Barriers to College Investment and Aggregate Productivity

Federico Rossi*

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Abstract

Family income shapes college opportunities for US students, even when its correlation with academic ability is taken into account. I propose a general equilibrium model to estimate the productivity losses deriving from the fact that human capital investment is not always allocated where its marginal product would be highest. Using the equilibrium conditions of the model, I back out the value of barriers to college investment for disadvantaged students from data on family income, ability, schooling and wages. Counterfactual experiments suggest that a more meritocratic access to college education could boost output by approximately 11%, and wages by between 9% and 12%. I conclude that returns from policies aimed to expand college opportunities are potentially very large.

1 Introduction

It is a well known fact that rich families tend to invest more in childrens' human capital compared to poor families. This is true in the US, and in virtually every country where enough data to document these intergenerational patterns are available.[1] This disparity

*London School of Economics and CFM. Corresponding email: f.rossi2@lse.ac.uk. I wish to thank my supervisor Francesco Caselli for continuous guidance and support. I am grateful to Esteban Aucejo, Caroline Hoxby, Pascal Michaillat, Tommaso Nannicini, Nicola Persico, Michael Peters, Ricardo Reis, Silvana Tenreyro as well as the participants to the LSE Macro Work in Progress, the Petralia Applied Economics Workshop and the Sixth Italian Congress of Econometrics and Empirical Economics for useful comments and suggestions.

[1]See Glewwe and Kremer (2006) for a discussion on developing countries.

holds for investments at different stages of the life cycle, from early childhood to higher education.

In the US, the relationship between socioeconomic status and college opportunities has become lately object of extensive public debate. Many observers, both academic and non academic, have expressed the concern that the US higher educational system is failing to provide students with a level playing field, where only merit and potential determine the access to better opportunities.[2] While most of the current debate emphasizes equity considerations, these facts might have important consequences also from an efficiency perspective.

In this paper, I investigate the impact of barriers to college investments for low income families on economy wide productivity. If high potential individuals are prevented from accessing to an adequate college education, then they will not be as productive as workers as they could be. The objective of my analysis is to quantify this productivity loss, therefore estimating how much it could be gained from policies that make access to college education more meritocratic.

The fact that individuals from rich families go to college more compared to individuals from poor families is not informative per se of an efficiency loss. Indeed, the burgeoning literature on skills formation emphasizes that the accumulation of human capital is a dynamic process, and that at each stage of the life cycle there are important complementarities between the current stock and the productivity of new investment (Heckman and Cunha, 2007; Cunha et al., 2010). Since children from rich families accumulate more human capital early on, it is natural (and efficient) that *at the college enrollment stage* they will be investing more.[3] In this paper I follow the skills formation literature by taking results in test scores administered at the end of high school as measures of the stock of human capital that individuals are endowed with when making decisions on college enrollment. In other words, I ask whether distortions due to family income are important once its effect on early human capital is controlled for.

As I will discuss more in detail below, there are in principle many possible reasons why family income, conditional on ability, correlates with human capital investments on children. A classic explanation is based on credit market imperfections: since future earnings might not be pledged as collateral, individuals from poor families are unable

[2]See for example Hoxby and Avery (2012) and Paul Tough, "Who Gets to Graduate?", *New York Times Magazine*, 15/05/2014.

[3]The efficiency considerations would be clearly very different if I were to consider the allocation of human capital investment at earlier stages. In ongoing work, I am developing a model appropriate for such an analysis. Still, taking a "snapshot" at the college enrollment stage is particularly interesting given the many policies are designed to correct inefficiencies arising at this stage.

to finance as much education as they would want. Credit constraints however receive mixed empirical support in US data, and several alternative explanations have been proposed.[4] Empirically distinguishing between these alternative frictions is a daunting task, given that many of them are likely to be present at the same time and to interact with each other.

I consider a setting that does not require to take a stand on exactly what is preventing low income families to invest on college as much as rich families do. Instead, I aim to capture the overall effect of this disparity through the reduced form approach introduced by Hsieh and Klenow (2009) in the misallocation literature. In particular, I propose a framework where individuals face different implicit “taxes” when making their college enrollment choices, depending on their family income. These objects should not be literally interpreted as taxes, but as the overall wedges between investment and return to education which might be due to credit constraints, imperfect information or any other friction. I back out these wedges from the structure of the model, and then I implement counterfactual experiments where barriers for low income families are eliminated.

The results of these exercises suggest that the productivity costs stemming from the inequality of college access opportunities might be substantial. Under my baseline parametrization, output and wages would increase by approximately 10% if individuals from low income families were to have the same possibilities of their peers from wealthy families. Most of these gains would come from what I call the “intensive margin” of college investment, which is the amount of human capital accumulated conditional on attending college (as opposed to the “extensive margin”, the choice between attending college or not). Therefore, policies aimed to improve efficiency should not aim to achieve large increases of college enrollment rates, but instead to help students from disadvantaged background to attend higher quality schools and make the most of their time there.

This paper speaks to several strands of the literature. First, it is clearly related to the huge literature on the determinants of college enrollment choices, and in particular the disparity in college opportunities between students of different family backgrounds. While this disparity is well documented (Ellwood and Kane, 2000; Hoxby and Avery, 2012) the debate on its determinants is quite open. An explanation explored in the economics literature is that poor families are subject to borrowing constraints that prevent them to invest in their children’s education as much as they would want to (Becker, 1962). The evidence on credit constraints for higher education is rather mixed:

[4] This literature is briefly reviewed below.

Cameron and Heckman (1998), Keane and Wolpin (2001) and Carneiro and Heckman (2002) argue that they are binding for at most a small share of students, while Brown et al. (2012) find that they do play an important role when the different incentives of parent and children are explicitly taken into account. Recent contributions have considered barriers of different nature: Hoxby and Avery (2012) and Carrell and Sacerdote (2013) find that providing information and mentoring are potentially effective ways to induce low income high school students to attend college, while Gorard et al. (2012) emphasize the role of differential attitudes towards college education. Differently from all these papers, my objective here is not to estimate the relative importance of specific barriers to college investment, but instead to evaluate their combined impact on aggregate productivity and wages.

My work is also closely related to a small literature that investigates the macroeconomic costs of human capital misallocation. I draw heavily from the framework proposed by Hsieh et al. (2013), who quantify the contribution of the relaxation of labor market frictions for women and black men to US economic growth in the last few decades. Buera et al. (2011) and Caselli and Gennaioli (2013) study the misallocation of entrepreneurial talent due to credit frictions, while Vollrath (2014) investigates the allocation of human capital across sectors. Differently from these paper, I study the allocation of human capital *investment*, rather than human capital per se.[5] Moreover, I focus on a different source of misallocation, namely the fact that family income shapes the access to education on top of academic ability. The interest in this source of misallocation is shared by Hanushek et al. (2014), who develop a dynamic general equilibrium model to quantify the impact of different policies aimed to relax credit constraints. Differently from their work, I do not restrict my attention to credit constraints, but instead I study a broader range of barriers to college investment.

The paper is structured as follows. In Section 2 I describe the evidence on the disparity of college investment between rich and poor families, both on the extensive and the intensive margin. Section 3 introduces the model, while Section 4 describes the calibration procedure. Section 5 presents the main results, while robustness checks and extensions are left for Section 6. Finally, Section 7 concludes by examining policy implications and avenues for future research.

[5] Hsieh et al. (2013) study the combined effect of frictions relative to educational investment and occupational choice.

2 Family Income and College Investment

2.1 Data

Throughout the paper, I use data from the 1979 wave of the National Longitudinal Survey of the Youth (NLSY79). This dataset provides a nationally representative panel of 12,687 young men and women that were between 14 and 22 years old in 1979. I focus on the main cross-sectional sample, and exclude the oversamples of ethnic minorities and disadvantaged individuals. The dataset includes detailled information on education, labor market outcomes and, crucially for my purposes, results of standardized tests designed to measure cognitive and noncognitive skills that were administered to sample members roughly at the end of high school.

As a measure of the family socioeconomic status, I use total net family income in 1978 and 1979. This should be informative of the resources available to families in the years where college choices are made.[6] I exclude from the sample individuals that do not live either with their parents or at a temporary address (such as a student dorm), since for those family income might not be informative of the actual resources at their disposal when choosing whether to go to college. To soften the concerns about the possible bias arising from short term fluctuations in income, I follow a common practice in the intergenerational mobility literature by taking the simple average of the two years.[7]

Individuals are considered to have attended some college when the highest grade they have completed is 13^{th} or higher.[8] Since the model is not aimed to capture the factors that determine high school completion, I discard all observations relative to high school dropouts (i.e., those individuals whose highest grade completed is 11^{th} or lower); however, results are very similar when these are included.

The main proxy for accumulated human capital that I use in the paper is the result in the Armed Forces Qualifications Test (AFQT). This test is widely used in the labor economics literature as a proxy of cognitive ability, and it is widely recognized

[6]Strictly speaking, these are the relevant years (mostly) for individuals that are 16 or 17 years old in 1979. I use them for all individual in the samples in order to have a directly comparable measure of family income, which can be used to construct quantiles of interest. Focusing on the younger part of the sample would considerably restrict the number of observations and not alter the major results of the paper (if anything, I find slightly bigger counterfactual gains when I limit the sample to individuals that are 16 or 17 years old in 1979; these results are available upon request).

[7]Whenever family income is available for only one of these two years, I include the available measure.

[8]I take the maximum grade completed up to 33 years old, since, as described below, wages are measured at 35.

to reflect both innate ability and human capital accumulated during childhood (Cascio and Lewis, 2005). I construct the raw AFQT scores by combining the results obtained in different sections of the Armed Services Vocational Aptitude Battery (ASVAB) test, according to the formula documented in NLS (1992). A complication arises from the fact that the test was taken in 1981 by all students in the sample, who at the time were at different grades. In order to clean test scores from the component due to schooling differences in 1981, I adopt the following procedure, which is similar to the one described in Carneiro and Heckman (2002): I divide students in groups according to the highest grade attended in their life, and within each group I take the sum of the constant and residual estimated from a regression of the raw AFQT score on the difference between the grade attended in 1981 and 12.[9,10]. The obtained scores are normalized so that they range from 0 to 100.

In the robustness section I also use measures of noncognitive ability, which the skills formation literature has showed to be important for educational and labor market outcomes. I clean these measures from schooling differences in 1981 using the same procedure outlined above for the AFQT. The exact tests used are described more in detail in the robustness checks section.

The identification strategy adopted in this paper requires a measure of adult labor market income. I construct hourly wages at 35 (or the closest possible alternative) from data on total labor earnings and hours worked available in the NLSY79. Observations for which hours per week are below 10 or above 100 are dropped. Since the measurement of labor earnings is notoriously imprecise at the very bottom and the very top of the distribution, I impute wages corresponding to the 1^{st} and 99^{th} percentiles for individuals below and above these thresholds. In order to net out the effect of characteristics which are not the main focus of the paper, I regress (log) wages on race, gender and age controls, and use the (exponential of the) estimated residuals throughout.

The final sample is composed by 3000 individuals for which I have complete information on family income, education, ability and wages. When I include measures of noncognitive skills, the sample size drops to 2934. All the summary statistics and regression results reported below make use of the provided sample weights.

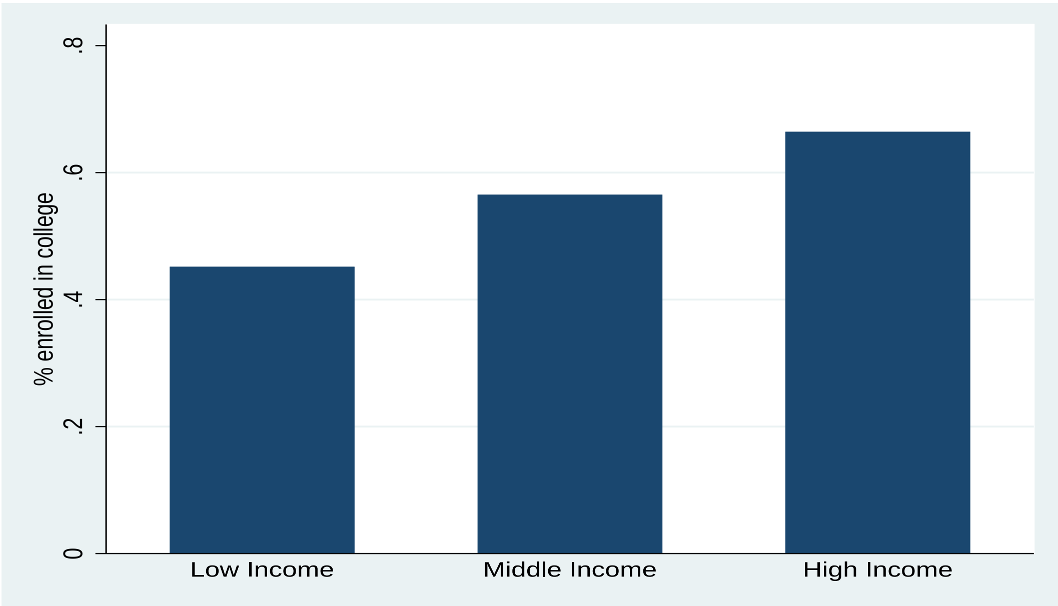
[9]Dividing by group according to the educational level achieved is necessary since there exist factors (such as family income, as stressed in this paper) that are positively correlated with both schooling at test date (for those with some college education) and ability, so that the effect of schooling on test scores would be overstated in a pooled regression. Instead, when I condition on total education achieved in life, the variation in schooling at test date should depend only on age in 1981.

[10]I also correct for age differences on top of this, even though this adjustment turns out to be mostly inconsequential.

2.2 The Extensive Margin

In this section I report evidence from the NLSY79 on to the extent to which family income is an important determinant of college enrollment. For this purpose, I split my sample in three groups according to family income terciles. Figure 1 shows the share of individuals in each group with at least some college education.[11]

Figure 1: College Enrollment by Family Income Terciles



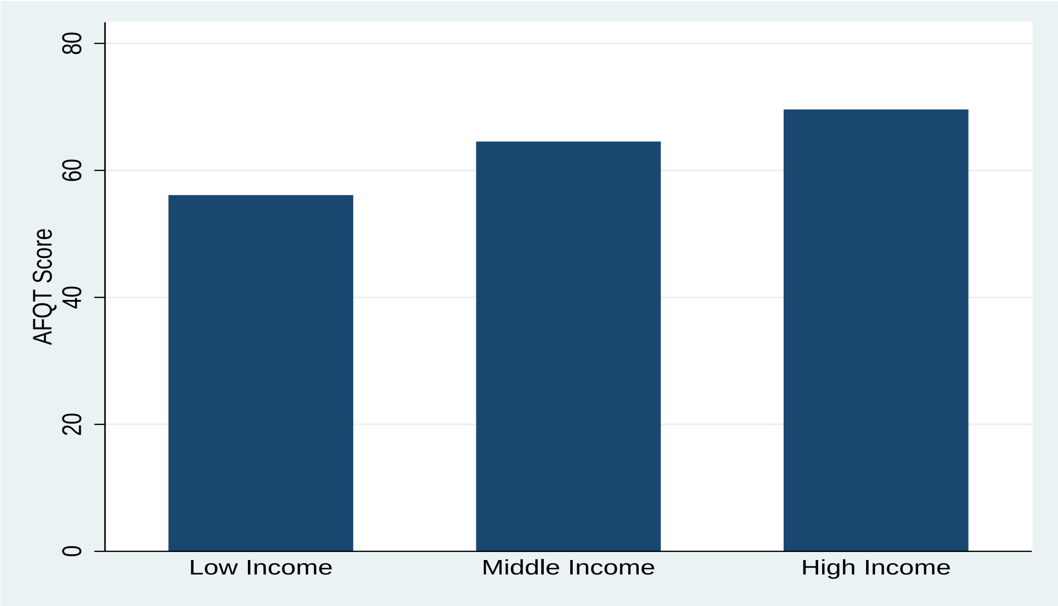
Notes: Height of the bar represents share with more than 12 years of schooling within each family income group. Source: NLSY79.

The differences between groups are quite substantial: more than 60% of children from "High Income" families get some education beyond high school, while the corresponding figure for the "Low Income" group is just above 40%. As discussed in the introduction, this disparity is not particularly puzzling, given that students coming from rich families are likely to be more prepared for college given that they have attended better schools and in general lived in environments more favourable to human capital accumulation. Indeed, Figure 2 documents how these students achieve substantially higher scores in the AFQT test.

In order to understand whether family income represents a barrier for college enrollment on top of its impact on ability, Figure 3 breaks down each income group in

[11]The college attendance figures reported is this paper are slight higher compared to the ones from other sources (such as, for example, Belley and Lochner (2007)), since here high school dropouts are excluded from the sample. As mentioned above, results do not depend on this sample restriction.

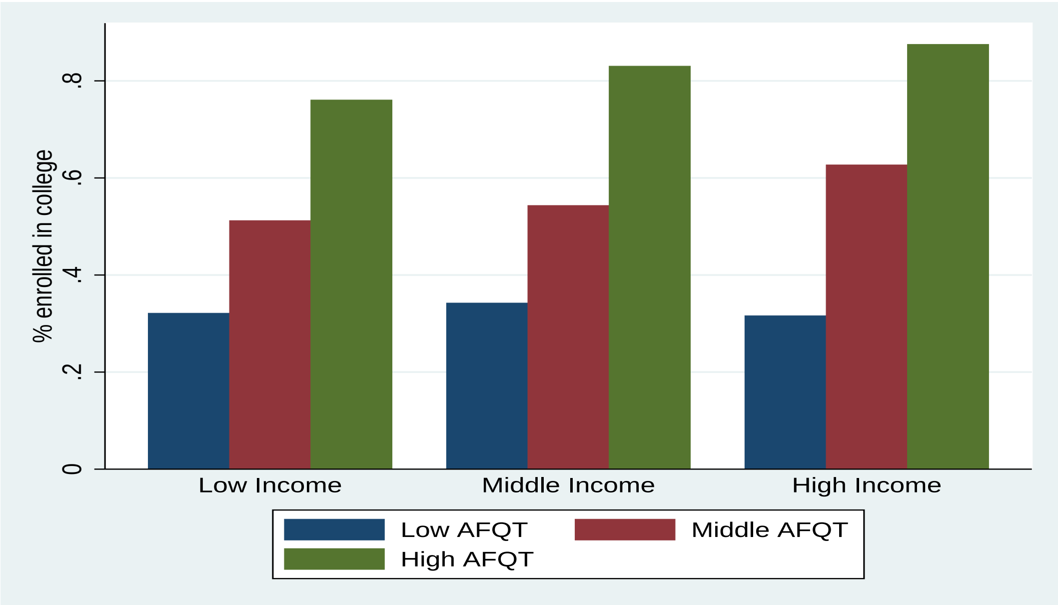
Figure 2: AFQT Scores by Family Income Terciles



Notes: Height of the bar represents the average AFQT score within each family income group. Source: NLSY79.

three subgroups according to test scores terciles.

Figure 3: College Enrollment by Family Income and AFQT Scores



Notes: Height of the bar represents share with more than 12 years of schooling within each family income and test scores group. Source: NLSY79.

While there seem to be some differences across income groups, overall the disparity

is far from being dramatic. Almost 85% of the individuals in the high income - high AFQT group attend college, while the corresponding figure for the high achievers in the low and middle income group is lower by approximately 10 percentage points. Similar gaps can be noted for the individuals in the Medium AFQT group, while the differences are even smaller between those that score poorly in the test. On the basis of this and further evidence, Carneiro and Heckman (2002) argue that credit constraints do not seem to play an important role in college enrollment, which is mainly determined by the human capital accumulated during childhood.[12]

2.3 The Intensive Margin

On the basis of the evidence presented in the last section, one might be lead to conclude the barriers to college investment for low income families are unlikely to be quantitatively important. However, the fact that conditional on ability individuals from different economic backgrounds are almost equally likely to extend their education does not mean that they accumulate the same amount of human capital once they are in college. Indeed, several recent papers have documented that family income is strongly correlated with the quality of college investment, and that this intensive margin is quantitatively important for wages. In this section I briefly review some of these studies, and then I offer some new evidence based on the NLSY79 data.

2.3.1 Existing Literature

Even when they attend college, students from low income families appear to pick schools that often are not up to their potential. The issue of "academic undermatch" has been at the center of a small but growing literature in educational economics, which has consistently shown that the problem is pervasive in the US, especially within low income groups and ethnic minorities (see, among the others, Cabrera and La Nasa (2001), Hill and Winston (2010), Pallais and Turner (2006) and Smith et al. (2013)). A particularly enlightening study for my purposes is Smith et al. (2013), which uses nationally representative data to quantify the extent of academic undermatch for students of different socioeconomic groups. According to their definitions, 49.6% of students with a lower socioeconomic status are undermatched, while the corresponding figure for students with a higher socioeconomic status is 34%. The contrast is starker for high achievers: 60% and 50.4% of disadvantaged students who potentially have access to "selective"

[12]Carneiro and Heckman (2002) also show that the relationship between college enrollment and family income is weakened further when factors such as parental education, family structure and place of residence are controlled for.

and "somewhat selective" colleges are undermatched, while the corresponding figures for richer students are 43.3% and 28.7%. A similar message emerges from the work of Hoxby and Avery (2012): the authors document that the majority of low income students who do extremely well in standardized tests do not even apply to selective colleges, and overall follow seemingly inefficient application strategies. In a subsequent paper Hoxby and Turner (2013) argue that a lack of information is at the origin of this puzzling behavior, and that very simple and cost effective policies can lead students to apply to colleges of the appropriate quality (and then succeed in them). Using the data from the 1979 and 1997 waves of the NLSY, Kinsler and Pavan (2011) document that family income strongly affects the quality of the college attended, and that the effect is weaker for the second wave (consistent with the development of more merit based policies over time).

A related finding reported by Hoxby and Avery (2012) and Belley and Lochner (2007) is that students from low income families choose to attend colleges closer to their place of origin. This might reflect a gap in information about better alternatives, as argued by Hoxby and Turner (2013), or more generally the fact that the distance from home embodies a larger cost for low income individuals. Moreover, since they usually come from disadvantaged regions, it is unlikely that they end up in selective institutions.

Substantial disparities in time use during college have also been documented. For example, Keane and Wolpin (2001) and Belley and Lochner (2007) document how poor students are disproportionately more likely to work part time during college, and discuss how this might impact their learning experience.

Are these margins important for productivity? While there is quite convincing evidence on the fact that college quality matters (Black and Smith, 2006; Kinsler and Pavan, 2011), the relevance of many other factors discussed in this section is obviously hard to identify. One advantage of the approach proposed in this paper is that, at the price of some admittedly restrictive assumption, it bypasses such identification problem by relying on the structure of the model to infer the importance of the intensive margin of college investment.

2.3.2 New Evidence from the NLSY79

A crucial dimension over which college experiences are highly heterogeneous across US students is given by the type of degree it terminates with. While Figures 1 and 3 classify as attending college any student who goes beyond the 12th grade, many eventually drop out without obtaining any formal recognition, while others are awarded with bachelors

and graduate degrees. Several papers document that the labor market offers a wage premium to individuals with a more advanced degree (Frazis, 1993; Jaeger and Page, 1996; Park, 1999); while it is difficult to disentangle to what extent this is due to a "sheepskin effect" or differential human capital accumulation, it seems uncontroversial that finishing a given degree entails benefits compared to stopping short of it

In this section I use data from the NLSY79 to document how, conditional on ability, students from low income families that attend some college fare worse in terms of the obtained degree. I do not necessarily wish to claim that the relationship is causal; instead, for the purpose of this paper, it is sufficient to document that there is some aspect associated with family income that correlates with these outcomes even when ability is controlled for.[13]

Table 1 shows the estimates from a multinomial logit regression where the dependent variable is the type of degree obtained in college.[14] Only students with some college education are included in the sample, and the considered categories are dropout without any degree (omitted), associate degree (including degrees from junior colleges), bachelor, graduate degree (including Masters, PhDs and professional degrees) and other degree. The regressors include (log) family income, ability (as measured by the AFQT score) and various demographic controls.[15] A positive coefficient on (log) family income implies that, conditional on ability, socioeconomic background is positively associated to the probability of obtaining a given degree. This is true for both bachelor and graduate degrees, while not significantly so for associate and other degrees. Not surprisingly, ability is positively related to the probability of obtaining all types of degrees (relative to not getting any).

In order to interpret the magnitude of the results, Table 2 displays the predicted probabilities of obtaining each type of degree (conditional on attending college) for individuals belonging to different terciles of the family income distribution, with the other controls evaluated at their sample average. It emerges that a student from the lowest family income tercile is approximately 10 percentage points more likely to dropout compared to one from the highest income tercile with the same (average) level of ability; by contrast, the latter is 11 and 4 percentage points more likely of obtaining a bachelor and graduate degree compared to the former.

[13]College quality and resources have been shown to influence whether a given student obtains a degree (Bound and Turner, 2007), so more dropouts for low income students could reflect the fact that they usually attend less selective colleges.

[14]I have experimented with other specifications, such as ordered multinomial logit and probit, obtaining similar results.

[15]Results are very similar when measures of non cognitive skills are included as well.

Table 1: Family Income and Type of Degree: Multinomial Logit

	Type of Degree			
	Associate	Bachelor	Graduate	Other
Log Family Income	0.121	0.464***	0.575***	0.034
	(0.147)	(0.136)	(0.207)	(0.337)
AQFT	0.012*	0.076***	0.114***	0.033**
	(0.006)	(0.006)	(0.011)	(0.013)

Notes: Table shows the coefficients from a weighted multinomial logit regression. Dependent variable indicates the type of degree obtained in college; omitted category is college dropouts. The sample is restricted to individuals with some college education. Additional controls include age, race, gender and urban status. Robust standard error in parentheses. Sample weights are provided by the NLSY79. ***, ** and * denote estimates significant at the 1%, 5% and 10% confidence level. Source: NLSY79

Table 2: Family Income and Type of Degree: Predicted Probabilities

	Type of Degree				
	Dropout	Associate	Bachelor	Graduate	Other
Low Income	0.336	0.186	0.345	0.084	0.046
Middle Income	0.277	0.168	0.410	0.107	0.039
High Income	0.238	0.153	0.450	0.125	0.033

Notes: Table shows the predicted probabilities for each type of degree from a multinomial logit model. Low, Middle and High Income refer to the first, second and third tercile of the family income distribution. Probabilities are evaluated at the average of Log Family Income within terciles, and at the overall sample average of the other regressors.

3 Model

The economy is populated by a unitary mass of agents who have just graduated from high school. They are heterogeneous along two dimensions: ability z and family income y. Ability here refers to the stock of human capital they have accumulated so far, which might be a composite of innate skills and previous investments. More specifically, agents belong to 1 of 3 ability groups and to 1 of 3 income groups, which map in the test scores and family income terciles considered in section 2; there are therefore 9 income - ability groups in the economy.[16]

The model is static. Agents choose whether they want to work as low skilled workers or go to college and work as high skilled. Moreover, if they go to college they have a choice on how much to invest in their university education; in particular, they acquire a certain number of "educational units" e. This is meant to capture the intensive margin of college investment discussed in the previous section: a higher e corresponds to attending a more selective school, putting more effort in the learning experience, participating to extra-curricular activities and in general taking advantage of every factor that affects the amount of human capital that is accumulated during college. I bundle all these aspects together because, as discussed above, it is very difficult to empirically separate between them, and, moreover, there are possibly many other important factors which are completely unobservable to the econometrician. As will become clear later, my strategy here is to use the structure of the model to back out the overall importance of these margins.

Going to college involves giving up a fraction s of the wage. This might be interpreted as a time cost: if an agent chooses to go to college, he will work only a fraction $1-s$ of his lifetime, while by opting for the low skill sector he can start working immediately.[17] The cost s is increasing in the amount of efficiency units that an individual wants to acquire. The rate at which individuals can convert s into e depends on ability and family income through an exogenous wedge $\tau(y,z)$; in particular

$$s = e(1+\tau(y,z)) \tag{1}$$

The fact that the wedge $\tau(y,z)$ is a function of ability reflects the finding in the skill formation technology literature that the existing stock of human capital directly affects the productivity of new investments (Heckman and Cunha, 2007; Cunha et al., 2010).

[16]This classification in 9 groups is convenient but clearly arbitrary. In Section 6.3 I consider deviations from this modeling choice.

[17]However, s does not have to be necessarily interpreted as a time cost. Any cost that enters proportionally to the wage would fit in this setting. Having only proportional costs greatly simplifies the analysis.

This might be because higher cognitive skills facilitate learning, or simply because new knowledge is more productive when built on a stronger basis. Therefore, I expect $\tau(y,z)$ to be decreasing in z.[18]

Barriers to college investment related to family income are captured by the fact that $\tau(y,z)$ is potentially a function of y. If $\tau(y,z)$ is decreasing in y, a student with high family income will be more efficient in accumulating educational units compared to one with low family income. To what extent this is the case is the main object of interest of the paper.

Agents make their educational choice to maximize consumption, which is simply equal to the wage (net of college cost if they choose to attend it). If agent i chooses to work in the low skill sector, he obtains a wage equal to

$$w_L(i) = r_L z(i)^{\alpha} \varepsilon_L(i) \tag{2}$$

where r_L is the price of an efficiency unit in the low skill sector and $\varepsilon_L(i)$ is an idiosyncratic shock. In the spirit of a Roy (1951) model, $\varepsilon_L(i)$ embodies all unobservable factors that make an individual more or less productive in a certain sector; this shock represents the only source of heterogeneity between agents in the same income - ability group.

If agent i chooses instead to work in the high skill sector, he obtains a wage equal to

$$w_H(i) = r_H e(i)^{\eta} \varepsilon_H(i) \tag{3}$$

where r_H is the price of an efficiency unit in the high skill sector, $\varepsilon_H(i)$ is an idiosyncratic shock and $e(i)$ is the amount of education units agent i acquires in college. This wage depends on $z(i)$ indirectly through the impact that the latter has on the choice of $e(i)$.[19]

The optimal amount of educational units acquired by an individual going to college is given by the solution of this simple problem

$$\max_{e(i)} \left[1 - e\left(1 + \tau\left(y(i), z(i)\right)\right)\right] r_H e(i)^{\eta} \varepsilon_H(i) \tag{4}$$

and is given by

$$e^*(i) = \frac{\eta}{(1+\eta)(1+\tau(y(i), z(i)))} \tag{5}$$

From (5) it emerges that the optimal amount of educational units does not depend on the realization of the idiosyncratic shock, and is therefore the same for every individual

[18] Under the time cost interpretation of s, this means that a student with low ability that wants to achieve the same number of educational units of a student with high ability will have to invest more time in college.

[19] Any direct impact of $z(i)$ on the number of efficiency units supplied to the high skill sector is also captured by $\tau(y,z)$. Such an impact is difficult to (separately) identify from the data.

belonging to the same income - ability group. This result greatly simplifies the inference problem, given that it requires me to back out only one object for each income - ability group.

Agent i anticipates how much he will be able to invest in college before deciding whether to enroll or not. Let $S(i)$ be a dummy variable equal to 1 if i goes to college and to 0 if he does not. Plugging $e^*(i)$ from (5) in the objective function given in (4), I obtain that consumption as a function of the educational choice is

$$c(i) = \begin{cases} r_L z(i)^\alpha \varepsilon_L(i) \text{ if } S(i) = 0 \\ \frac{\bar{\eta} r_H}{(1+\tau(y(i),z(i)))^\eta} \varepsilon_H(i) \text{ if } S(i) = 1 \end{cases}$$

where $\bar{\eta} = \frac{\eta^\eta}{(1+\eta)^{1+\eta}}$. The choice between going and not going to college takes the form of a standard discrete choice problem, where the value of the two alternatives is proportional to two unobservable shocks. I follow a common practice in discrete choice econometrics by assuming that these shocks are extracted from two independent Frechet distributions, with cumulative density functions given by

$$F(\epsilon_L) = e^{-\epsilon_L^{-\theta}}$$

$$F(\epsilon_H) = e^{-\epsilon_H^{-\theta}}$$

where θ is a parameter inversely related to the variance of the shock.[20] Under this distributional assumption, it is straightforward to show that the probability that agent i with family income y and ability z goes to college is[21]

$$P[S(y,z) = 1] = \frac{(\bar{\eta} r_H)^\theta}{(\bar{\eta} r_H)^\theta + (r_L z^\alpha (1+\tau(y,z))^\eta)^\theta} \tag{6}$$

By the law of large numbers, this also represents the share of individuals in the (y,z) group enrolling in college. From (6) it is immediate to see that this share is decreasing in $\tau(y,z)$: the more inefficient a group is in accumulating educational units, the lower the share of individuals in that group that choose to attend college.

Applying again the law of large numbers, the average wage for individuals in the (y,z) group employed in the low skilled sector is given by

$$\begin{aligned} w_L(y,z) &= r_L z^\alpha E[\epsilon_L(i) | S(y,z) = 0] \\ &= \left[\left(\frac{\bar{\eta} r_H}{(1+\tau(y,z))^\eta} \right)^\theta + \left(r_L z^\alpha \right)^\theta \right]^{\frac{1}{\theta}} \Gamma\left(1 - \frac{1}{\theta}\right) \end{aligned} \tag{7}$$

[20] The independence assumption can be relaxed without particular complications.

[21] See the Appendix for a complete derivation.

while the average wages of those employed in the high skill sector is

$$\begin{aligned} w_H(y,z) &= \tfrac{\bar{\eta}(1+\eta)r_H}{(1+\tau(y,z))^\eta} E[\epsilon_H(i)|S(y,z)=1] \\ &= (1+\eta)\left[\left(\tfrac{\bar{\eta}r_H}{(1+\tau(y,z))^\eta}\right)^\theta + (r_L z^\alpha)^\theta\right]^{\frac{1}{\theta}} \Gamma\left(1-\tfrac{1}{\theta}\right) \end{aligned} \tag{8}$$

where $\Gamma(.)$ is the gamma function. These results follow from the standard extreme value property of the Frechet distributions; a complete derivation is relegated to the Appendix. Plugging (8) in (6), the share of individuals in the (y, z) group attending college can be written as

$$P[S(y,z)=1] = \left[\frac{(1+\eta)(\bar{\eta}r_H)}{w_H(y,z)(1+\tau(y,z))^\eta}\right]^\theta$$

Therefore, for any pair of income - ability groups (y, z) and $(\hat{y}, \hat{z})$ we have that

$$\frac{1+\tau(y,z)}{1+\tau(\hat{y},\hat{z})} = \left[\frac{w_H(\hat{y},\hat{z})}{w_H(y,z)}\left(\frac{P[S(\hat{y},\hat{z})=1]}{P[S(y,z)=1]}\right)^{\frac{1}{\theta}}\right]^{\frac{1}{\eta}} \tag{9}$$

Equation (9) relates the relative friction faced by two income - ability groups to the relative average wage and the relative share of those attending college. Since both wages and college enrollment decisions are observable in the data, I can use (9) to back out the relative friction faced by each group (conditional on setting a value for the parameters η and θ; more on this below). Through the lens of the model, a group is inferred to face a large barrier to college investment whenever a few members of that group go to college (low $P[S(y, z) = 1]$), and the ones who do earn a low wage afterwards (low $w_H(y, z)$). The overall importance of the (partially) unobservable intensive margin of college investment can therefore be inferred from data on wages: a low investment implies that few educational units were accumulated in college, and this is reflected in a low productivity in the labor market.

The model is closed by the postulation of an aggregate production function that combines the efficiency units supplied in the low and high skill sector to produce an homogeneous good. I assume that the production function takes the standard CES form,

$$Y = A\left[L^\rho + BH^\rho\right]^{\frac{1}{\rho}} \tag{10}$$

where L and H are the total efficiency units supplied in the two sectors and $\frac{1}{1-\rho}$ is the elasticity of substitution. The equilibrium definition is standard; see the Appendix for a formal statement.

4 Calibration

In order to perform the counterfactual analysis, I need to set a value for the following parameters: α, η, θ, ρ and B.[22] Moreover, equation (9) only provides me with the relative $\tau(y,z)$'s across groups: in order to back out the absolute value of these frictions, I need to impose a normalization on one of them. In this section I discuss the calibration procedure and evaluate its success in matching quantities which are not directly targeted.

First of all, I normalize $\tau(y,z) = 0$ for individuals in the top tercile for both family income and ability. This amounts to saying that these individuals do not face frictions in the acquisition of educational units; since the counterfactual analysis will consist in removing differences in frictions between groups, this is without loss of generality.

I follow Hsieh et al. (2013) in mapping θ to the variance of the residual wages (after the contribution of ability and schooling has been washed out). In particular, it can be verified that within each income - ability group wages follow a Frechet distribution with shape parameter θ. As a consequence of this, the (squared) coefficient of variation of residual wages is equal to

$$\frac{Var\left[w(y,z)|y,z\right]}{\left(\mathbb{E}\left[w(y,z)|y,z\right]\right)^2} = \frac{\Gamma(1-\frac{2}{\theta})}{\left(\Gamma(1-\frac{1}{\theta})\right)^2} - 1 \tag{11}$$

In order to construct a measure of residual wages, I take the exponential of the residuals from a regression of log wages on income - ability group dummies, schooling attainment and experience. I then compute the mean and the variance of the exponential of such residuals, and I solve equation (11) numerically. The resulting value for θ is 3.27, which is close to the one used by Hsieh et al. (2013).

I estimate α and η using the structure that the model imposes on wages. In particular, the average wage conditional on family income, ability and college enrollment choice is given by

$$\mathbb{E}\left[w(i)|y(i),z(i),S(i)\right] = (1+\eta S(i))\left[\left(\frac{\bar{\eta} r_H}{(1+\tau(y(i),z(i)))^{\eta}}\right)^{\theta} + \left(r_L z(i)^{\alpha}\right)^{\theta}\right]^{\frac{1}{\theta}}\Gamma\left(1-\frac{1}{\theta}\right) \tag{12}$$

I plug in (12) the values of θ and the $\tau(y,z)$'s obtained from (11) and (9), and I estimate α and η by non-linear least squares. In order to be consistent with the assumptions of the model, I use only the between groups variation in z when estimating (12): in other words, for each individual I set z equal to the mean of the ability tercile to which he belongs.[23] The resulting value for η is 0.32, while the estimate of α is small and not

[22] The value of A is not needed to compute the counterfactual percental change in output and wages.

[23] Section 6.3 discusses the importance of this feature of the model for the counterfactual results.

significantly different from zero; I therefore set it equal to zero and examine the effect of different values in the robustness checks.[24]

I set ρ so that the elasticity of substitution between low and high skilled workers is 1.4, as estimated by Ciccone and Peri (2006). Finally, B is set to match the overall share of individuals with some education beyond high school, which is equal to 56%.

4.1 Model Fit

Before moving to the results, it is useful to evaluate how closely the model matches quantities which are not directly targeted by the calibration procedure.

Table 3 shows data on college attendance probabilities by income - ability groups, and the corresponding figures implied by the model. In my calibration, $\tau(y, z)$'s are picked so that the relative college shares are consistent with the data, according to equation (9). However, nothing ensures that the absolute figures are matched as well.

Table 3: College Shares by Group

	College Share	
Group	Model	Data
Low Income - Low Ability	0.27	0.28
Low Income - Middle Ability	0.44	0.48
Low Income - High Ability	0.75	0.77
Middle Income - Low Ability	0.34	0.30
Middle Income - Middle Ability	0.50	0.55
Middle Income - High Ability	0.73	0.83
High Income - Low Ability	0.43	0.32
High Income - Middle Ability	0.75	0.62
High Income - High Ability	0.85	0.88

Notes: College Share is the share of individuals with more than 12 years of education. Source: NLSY79.

The model does a reasonable job in capturing the patterns of college enrollment

[24] According to this result, the widely documented positive correlation between wages and cognitive test scores for high school educated workers would be entirely due to a selection effect: high cognitive ability makes getting a college education easy, therefore a worker with such an attribute that chooses to work in the low skill sector must have some unobserved comparative advantage in that sector, which is responsible for his high wage. In the robustness checks I document that the results are essentially unchanged when I instead attribute all the positive correlation to a productivity enhancing role for cognitive ability (as estimated by OLS).

across groups. While the fit is very good for the low income groups, the model somewhat overstates the differences between middle and high income groups.

Table 4 reports wage ratios relative to a few groups of interest. The main calibrated parameter that determines relative wages is η, which in the model corresponds to the (constant across groups) college premium. Not too surprisingly then, through the choice of this parameter it is possible to generate an average college premium quite close to the one observed in the data, as shown in the first row of Table 4. The model is also quite successful in replicating the wage gaps between the first and third terciles of family income, while it overstates the ability premium. The second and third panel of Table 4 display ability and family income gaps within educational groups. While the fit is reasonably good for the income gaps, the model tends once again to exaggerate the importance of ability for wages, especially for high school educated workers. Recall that α, the parameter that controls the "productive" role of ability in the low skill sector, is estimated to be 0, and therefore the entire gap is explained by a selection effect (see footnote 24). The fact that this selection effect is so strong might suggest that the model is slightly overstating the extent of comparative advantage dispersion in the low skill sector (and, to a lower extent, in the high skill sector as well).

Table 4: Relative Wages

	Relative Wage	
	Model	Data
College / Non College Educated	1.53	1.48
High Ability / Low Ability	1.64	1.54
High Income / Low Income	1.53	1.52
College Educated		
High Ability / Low Ability	1.45	1.39
High Income / Low Income	1.25	1.32
Non College Educated		
High Ability / Low Ability	1.42	1.18
High Income / Low Income	1.23	1.21

Notes: College Educated are individuals with more than 12 years of education. High (low) ability and income refer to individuals in the third (first) tercile of the distribution of AFQT scores and family income. Source: NLSY79.

With the caveats described above, the model overall does a reasonable job in match-

ing key facts from the data, and therefore can be used informatively for counterfactual analyses.

5 Results

Figure 4 shows the $\tau(y, z)$'s backed out from (9). By construction, members of the high income high ability group have $\tau(y, z) = 0$, so that the other $\tau(y, z)$'s should be interpreted as differences with this benchmark group of privileged individuals.

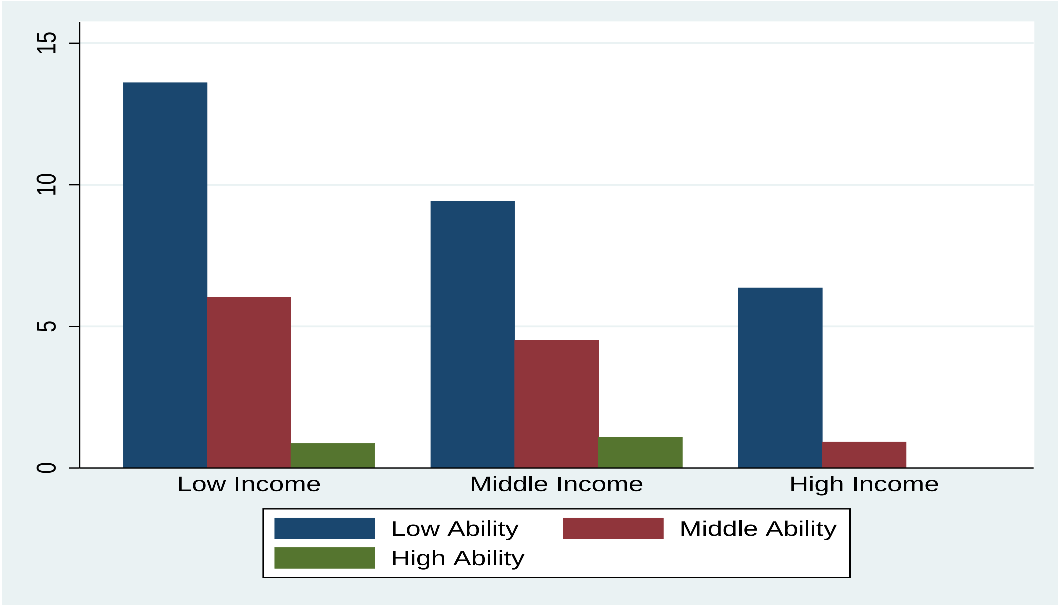
First of all, within each income group frictions are decreasing in ability at the end of high school. This was to be expected, given that ability is known to be an important input of the human capital production function during college: more able individuals are just more efficient at accumulating further knowledge. Moreover, for any ability level, family income is negatively associated with the magnitude of the estimated barriers: through the lens of model, this reflects the inequality of opportunity of access to college resources. It is interesting to note that individuals with high ability belonging to the intermediate income group face slight bigger frictions compared to individuals with the same ability level belonging to the bottom income group. This could be due to the fact that governmental support (through reduced tuition, student loans..) is mainly targeted to well performing students at the bottom of the income distribution (Hoxby and Avery, 2012), which therefore face a lower effective price of schooling compared to their peers from the middle class.

Given that these $\tau(y, z)$ are reduced form and fundamentally a-theoretical objects, their overall importance is difficult to evaluate just by staring at Figure 4. A more fruitful exercise is instead to use the model to have a sense of the possible economic gains that could be achieved through their elimination: this will be provide us with a readily interpretable measure of the efficiency losses stemming from the inequality of educational opportunities.

What is the relevant counterfactual? As discussed above, the frictions displayed in Figure 4 reflect in part "technological" barriers due to differences in ability, and therefore a complete elimination of those is not something that policy would achieve easily, at least in the short run.[25] Instead, the counterfactual of interest is getting rid of the variation in the barriers which is due to family income, as shown in Figure 5. This corresponds to a world where all individuals belonging to the same ability group have ex ante the same opportunites to attend college, while family background is not a

[25] Of course there might be sensible policies aimed to reduce the disparity in ability at the end of high school, but this framework is not well suited to analyze them.

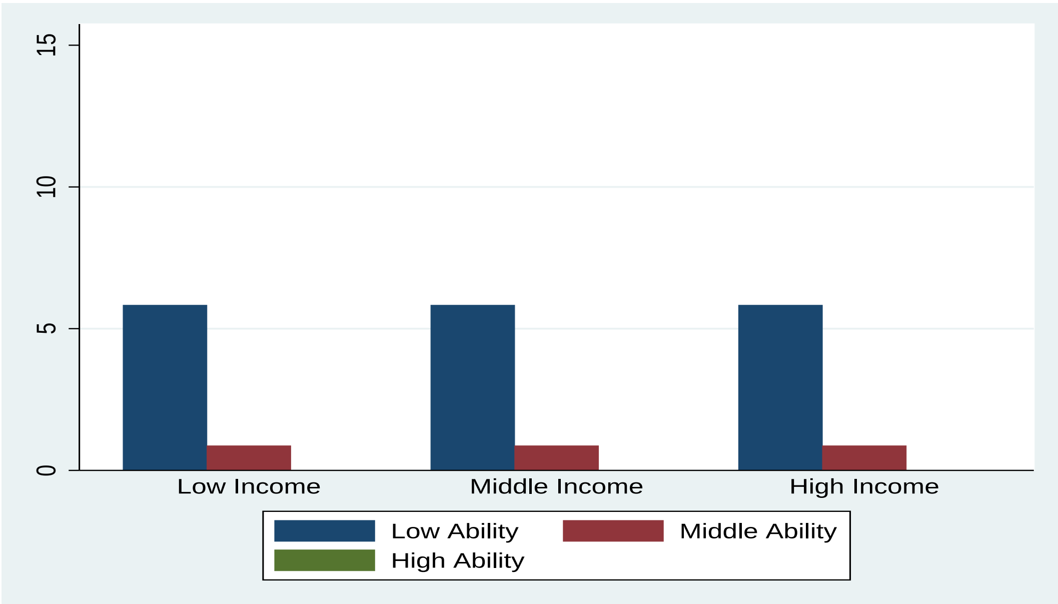
Figure 4: Estimated $\tau(y, z)$'s



Notes: Height of the bar represents the estimated $\tau(y, z)$ for each income - ability group.

relevant factor for educational choices (after having accounted for its correlation with academic ability).

Figure 5: Counterfactual $\tau(y, z)$'s



Notes: Height of the bar represents the counterfactual $\tau(y, z)$ for each income - ability group.

This counterfactual exercise measures the overall gains stemming from a more mer-

Table 5: Counterfactual Results

	Counterfactual Change
$\Delta Y/Y$ (%)	10.78
$\Delta w_H/w_H$ (%)	8.58
$\Delta w_L/w_L$ (%)	12.37
$\Delta P[S(i)=1]$	2.25

Notes: Table shows the counterfactual changes in output, average wages in the low and high skill sector and college attendance rate.

itocratic allocation of college investment, but obviously it does not say much on which (if any) policy should be implemented in order to reap these benefits. The main objective of this analysis is to understand whether potential gains are large, and therefore to what extent it is worthwhile to explore in detail the effectiveness of different policy tools that might achieve some of them.

Table 5 displays the counterfactual responses of output, wages and college enrollment share should such a reduction in barriers to college investment be implemented. Gains are substantial: output increases by approximately 11%, while wages in the low and high skill sector increase by 12% and 9% respectively. These gains are due to both an overall increase in investment in educational units and to a better allocation of the existing investment, in the sense that more individuals with high ability at the end of high school are able to go to college (section 6.4 discusses the relative importance of these two forces). It is interesting to note how these large increases in productive efficiency would not require a large expansion of the pool of the college enrollment rate, which goes up only by 2 percentage points (from a baseline of 56%). Intuitively, decreasing returns for high skilled workers in the production function put a limit on how much college enrollment can increase, and as students from disadvantaged backgrounds manage to enroll, others that are currently attending would find it convenient to do with the high school diploma in the counterfactual.[26]

An additional result that emerges from Table 5 is that the increase in average wages is highest for the low skill sector, so that the elimination of barriers would reduce the skill premium by approximately 3 percentage points.[27] In order to better understand

[26] The fact that individuals from low income families that start to attend college in the counterfactual have high ability on average amplifies the extent to which this general equilibrium effect kicks in, since they provide a large number of efficiency units to the high skill sector.

[27] This does not strictly correspond to the college premium usually estimated in the literature, since here I label as skilled all individuals with some education beyond high school (and not only college graduates).

Table 6: Decomposing the Wage Changes

	Low Skill Sector	High Skill Sector
Price (%)	10.12	-4.66
Quantity (%)	2.04	13.88
Wage (%)	12.37	8.58

Notes: Table shows the counterfactual changes in wages in the low and high skill sector decomposed between changes in quantity of efficiency units and changes in the price of an efficiency unit.

this finding, Table 6 decomposes the variation in average wages between changes in the price of an efficiency unit (r_L and r_H in the model) and the average number of efficiency units provided to each sector. The elimination of barriers to college investment causes a large increase in the productivity of high skilled workers: more students of high ability can now access higher education and accumulate a large number of educational units. This implies, through a standard general equilibrium effect, a decrease of 5% in the price of one educational unit supplied to the high skill sector; decreasing returns in the production function therefore mitigate the increase in wages for college educated workers. Conversely, in the low skill sector there is a modest increase in the number of efficiency units per worker, accompanied by a substantial increase in the price of one efficiency units, due to the complementarity between low and high skill labor.

Table 7 documents how the average wages for different income - ability groups are affected by the counterfactual experiment. Intuitively, individuals from low and middle income families reap most of the benefits stemming from this experiment, with increases in wages of 21% and 19% respectively. Within these groups, students of all ability levels see their wages increase, and particularly so the ones at the middle and top of the spectrum. The only "losers" from the abolition of barriers to college investments are those coming from a high income family, who see vanishing their previous advantage in college access. Perhaps counter intuitively, the low ability members of this group are relatively better off: this is due to the fact that many of them were opting for the low skill sector anyway, and now they enjoy an higher price per efficiency unit because of the general equilibrium effect.

What is the relative importance of the extensive and intensive margin of college investment for these results? The second column of Table 7 provides an answer to this question. Here I display the counterfactual changes in average wages that take place in when only the college attendance rate (extensive margin) is allowed to respond to the reduction in barriers as in the counterfactual, while the number of efficiency units per

Table 7: Wage Changes by Group

	Wage Changes	
	Total (%)	Extensive Margin Only (%)
Low Income	20.89	3.68
Low Income - Low Ability	14.08	1.41
Low Income - Middle Ability	34.75	5.83
Low Income - High Ability	15.56	0.77
Middle Income	18.88	2.01
Middle Income - Low Ability	8.11	-0.70
Middle Income - Middle Ability	27.78	4.04
Middle Income - High Ability	19.28	1.33
High Income	-2.81	-3.13
High Income - Low Ability	1.18	-3.03
High Income - Middle Ability	-2.95	-2.49
High Income - High Ability	-3.84	-1.71

Notes: Table shows the counterfactual changes (in percentage terms) in average wages across income - ability groups. For the extensive margin results, only the group specific college attendance rate is allowed to adjust.

worker and their prices are kept constant.[28]

It emerges that the extensive margin plays only a minor role in the counterfactual increase of wages for individuals in the low and middle income groups, and approximately 85% of the wage gains are accounted for by the intensive margin.[29] This result confirms the importance of not ignoring the intensive margin when discussing the disparity in educational opportunities between students of different backgrounds.

[28]The percentage change in average wages for the (y, z) group can be written as

$$\frac{\Delta w(y,z)}{w(y,z)} = \frac{\Delta w_L(y,z) + \Delta P[S(y,z)=1](w_H(y,z) - w_L(y,z)) + P_c[S(y,z)=1](\Delta w_H(y,z) - \Delta w_L(y,z))}{w(y,z)}$$

where the lower script c denotes counterfactual quantities. The contribution of the extensive margin is defined as

$$\frac{\Delta P[S(y,z)=1](w_H(y,z) - w_L(y,z))}{w(y,z)}$$

[29]Not surprisingly, the extensive margin is important for students from high income families, for whom the counterfactual experiment does not imply any change in barriers to investment.

6 Robustness and Extensions

6.1 Non Cognitive Skills

The results exposed in the previous section might be misleading if scores in the AFQT test did not reflect properly the actual differences in the productivity of college investment between students coming from high and low income families. In particular, the gains from the counterfactual experiment would be overestimated if there existed some component of academic ability which (*i*) is not fully captured by the AFQT test, (*ii*) is nevertheless important for productivity in college and (*iii*) is more abundant in children coming from rich families.

A natural candidate is given by a set of personal traits that is commonly summarized as *noncognitive skills*, and includes motivation, persistence, self-esteem and self-control. There is growing evidence that noncognitive skills matter at least as much as cognitive ones for schooling performance and labour market outcomes, both in the economics (Rubinstein and Heckman, 2001; Heckman et al., 2006; Cunha et al., 2010) and in the psychology literatures (Wolfe and Johnson, 1995; Duckworth and Seligman, 2005). If the $\tau(y, z)$'s backed out from the data capture in part differences in non cognitive skills, then the counterfactual experiment considered in the previous Section is not appropriate, given that differences in skill endowments is not something that policy can easily address at the college enrollment stage.

In this section I construct an alternative measure of ability that takes into account noncognitive skills, and I describe the results of the corresponding counterfactual experiment. I use two proxies of noncognitive skills which are commonly employed in the literature and both available in the NLSY79: the Rosenberg Self-Esteem Scale and the Rotter Locus of Control Scale. The Rosenberg Self-Esteem Scale measures an individual's degree of approval or disapproval toward himself; it is composed of 10 statements (such as "*I feel that I have a number of good qualities*", or "*I take a positive attitude toward myself*") to which respondents are asked to agree or disagree. The Rotter Locus of Control Scale measures the extent to which individuals believe to have control over their lives, as opposed to the extent to which external factors (such as luck) determine their personal outcomes; it is composed by four pairs of statements (such as "*What happens to me is my own doing*" versus "*Sometimes I feel that I don't have enough control over the direction my life is taking*"), between which respondents choose the one closer to their opinion. Both measures are converted to the same scale of the AFQT test (from 0 to 100).

Before setting up the alternative counterfactual experiment, it is worthwhile to check

whether it is the case that individuals with a similar AFQT score and different family background have very different noncognitive skills. Table 8 displays the average scores in the Rosenberg and Rotter Scales for each family income - ability group, where ability is measured by the AFQT as in the previous sections.

Table 8: Noncognitive Skills by Group

	Rosenberg Scale	Rotter Scale
Low Income		
Low AFQT	59.97	55.01
Middle AFQT	64.69	61.12
High AFQT	66.55	63.54
Middle Income		
Low AFQT	60.64	57.18
Middle AFQT	62.08	59.85
High AFQT	66.73	63.85
High Income		
Low AFQT	62.97	57.71
Middle AFQT	65.77	62.21
High AFQT	67.53	65.82

Notes: Table shows the average scores in the Rosenberg Self-Esteem Scale and in the Rotter Locus of Control Scale for each income - cognitive ability group. Scores range from 0 to 100; the standard deviations are 16.01 (Rosenberg) and 17.15 (Rotter). Source: NLSY79.

There do not seem to be large differences between income groups for people with a similar AFQT score. While high income groups do obtain slightly higher scores, the gaps are very small, suggesting that the cognitive test does not systematically underestimates differences in academic ability across different economic backgrounds.

In order to investigate the importance of noncognitive skills for the counterfactual results, I construct a new measure of ability that combines the AFQT, Rosenberg and Rotter scores, and perform the whole analysis using terciles of this new measure (instead of the AFQT alone). How to evaluate the relative importance of the 3 tests? I adopt the following approach: I estimate the elasticities of wages with respect to the 3 test scores, α_{AFQT}, $\alpha_{Rosenberg}$ and α_{Rotter}, from a log-wage regression with schooling and experience

Table 9: Counterfactual Results when Including Noncognitive Ability

	Counterfactual Change
$\Delta Y/Y$ (%)	11.50
$\Delta w_H/w_H$ (%)	8.79
$\Delta w_L/w_L$ (%)	13.77
$\Delta P[S(i)=1]$	2.60

Notes: Table shows the counterfactual changes in output, average wages in the low and high skill sector and college attendance rate when the measure of ability that includes noncognitive skills is used.

as additional controls. Then I combine the 3 measures with a simple Cobb-Douglas aggregator,

$$\tilde{z} = (z_{AFQT})^{\alpha_{AFQT}} (z_{Rosenberg})^{\alpha_{Rosenberg}} (z_{Rotter})^{\alpha_{Rotter}}$$

and I use the terciles of $\tilde{z}$ to construct the new income-ability groups. The estimated elasticities are $\hat{\alpha}_{AFQT} = 0.25$, $\hat{\alpha}_{Rosenberg} = 0.17$ and $\hat{\alpha}_{Rotter} = 0.02$.[30] The model is then re-calibrated using the same procedure described above.

Table 9 shows the counterfactual results when using this more comprehensive measure of ability. The order of magnitude of the impact on output, wages and college enrollment rate is very similar to the one of Table 5. If anything, the gains are slightly bigger when noncognitive ability is taken into account: this reflects the fact that noncognitive skills are more equally distributed across family income groups, resulting in higher estimated barriers. Overall, the inclusion of noncognitive skills seems unlikely to affect the main conclusion from the counterfactual exercise.

6.2 The Productive Role of Ability

According to the calibration procedure adopted in this paper, ability does not seem to play a direct role in affecting the efficiency units supplied to the low skill sector, and the positive correlation with wages observed in the data is entirely due to a selection effect (see footnote 24). Since this selection effect is, to my knowledge, unexplored in the literature, one might wonder how much the large counterfactual increases in output and wage hinge on this feature of the model.

To address this issue, in this section I examine the sensitivity of the results to the value of α. In particular, I consider the opposite extreme to what it emerges from the baseline calibration, by attributing all the observed positive correlation to a direct productive role of ability. I estimate a log wage regression on ability and experience

[30] The standardized coefficients are $\hat{\alpha}^S_{AFQT} = 0.12$, $\hat{\alpha}^S_{Rosenberg} = 0.07$ and $\hat{\alpha}^S_{Rotter} = 0.01$.

Table 10: Counterfactual Results with α Estimated by OLS

	Counterfactual Changes	
	Baseline Ability	Cognitive & Noncognitive Ability
$\Delta Y/Y$ (%)	10.69	11.53
$\Delta w_H/w_H$ (%)	8.53	8.63
$\Delta w_L/w_L$ (%)	12.28	14.13
$\Delta P[S(i) = 1]$	2.23	2.72

Notes: Table shows the counterfactual changes in output, average wages in the low and high skill sector and college attendance rate when α is calibrated as described in the text. Baseline Ability refers to the case where only AFQT scores are used; Cognitive & Noncognitive Ability refers to the case where AFQT, Rosenberg and Rotten scores are used.

controls (restricting the sample to high school graduates), and I use the estimated elasticity with respect to ability to calibrate α. I do so for both the baseline measure and the one that includes noncognitive skills: the resulting coefficients are 0.3 and 0.94.[31]

Table 10 shows the counterfactual results when these values for α are used in the calibration, for both measures of ability. Output, wages and college attendance rate increase by a very similar amount to the one displayed in Tables 5 and 9. Therefore, results do not seem very sensitive to the value of α.

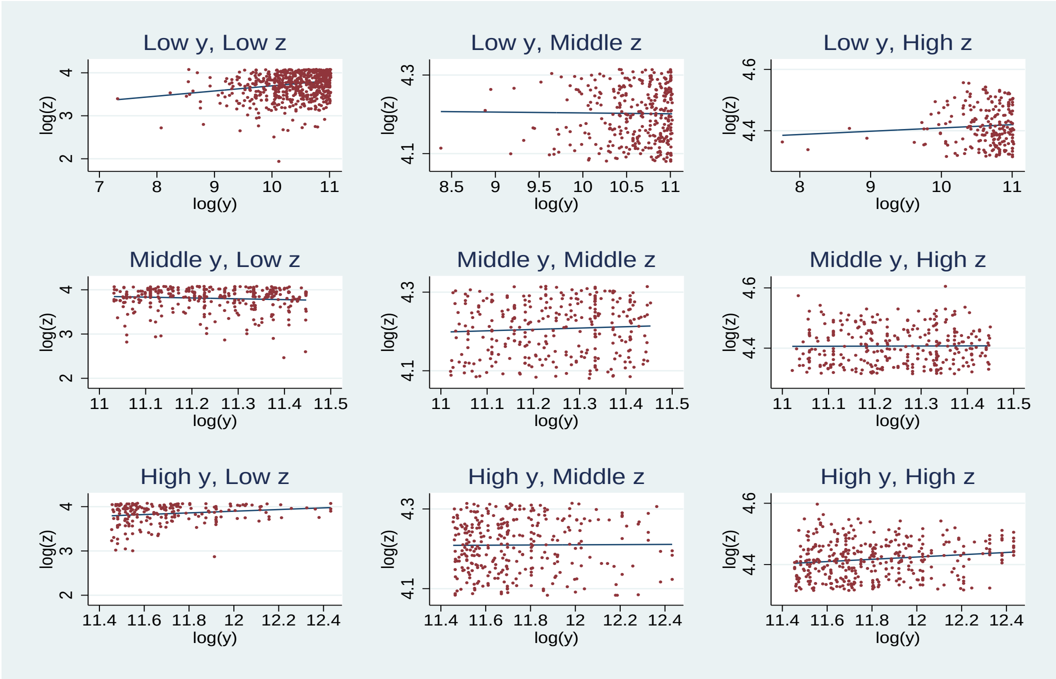
6.3 Functional Form of $\tau(y, z)$

The model postulates that $\tau(y, z)$ varies only across family income and ability terciles, and not within them. This assumption has the merit of allowing a transparent exposition of the underlying identification strategy, but it is clearly ad hoc and potentially restrictive. In particular, an obvious concern derives from the fact that the within group variation in family income and ability is ignored: if, within each group, students from rich families are also the one with higher ability, the counterfactual exercise might be overstating the extent to which barriers could possibly be removed. In order to have a first check on whether this is likely to be a substantial problem, Figure 6 displays for each group the scatter plot of (log) ability and (log) family income, and the linear best fit. While some of the relationships appear to be upward sloping (particularly so for the low income - low ability group), most of them look pretty flat, suggesting that the 9 groups capture most of the relevant variation.

Nevertheless, it is important to investigate to what extent the counterfactual results

[31] The standardized coefficients are 0.12 and 0.14.

Figure 6: Ability and Family Income by Group



Notes: Each panel shows the (weighted) scatter plot of log ability (measured by AFQT scores) and log family income for the specified group. Line shows the best (weighted) linear fit.

depend on this restrictive specification. A natural way to do so within the current framework is to consider a finer classification of ability: if the within group correlation of family income and ability leads to overstate the counterfactual gains, reducing the extent to which ability varies within groups should alleviate this bias and give more reliable results. Of course there is a trade-off between the number of ability quantiles considered and the sample size within each group: in particular, smaller groups imply noisier estimates of the average wages for low and high skilled workers.

Table 11 shows how the counterfactual results case when the number of ability quantiles used varies.[32] The magnitude of the results is essentially constant across specifications, with output gains ranging from 9.7% to 10.8%. Allowing more variation in ability within family income groups does not seem to have appreciable impact on the implied counterfactual gains.

As an additional test, I consider a version of the model in which $\tau(y, z)$ is assumed to depend linearly on ability. In particular, I assume that

$$\tau(y, z) = \alpha_y + \beta_y z \tag{13}$$

where both the intercept α_y and the slope $\beta_y z$ parameters are specific to each family

[32]When 7 ability quantiles are used, average wages for skilled workers are estimated from as little as 11 observations in one income-ability group.

Table 11: Counterfactual Results with a Finer Classification of Ability

	Counterfactual Changes				
# of Ability Quantiles:	3	4	5	6	7
$\Delta Y/Y$ (%)	10.78	10.45	9.66	9.67	10.28
$\Delta w_H/w_H$ (%)	8.58	8.29	7.87	8.13	8.35
$\Delta w_L/w_L$ (%)	12.37	12.42	11.18	10.80	11.53
$\Delta P[S(i)=1]$	2.25	2.36	2.07	1.92	2.04

Notes: Table shows the counterfactual changes in output, average wages in the low and high skill sector and college attendance rate when the specified number of ability quantiles is used. Ability refers to the baseline case where only AFQT scores are used.

income group. While obviously imposing a specific functional form, this specification has the the merit of exploiting the whole variation in z observed in the data.[33]

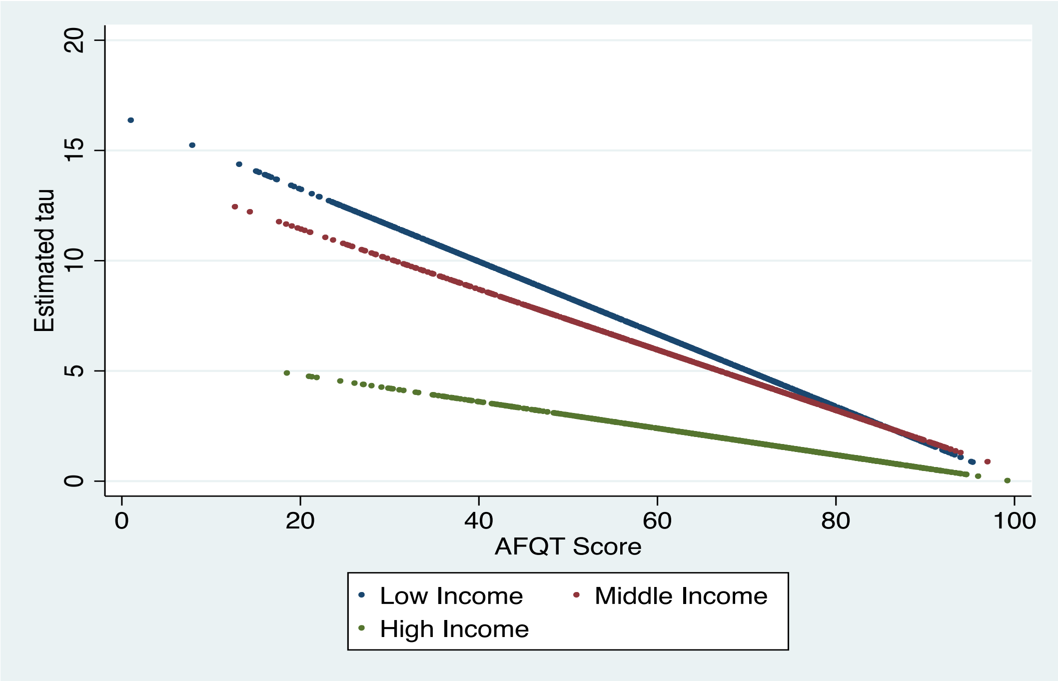
I estimate the parameters of (13) directly from the wage equation (12) by NLS. Figure 7 displays the fitted $\tau(y,z)$'s for all the individuals in the sample. Similarly to what emerges from the baseline version of the model, there seem to be significant gaps in educational opportunities between individuals belonging to different family income group and with a given level of ability. These gaps decline in magnitude throughout the ability distribution, reflecting the fact that an increase in ability brings a relatively large benefit in terms of college opportunities to students from disadvantaged backgrounds. The relevant counterfactual experiment involves once again eliminating all the variation in $\tau(y,z)$ brought about by y, while keeping the part stemming from z, as shown in Figure 12.

Setting up the counterfactual in this version of the model involves some additional difficulties. To see why, recall that in the baseline model the probability of attending college (6) and average wages (7) and (8) conditional on y and z are directly mapped to the data through a "law of large numbers" type of argument; such a logic does not apply here, given that I observe at most one individual for any relevant pair (y,z). While a full description of the procedure I use is relegated to the Appendix, I provide here a short outline of the key steps.

First, I estimate r_L and r_H, along with the parameters of (13), directly from (12) by NLS. From the coefficients' estimates and data on wages, I back out the implied $\varepsilon_L(i)$ for all individuals not attending college and $\varepsilon_H(i)$ for those attending college, and

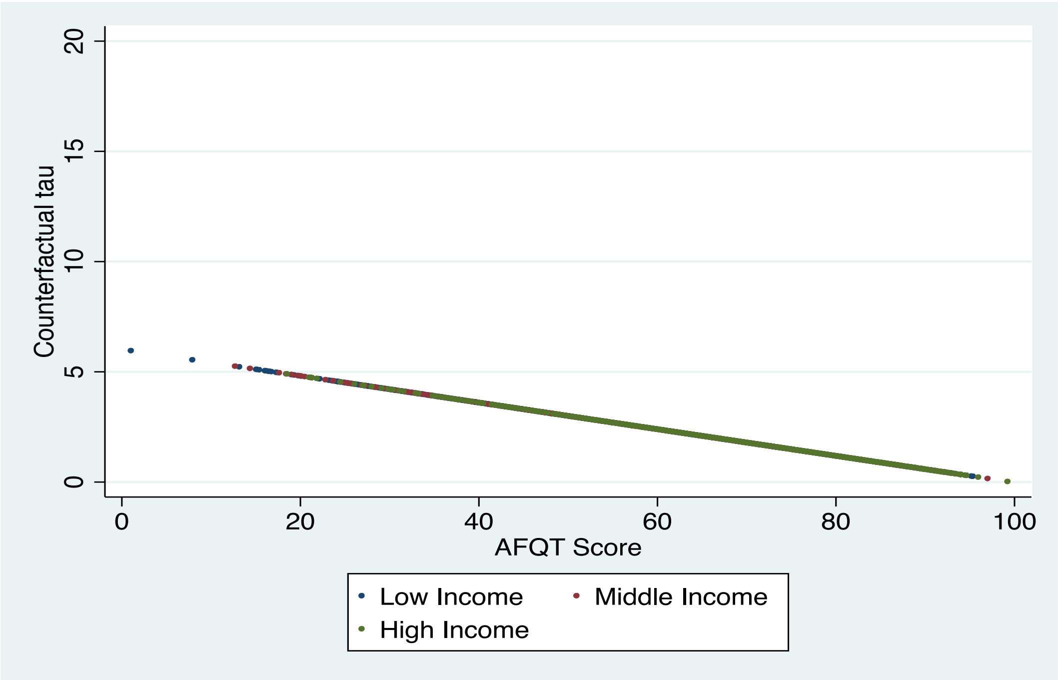
[33] In principle one could go beyond this and allow $\tau(y,z)$ to be a flexible polynomial in z and y. In practice, such a specification is difficult to implement because of multicollinearity problems in the estimation of the polynomial's parameters.

Figure 7: Estimated $\tau(y, z)$'s - Linear in ability



Notes: Dots represent the estimated $\tau(y, z)$'s for each individual in the sample. Blue dots refer to the first family income terciles, red dots to the second and green dots to the third.

Figure 8: Counterfactual $\tau(y, z)$'s - Linear in ability



Notes: Dots represent the counterfactual $\tau^C(y, z)$'s for each individual in the sample. Blue dots refer to the first family income terciles, red dots to the second and green dots to the third.

compute L and H by summing up all the efficiency units supplied to the two sectors. To perform a counterfactual analysis, I need however to impute a value also for the shock relative to the occupation that is not chosen by the individuals in the sample, in order to be able to evaluate whether they would be attending college under the new set of counterfactual parameters. Given that obviously I do not observe any wage for the unchosen occupation, all that I know is that these shocks are distributed according to a truncated Frechet distribution, where the truncation point is individual specific and represents the highest possible realization consistent with the observed educational choice.

To make progress, I simulate the unobservable shocks from these individual specific distributions. In particular, I draw 1000 sets of shocks, and compute the counterfactual outcomes for each realization. Table 12 reports the 5^{th} and 95^{th} of the simulated counterfactual changes in output, wages and college attendance share. The range of results is rather narrow, and the gains, while slightly smaller, are still of comparable magnitude to the baseline counterfactual.

Table 12: Counterfactual Results with $\tau(y, z)$ Linear in Ability

	5^{th} percentile	95^{th} percentile
$\Delta Y/Y$ (%)	9.16	9.35
$\Delta w_H/w_H$ (%)	7.79	8.02
$\Delta w_L/w_L$ (%)	11.75	12.08
$\Delta P[S(i) = 1]$	1.87	1.98

Notes: Table shows 5^{th} and 95^{th} percentiles of the simulated counterfactual changes in output, average wages in the low and high skill sector and college attendance rate. Ability refers to the baseline case where only AFQT scores are used.

Overall, the results in this section suggest that the within group correlation between family income and ability is unlikely to be quantitatively important for the conclusions of the paper.

6.4 Misallocation of College Investment

In the previous sections I have documented how large gains in output and wages can be achieved by expanding college opportunities for students from low and middle income families. These gains come from two different sources: on one hand the overall investment in college education increases, on the other hand existing resources are allocated more efficiently, i.e. to students that are better equipped to make the most out of them.

It is natural to ask what is the relative importance of these two forces, since they have different implications on the feasibility of policies aimed to achieve these gains: while improving the allocation of existing resources might be relatively cost-effective, there might be economical and physical limitations to the extent to which these resources can be expanded.

It is unfortunately difficult to pin down the exact answer to this question within the current framework. The reduced form modeling strategy that I adopt in this paper has the merit to allow a quantification of a very broad notion of college investment, but this comes at the cost of not being able to separate its various components. The crucial missing link needed to answer this question is to what extent the intensive margin of college investment makes use of resources that are *rival* between students: if this not the case, most of the gains can be achieved without a large expansion of college resources. It is useful to discuss this distinction with two examples of intensive margins that have received attention in the literature: time use and quality of the college attended. If the most relevant frictions for low income students are those that prevent them from using their own time productively in college (for example because they work part time, they spend hours on the bus or simply they lack information on the most effective way to invest their time), then easing these barriers would allow to achieve gains without affecting the college opportunities of other students. On the contrast, since the capacity of high quality colleges is fixed (at least in the short run), empowering more students from poor background to attend places like Harvard or Princeton would require some of the current attenders to receive a lower quality education.[34]

Something that this framework can definitely document is that the elimination of barriers to college investment would not require a large expansion of the *number* of students attending college. As discussed in Section 5, the counterfactual increase in the college enrollment rate is minimal, and therefore it is reasonable to conjecture that most of the gains could be achieved even keeping this quantity fixed. However, further research is needed to clarify the extent to which the expansion on the intensive margin would require more resources to be invested in the US higher educational system.

7 Conclusions

Family income shapes the college careers of US students, even when its effect on pre-college human capital accumulation is accounted for. While this inequality of educa-

[34] The model does not fully capture this dimension, since the supply of educational services is not explicitly characterized. However, decreasing returns in the production function endogenously put a boundary on how many educational units can be profitably accumulated.

tional opportunities might be problematic for many reasons, in this paper I study its effect on a relatively under appreciated dimension: productive efficiency.

I argue that a more meritocratic access to higher education might have large benefits in terms of aggregate output and average wages. In the baseline counterfactual experiment, I estimate a potential output gain of approximately 11%, and wage gains of approximately 12% and 9% for high school and college educated workers respectively. Most of these benefits can be achieved without a large expansion of the share of students attending college; instead, they mostly come from a more equal access to investment on the intensive margin, which includes elements like school quality, major and time use during college.

Which policies should be implemented in order to achieve all of this? This paper is rather silent on this dimension. An inherent cost of the reduced form approach adopted here is that it does not allow to separately identify the importance of different components of college investment, and therefore it can not provide definite suggestions on the ones that should be targeted. Recent research shows that very simple and cost effective interventions that provide information to low income students can go a long way in reducing the disparity in educational outcomes (Hoxby and Turner, 2013); more micro studies are needed to verify whether other approaches might be equally or more effective.

This paper shows that the returns from finding and implementing the appropriate policies are potentially very high. In an era where the human capital boost due to the baby boom generation is fading out and new sources of growth are difficult to come by, a more equal access to educational resources might be exactly what is needed.

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Appendices

A Derivations

A.1 Probability of attending college

The probability that an agent with family income y and ability z goes to college is given by

$$\begin{aligned}
P[S(y,z)=1] &= P\left[\frac{\bar{\eta} r_H}{[1+\tau(y,z)]^{\eta}}\varepsilon_H > r_L z^{\alpha}\varepsilon_L\right] \\
&= P\left[\varepsilon_L < \frac{\bar{\eta} r_H}{[1+\tau(y,z)]^{\eta}\, r_L z^{\alpha}}\varepsilon_H\right] \\
&= \int_0^{\infty} F_H\left(\frac{\bar{\eta} r_H}{[1+\tau(y,z)]^{\eta}\, r_L z^{\alpha}}\varepsilon, \varepsilon\right) \mathrm{d}\varepsilon
\end{aligned}$$

where $F_H(\varepsilon_L, \varepsilon_H)$ is the derivative of the joint distribution of ε_L and ε_H with respect to ε_H. Given that

$$F_H(\varepsilon_L, \varepsilon_H) = \theta \varepsilon_H^{-\theta-1} \exp\left\{-\varepsilon_L^{-\theta} - \varepsilon_H^{-\theta}\right\}$$

we have

$$F_H\left(\frac{\bar{\eta} r_H}{[1+\tau(y,z)]^{\eta}\, r_L z^{\alpha}}\varepsilon, \varepsilon\right) = \theta \varepsilon^{-\theta-1} \exp\left\{-\varepsilon^{-\theta}\left(\frac{(\bar{\eta} r_H)^{\theta} + \left([1+\tau(y,z)]^{\eta}\, r_L z^{\alpha}\right)^{\theta}}{(\bar{\eta} r_H)^{\theta}}\right)\right\}$$

Substituting in the integral above we get

$$\begin{aligned}
P[S(y,z)=1] &= \int_0^{\infty} \theta \varepsilon^{-\theta-1} \exp\left\{-\varepsilon^{-\theta}\left(\frac{(\bar{\eta} r_H)^{\theta} + \left([1+\tau(y,z)]^{\eta}\, r_L z^{\alpha}\right)^{\theta}}{(\bar{\eta} r_H)^{\theta}}\right)\right\} \mathrm{d}\varepsilon \\
&= \frac{(\bar{\eta} r_H)^{\theta}}{(\bar{\eta} r_H)^{\theta} + \left([1+\tau(y,z)]^{\eta}\, r_L z^{\alpha}\right)^{\theta}} \int_0^{\infty} \theta \left(\frac{(\bar{\eta} r_H)^{\theta} + \left([1+\tau(y,z)]^{\eta}\, r_L z^{\alpha}\right)^{\theta}}{(\bar{\eta} r_H)^{\theta}}\right) \varepsilon^{-\theta-1} * \\
&* \exp\left\{-\varepsilon^{-\theta}\left(\frac{(\bar{\eta} r_H)^{\theta} + \left([1+\tau(y,z)]^{\eta}\, r_L z^{\alpha}\right)^{\theta}}{(\bar{\eta} r_H)^{\theta}}\right)\right\} \mathrm{d}\varepsilon
\end{aligned}$$

Solving the integral,

$$
\begin{aligned}
P[S(y,z)=1] &= \frac{(\bar{\eta} r_H)^\theta}{(\bar{\eta} r_H)^\theta + \left([1+\tau(y,z)]^\eta r_L z^\alpha\right)^\theta} \left[\exp\left\{-\varepsilon^{-\theta}\left(\frac{(\bar{\eta} r_H)^\theta + \left([1+\tau(y,z)]^\eta r_L z^\alpha\right)^\theta}{(\bar{\eta} r_H)^\theta}\right)\right\}\right]_0^\infty \\
&= \frac{(\bar{\eta} r_H)^\theta}{(\bar{\eta} r_H)^\theta + \left([1+\tau(y,z)]^\eta r_L z^\alpha\right)^\theta} [1-0] \\
&= \frac{(\bar{\eta} r_H)^\theta}{(\bar{\eta} r_H)^\theta + \left([1+\tau(y,z)]^\eta r_L z^\alpha\right)^\theta}
\end{aligned}
$$

The probability of not attending college is just the complement of this,

$$
P[S(y,z)=0] = \frac{\left([1+\tau(y,z)]^\eta r_L z^\alpha\right)^\theta}{(\bar{\eta} r_H)^\theta + \left([1+\tau(y,z)]^\eta r_L z^\alpha\right)^\theta}
$$

A.2 Average wages

In order to compute average wages, I need to derive an expression for the expected value of the idiosincratic shock for individuals that choose a given occupation. For the high skill sector,

$$
\begin{aligned}
P[\varepsilon_H < x | S(y,z)=1] &= \frac{P[\varepsilon_H < x \wedge \varepsilon_L < \frac{\bar{\eta} r_H}{[1+\tau(y,z)]^\eta r_L z^\alpha} \varepsilon_H]}{P[S(y,z)=1]} \\
&= \frac{1}{P[S(y,z)=1]} \int_0^x F\left(\frac{\bar{\eta} r_H}{[1+\tau(y,z)]^\eta r_L z^\alpha}\varepsilon\right) f(\varepsilon) \mathrm{d}\varepsilon \\
&= \exp\left\{-x^{-\theta}\left(\frac{(\bar{\eta} r_H)^\theta + \left([1+\tau(y,z)]^\eta r_L z^\alpha\right)^\theta}{(\bar{\eta} r_H)^\theta}\right)\right\} \\
&= G_H(x)
\end{aligned}
$$

That is, the idiosincratic shock for agents choosing the high skill sector follows a Frechet distribution with shape parameter θ and scale parameter $\left(\frac{(\bar{\eta} r_H)^\theta + \left([1+\tau(y,z)]^\eta r_L z^\alpha\right)^\theta}{(\bar{\eta} r_H)^\theta}\right)^{\frac{1}{\theta}}$. The expected value of this random variable is

$$
\mathbb{E}\left[\varepsilon_H | S(y,z)=1\right] = \left(\frac{(\bar{\eta} r_H)^\theta + \left([1+\tau(y,z)]^\eta r_L z^\alpha\right)^\theta}{(\bar{\eta} r_H)^\theta}\right)^{\frac{1}{\theta}} \Gamma\left(1-\frac{1}{\theta}\right) \tag{14}
$$

Plugging (14) in (8), we obtain

$$
\begin{aligned}
w_H(y,z) &= \frac{\bar{\eta}(1+\eta) r_H}{(1+\tau(y,z))^\eta} E[\epsilon_H(i)|S(y,z)=1] \\
&= (1+\eta)\left[\left(\frac{\bar{\eta} r_H}{(1+\tau(y,z))^\eta}\right)^\theta + \left(r_L z^\alpha\right)^\theta\right]^{\frac{1}{\theta}} \Gamma\left(1-\frac{1}{\theta}\right)
\end{aligned}
$$

Similarly, for the low skill sector

$$
\begin{aligned}
P[\varepsilon_L < x | S(y,z) = 0] &= \frac{P[\varepsilon_L < x \wedge \varepsilon_H < \frac{[1+\tau(y,z)]^\eta r_L z^\alpha}{\bar{\eta} r_H}\varepsilon_L]}{P[S(y,z)=0]} \\
&= \frac{1}{P[S(y,z)=0]} \int_0^x F\left(\frac{[1+\tau(y,z)]^\eta r_L z^\alpha}{\bar{\eta} r_H}\varepsilon\right) f(\varepsilon)\mathrm{d}\varepsilon \\
&= \exp\left\{-x^{-\theta}\left(\frac{(\bar{\eta} r_H)^\theta + \left([1+\tau(y,z)]^\eta r_L z^\alpha\right)^\theta}{\left([1+\tau(y,z)]^\eta r_L z^\alpha\right)^\theta}\right)\right\} \\
&= G_L(x)
\end{aligned}
$$

The idiosincratic shock for agents employed in the low skill sector follows a Frechet distribution with shape parameter θ and scale parameter $\left(\frac{(\bar{\eta} r_H)^\theta + ([1+\tau(y,z)]^\eta r_L z^\alpha)^\theta}{([1+\tau(y,z)]^\eta r_L z^\alpha)^\theta}\right)^{\frac{1}{\theta}}$. The expected value of this random variable is

$$
\mathbb{E}\left[\varepsilon_L | S(y,z) = 0\right] = \left(\frac{(\bar{\eta} r_H)^\theta + \left([1+\tau(y,z)]^\eta r_L z^\alpha\right)^\theta}{\left([1+\tau(y,z)]^\eta r_L z^\alpha\right)^\theta}\right)^{\frac{1}{\theta}} \Gamma\left(1 - \frac{1}{\theta}\right) \tag{15}
$$

Plugging (15) in (7), we obtain

$$
\begin{aligned}
w_L(y,z) &= r_L z^\alpha E[\epsilon_L(i) | S(y,z) = 0] \\
&= \left[\left(\frac{\bar{\eta} r_H}{(1+\tau(y,z))^\eta}\right)^\theta + (r_L z^\alpha)^\theta\right]^{\frac{1}{\theta}} \Gamma\left(1 - \frac{1}{\theta}\right)
\end{aligned}
$$

B Competitive Equilibrium

A competitive equilibrium is given by a set of agents' choices on college attendance $\{S(i)\}_{i \in N}$, investment in educational units $\{e(i)\}_{i \in N}$, total efficiency units $\{L, H\}$ and factor prices $\{r_L, r_H\}$ such that

- Conditional on attending college, agents choose $e(i)$ to maximize their consumption net of college costs
- Agents make the college attendance choice that maximizes their utility, taking prices as given
- A representative firm hires low and high skill efficiency units to maximize profits, taking prices as given

$$
\max_{H,L} A\left[L^\rho + BH^\rho\right]^{\frac{1}{\rho}} - r_L L - r_H H
$$

- r_L and r_H clear the low skilled and high skilled labour market respectively,

$$L = \sum_i z(i)^{\alpha} \varepsilon_L(i)$$

$$H = \sum_i e(i)^{\eta} \varepsilon_H(i)$$

C Algorithm for the Counterfactual in Section 6.3

To implement the counterfactual analysis when $\tau(y, z)$ is allowed to depend linearly on z, I follow these steps

1. Estimate r_L, r_H, α, η, α_1, β_1, α_2, β_2, α_3 and β_3 from (12) by NLS

2. Back out the realization of ε_H for those employed in the high skill sector and the realization of ε_L for those employed in the low skill sector from

$$\widehat{\varepsilon}_L(i) = \frac{w_L(i)}{\widehat{r}_L z^{\widehat{\alpha}}}$$
$$\widehat{\varepsilon}_H(i) = \frac{w_H(i)}{\widehat{r}_H \widehat{\bar{\eta}}(1+\widehat{\eta})(1+\widehat{\tau}(y,z))^{\widehat{\eta}}}$$

   where $\widehat{r}_L$, $\widehat{r}_H$, $\widehat{\alpha}$, $\widehat{\eta}$ and $\widehat{\tau}(y, z)$ are the estimates coming from Step 1.

3. Compute H and L by summing up all the efficiency units (weighted by the provided sample weights) supplied by all individuals in the two sectors

4. Back out B using

$$B = \frac{\widehat{r}_H}{\widehat{r}_L} \left(\frac{H}{L} \right)^{1-\rho}$$

5. For each individual attending college, draw a $\varepsilon_L(i)$ shock from the truncated Frechet distribution with CDF

$$\begin{aligned} P[\varepsilon_L(i) < x | S(i) = 1] &= P[\varepsilon_L(i) < x | \varepsilon_L(i) < \frac{\bar{\eta} r_H}{[1+\tau(y,z)]^{\eta} r_L z^{\alpha}} \widehat{\varepsilon}_H(i)] \\ &= \exp\left\{ -x^{-\theta} + \left(\frac{\bar{\eta} r_H \widehat{\varepsilon}_H(i)}{[1+\tau(y,z)]^{\eta} r_L z^{\alpha}} \right)^{-\theta} \right\} \end{aligned}$$

   Similarly, for each individual not attending college, draw a $\varepsilon_H(i)$ shock from the truncated Frechet distribution with CDF

$$\begin{aligned} P[\varepsilon_H(i) < x | S(i) = 0] &= P[\varepsilon_H(i) < x | \varepsilon_H(i) < \frac{[1+\tau(y,z)]^{\eta} r_L z^{\alpha}}{\bar{\eta} r_H} \widehat{\varepsilon}_L(i)] \\ &= \exp\left\{ -x^{-\theta} + \left(\frac{[1+\tau(y,z)]^{\eta} r_L z^{\alpha}}{\bar{\eta} r_H} \right)^{-\theta} \right\} \end{aligned}$$

6. Determine the counterfactual college attendance choices for all individuals setting $\tau^C(y,z) = \widehat{\alpha}_3 + \widehat{\beta}_3 z$ and the corresponding changes in output and wages. In order to compute the new counterfactual equilibrium, first guess a value for $\frac{H}{L}$ and the update until convergence

7. Repeat Steps 5-6 1000 times and compute the 5^{th} and 95^{th} percentiles of the distribution of each counterfactual outcome