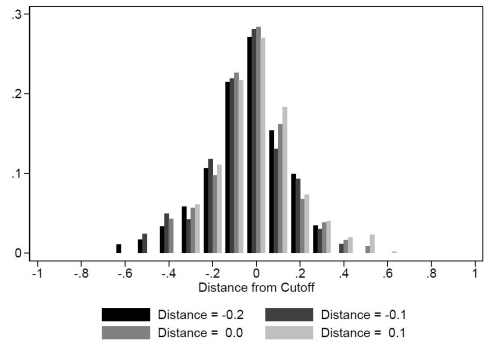
Note: This table presents the robustness of our main results of Table 4 to different assumptions about the earnings process. Specfically, it presents the results of estimating equation (5) by IVs. Each cell presents the result from either a second stage of an IV regression or from a non-instrumented regression. The outcome variable for each regression is the student's own estimate of the variable studied, while the explanatory variables are program-level average outcomes in Panels A to D, and individual-level average outcomes in Panels E to H. Stock market participation is estimated with a probit model, from which we report the marginal effects of participation, while the share of risky assets in the portfolio is estimated with a tobit model, from which we report marginal effects for the share of risky assets, conditional on participation. Each explanatory variable is instrumented using the reach and safety program-level instruments in equation (8). In all panels, we use the sample of 10,567 students who have a reach–safety programs pair in application years 1994 to 2006 and present the results for a bandwidth of +/− 0.5 around the admission cutoff for the reach program. Earnings are assumed to follow the process described in equation (2). The definitions of the different attributes of the earnings process follow from this equation and are averaged over the period 8 to 12 years after enrollment. Financial wealth is averaged over the period 8 to 12 years after enrollment. The IV estimation controls for the reach and safety averages of the program-level variables being instrumented, admission system (quota 1 or 2) fixed effects, distance from the admission cutoff fixed effects and their interaction with admission quota fixed effects, the probability of being accepted given last year's admission cutoff and its interaction with quota fixed effects, and calendar year FE. The OLS results control for parents' wealth, income, and education, students' grade, age, and gender, and calendar year FE. Standard errors corrected for heteroscedasticity are presented in parentheses. ***, **, and * represent significance at the 1, 5 and 10 percent level, respectively.

Appendix Figures

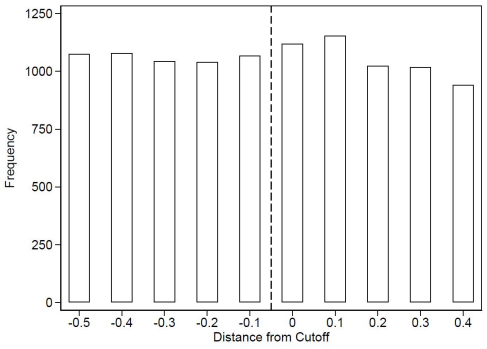
Figure A1: Bunching and Annual Changes in Cutoffs



(a) Annual Changes Cutoff



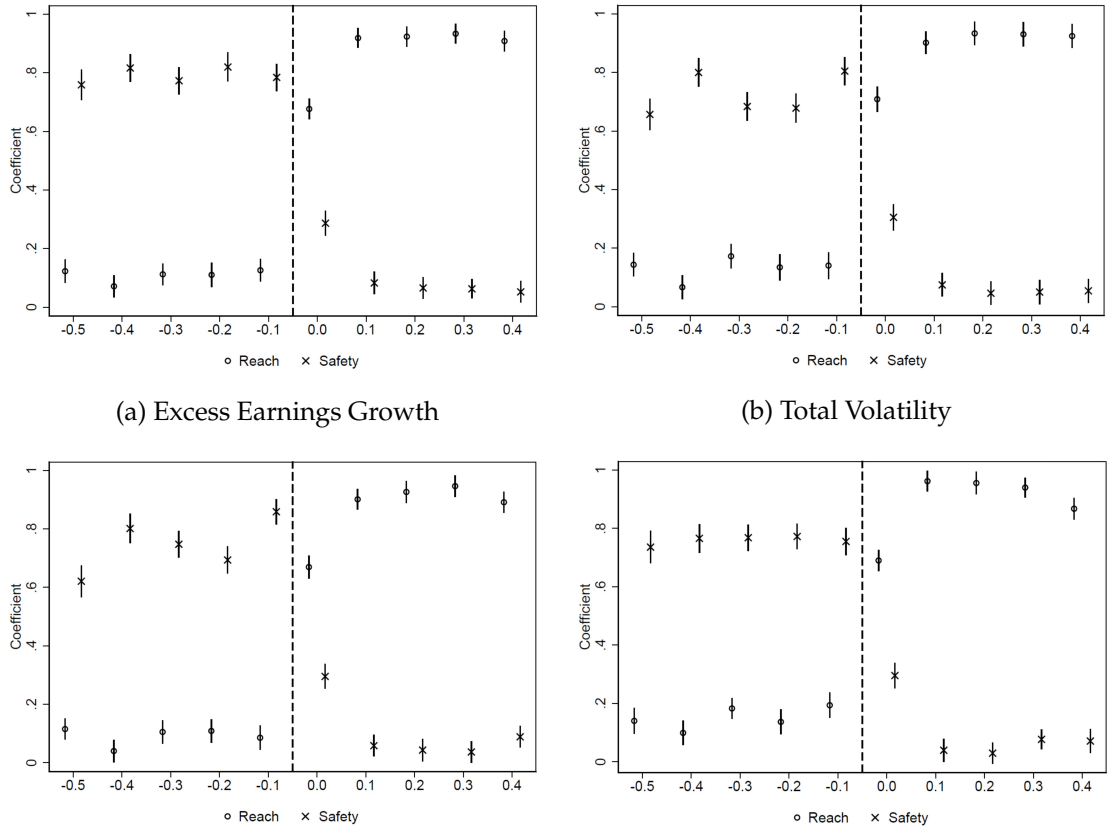
(b) Change in Cutoff Given Distance from Reach



(c) Total Counts

Note: This figure presents the number of applications around admission cutoffs, and year-to-year changes in admission cutoffs. We use the sample of 10,567 students who have a reach–safety programs pair in application years 1994 to 2006. We pool all programs and years and present the distance between the application score and the admission cutoff of the reach program on the x-axis. Panel (a) presents the number of applications around admission cutoffs for the entire sample. Panel (b) presents the difference between the admission cutoff of the student's reach program in the year of application and the cutoff for the same program in the previous year. We restrict the histogram to changes in program admission cutoffs that are between –1 and 1 because they account for most of the data; 1,198 observations are for programs that have an increase in the admission cutoff of greater than 1, while 28 observations are for programs that have a decrease in the admission cutoff of less than –1. Panel (c) shows the year-to-year changes in the admission cutoff of a student's reach program conditional on the student's distance from the admission cutoff for the reach program in the year prior to his or her application.

Figure A2: First-stage Results



(a) Excess Earnings Growth

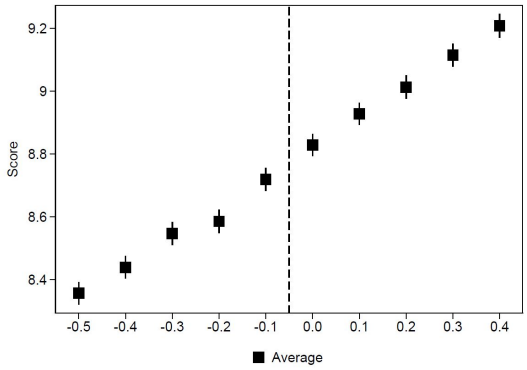
(b) Total Volatility

(c) Transitory Volatility

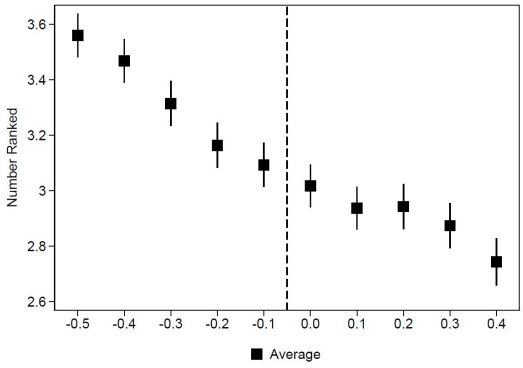
(d) Permanent Volatility

Note: This figure provides a graphical illustration of the first-stage earnings and earnings gap results. We use the sample of 6,339 students who applied through the Quota 1 system of admission and have a reach–safety programs pair in application years 1994 to 2006. We pool all programs and years and present the distance between the application score and the admission cutoff for the reach program on the x-axis. The results show the coefficients estimated separately for the reach and safety programs using 10 dummy bins centered around the admission cutoff. Each student has exactly one dummy bin variable equal to 1, with the rest equal to zero. In each panel, the dependent variable is a attribute of the earnings process of enrollees in the program of admission, and we plot the coefficients of earnings in the reach and safety programs interacted with distance from cutoff dummies. Earnings are assumed to follow the process described in equation (2). The definitions of the different attributes of the earnings process follow from this equation and are averaged over the period 8 to 12 years after enrollment. Point estimates are given along with the 95% confidence interval.

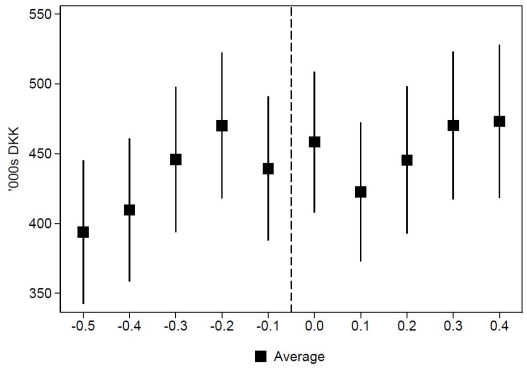
Figure A3: Covariate Balance



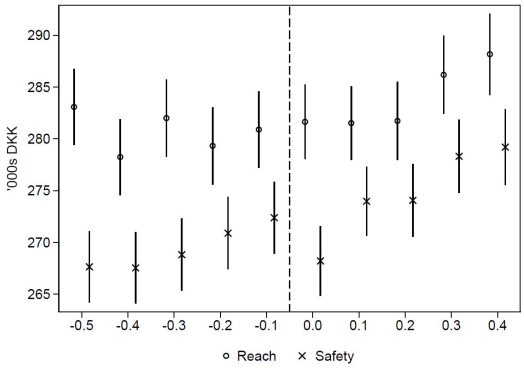
(a) High School Score



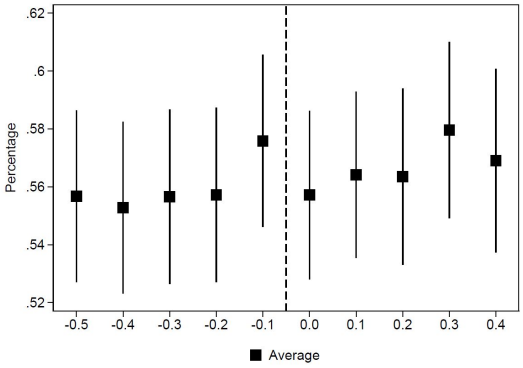
(b) Number of Programs Ranked



(c) Parental Wealth



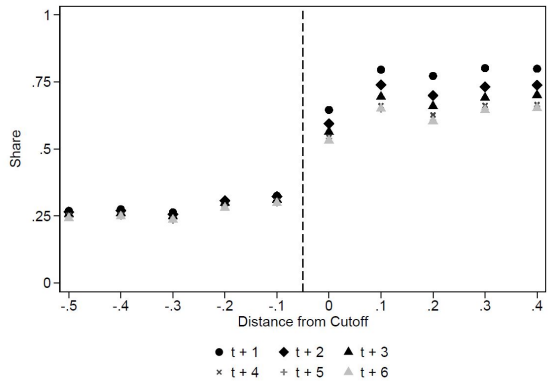
(d) Earnings



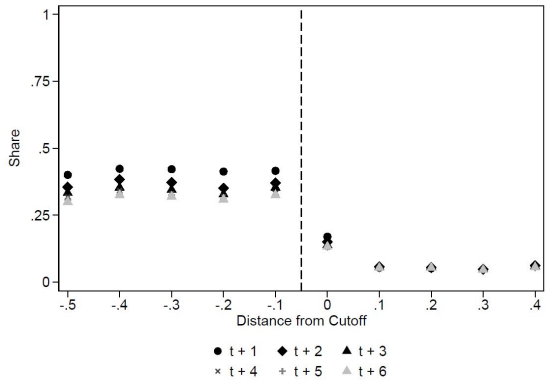
(e) Same Field for Reach and Safety

Note: This figure presents averages of the covariates used in the analysis by application score bins. We use the sample of 10,567 students who have a reach–safety programs pair in application years 1994 to 2006. We pool all programs and years and present the distance between the application score and the admission cut-off of the reach program on the x-axis. Point estimates are given along with the 95% confidence interval.

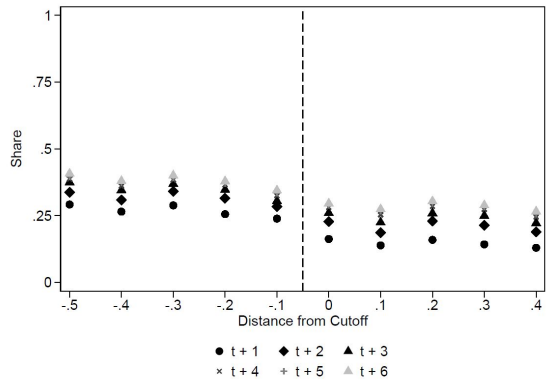
Figure A4: Proportions of Students in Reach, Safety, or Other Programs Over Time



(a) Reach



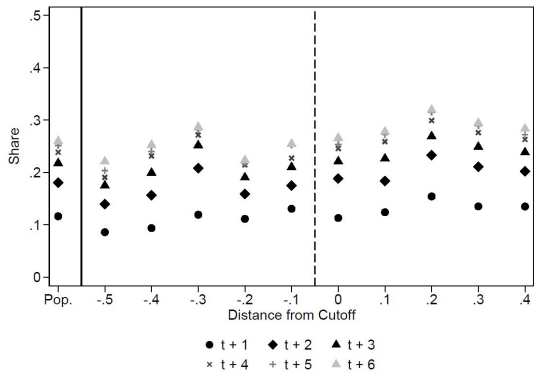
(b) Safety



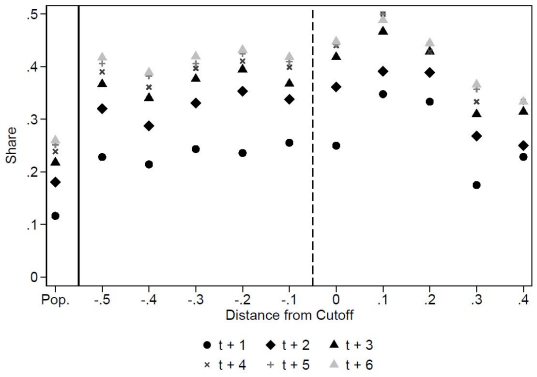
(c) Other

Note: This figure presents the proportions of students whose latest admission data show that they are enrolled in their (a) reach, (b) safety, or (c) other programs one to six years after their initial admission by application score bins. We pool all programs and present the distance between the student's score and the admission cutoff for the reach program on the x-axis.

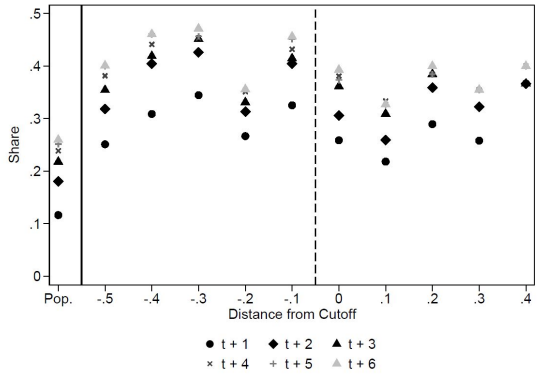
Figure A5: Switching Conditional on Reach, Safety, or Other Programs



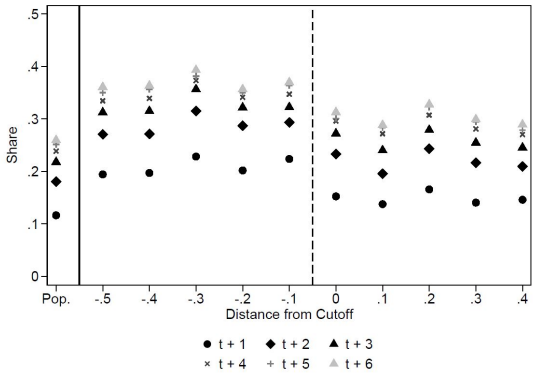
(a) Switching | Reach



(b) Switching | Safety



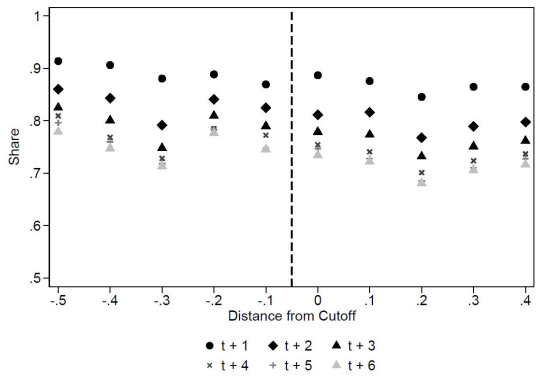
(c) Switching | Other



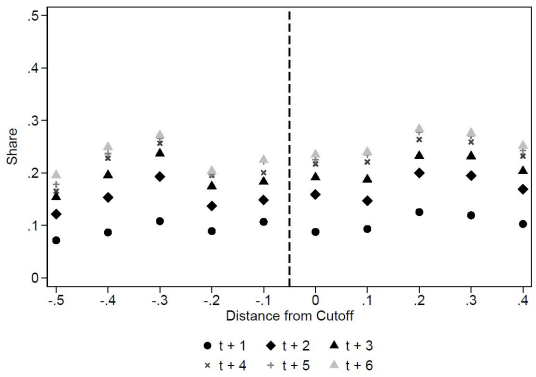
(d) Switching

Note: This figure presents the proportions of students whose latest admission data show that they have switched to another program following their initial admission into (a) their reach program, (b) their safety program, (c) another program, or (d) unconditionally one to six years after their initial admission by application score bins. We pool all programs and present the distance between the application score and the admission cutoff for the reach program on the x-axis.

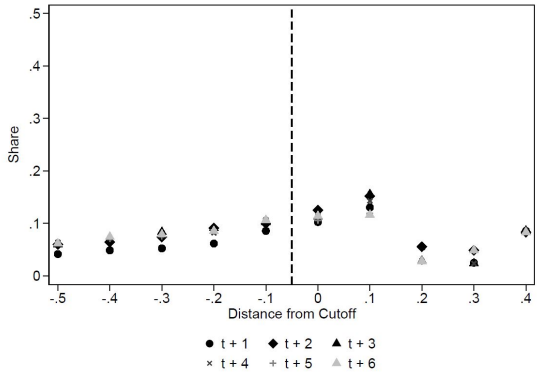
Figure A6: Transitions in and out of Reach, Safety, or Other Programs



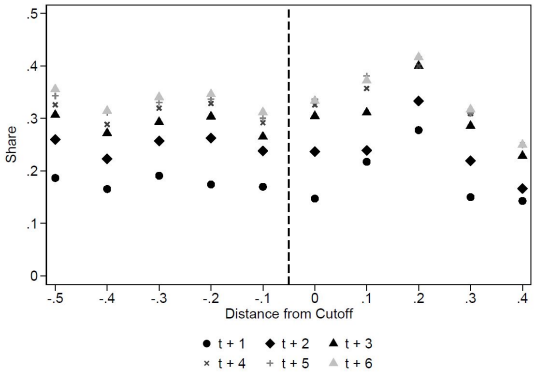
(a) Safety | Reach



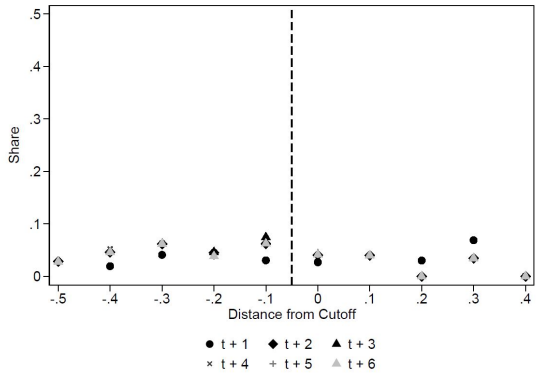
(b) Other | Reach



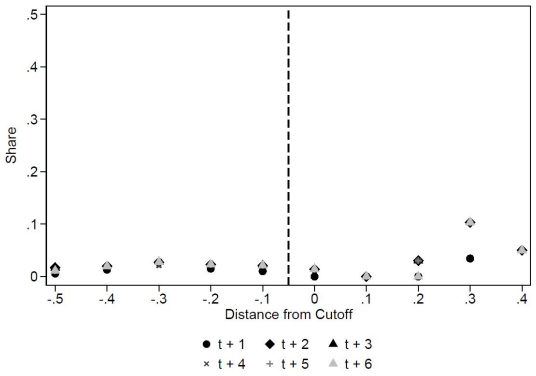
(c) Reach | Safety



(d) Other | Safety



(e) Reach | Other



(f) Safety | Other

Note: This figure presents the proportions of students whose latest admission data show that they have transitioned (a) from their reach program to their safety program, (b) from their reach program to another program, (c) from their safety program to their reach program, (d) from their safety program to another program, (e) from another program to their reach program, or (f) from another program to their safety program one to six years after their initial admission by application score bins. We pool all programs and present the distance between the student's score and the admission cutoff for the reach program on the x-axis.