The younger, the better? Age related differences in academic performance at university *

Michele Pellizzari

Department of Economics, Bocconi University,

IGIER, IZA and "Carlo F. Dondena" Centre for Research on Social Dynamics

Francesco Billari

Department of Decision Sciences, Bocconi University

IGIER and "Carlo F. Dondena" Centre for Research on Social Dynamics

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Abstract

In this paper we estimate relative age effects in academic performance using a unique database of students at Bocconi University. The identification exploits school entry cut-off ages that generate a difference of up to 11 months between the youngest and the oldest students within each cohort. Our data allow to control for potential selection as well as for differences in cognitive ability, as measured by an attitudinal entry test. Contrary to most of the existing evidence for primary school children, we document that in university the youngest students perform better compared to their oldest peers across almost all subjects. To rationalize this result we produce additional evidence on relative age effects in cognitive ability and in social behavior, using a combination of data from Bocconi admission tests and from a survey about the social behavior of Italian first-year university students. We find that the youngest students in a cohort perform slightly better in cognitive tests and also appear to have less active social lives, particularly regarding romantic relationships. These results suggest that negative relative age effects at university are generated by the combination of two mechanisms: (i) early learning effects combined with a peak in the profile of cognitive development around age 20; (ii) psychological relative age effects that lead the youngest in a cohort to develop social skills (self-esteem, leadership) at a slower pace. Relatively younger students, thus, have less active social lives and devote more time to studying, as confirmed by additional evidence from the PISA study.

1 Introduction

Relative age effects in education have been documented by several studies: within a given cohort or class, relatively younger individuals have a different performance with respect to relatively older individuals. More specifically, the oldest pupils in a given class or cohort typically outperform their youngest mates in a wide array of cognitive and academic outcomes (Bedard and Dhuey, 2006; Crawford, Dearden, and Meghir, 2007; Mayer and Knutson, 1999). Such differences are more marked at early ages and tend to fade away as children grow older, usually during early adolescence.[1]

In this paper, we analyze the academic performance of university undergraduate students and, contrary to most of the existing evidence, we find that at the university level the youngest students within a cohort perform better than their oldest peers, particularly in the most technical subjects. Our main estimates are based on an extremely rich dataset of students who enrolled at Bocconi University in Milan, Italy, between 1995 and 1998. These data allow us to compare a homogeneous group of students for whom we have particularly detailed information about their pre-university school careers, their performance during university and, importantly, their cognitive ability, as measured by an admission test. We can, thus, control for selectivity and unobservable individual and institutional factors that plague most previous studies.

Since in Italy parents have some freedom in deciding when to send their children to primary school, we face an identification problem due to the presence of early and late enrollees. Bedard and Dhuey (2006) face exactly the same problem and they solve it by instrumenting relative age with (a function of) the student's calendar month of birth. We show that in our data such an instrument does not satisfy the monotonicity assumption. Hence, we resort to a different source of exogenous variation in the likelihood of entering school early (or late), using the incidence of private pre-schools in the province of birth as an instrument for relative age. As we discuss in Sections 2 and 3, for the cohorts that we study early school entry was subject to a simple math and reading test and preparatory courses were usually offered by private (especially religious) pre-schools during the last year of their programs.

Furthermore, we investigate potential explanations for why the youngest students in a cohort outperform their oldest mates in our study, while they are consistently observed to do worse at lower schooling levels by many other authors. The first of such explanations is a combination of early learning and progression over the age-profile of cognitive development. Several papers have shown that starting school earlier is associated with better long-run outcomes (Black, Devereux, and Salvanes, 2009; Fredriksson and Ockert, 2005; Goodman and Sianesi, 2005; Skirbekk, 2005; Skirbekk, Kohler, and Prskawetz, 2004).[2] This is consistent with the recent theories in Cunha and Heckman (2007a) and Cunha and Heckman (2007b), who argue that early investment in skills improves the return of later human capital investments. Thus, younger students should be advantaged by early learning, either at school or in the family. On the other hand, since the natural profile of cognitive development is inversed-U shaped (Salthouse, Schroeder, and Ferrer, 2004), the youngest in a cohort are penalized at early stages and such a disadvantage levels off, and possibly reverses, at some later age. Salthouse et al. (2004) and Jones (2005) suggest that the turning point in the profile of cognitive development might, in fact, be between age 20 and 25. The combination of these two effects can easily reconcile our results with previous findings. While in earlier school levels the cognitive dis-

[1] Although, Crawford et al. (2007) do find some effects on 18 year olds and Bedard and Dhuey (2006) document a higher probability of college enrollment for the relatively older students in British Columbia, Canada and in the US.

[2] Although this is still a rather controversial result. For example, both McEwan and Shapiro (2008) and Elder and Lubotsky (2008) find opposite results.

advantage of being young overcomes the advantages of early learning, during university this second effect dominates. Consistently with this idea, we do find evidence of negative age effects in cognitive ability, as measured by entry test scores. However, these effects account only for a very minor fraction of the observed age related differences in academic performance.

We also explore a second explanation, which is motivated by a series of studies that look at the psychological effects of relative age (Dhuey and Lipscomb, 2006; Persico, Postlewaite, and Silverman, 2004; Thompson, Barnsley, and Battle, 2004), where it is shown that the youngest pupils in a group develop important personality traits and social skills, such as self-esteem and leadership, to a lower extent or at a slower pace than their oldest mates. In a simple model of efficient time/effort allocation, these psychological effects lead to lower returns to effort in social activities for younger students who, then, devote more time to studying and perform better at university. This mechanism becomes more and more important as students grow older and gain control over their time, and, thus, it emerges more evidently in our analysis than in previous works that were focused on younger pupils.

To explore the potential of this explanation, we produce additional evidence from a survey about the social behavior of a sample of first-year university students in Italy, the *International Survey on Affectivity and Sex*.[3] We find that, within a given birth cohort, the youngest students are also those with the least active social lives, particularly regarding romantic relationships. Consistently with our interpretation, we also document that, in the PISA study, relatively younger students spend more time on their homework.

Overall, we believe that our results can be rationalized and reconciled with the findings of previous studies by a combination of the above explanations. At younger ages the steep profile of cognitive development led other authors to estimate negative age effects, even in the presence of early schooling. At those younger ages, in fact, the offsetting effect of older students engaging relatively more in social activities is strongly mitigated by the often rigid parental control over the time allocation of their children. At the age of college attendance, instead, the development of cognitive abilities flattens out, without necessarily reverting, while students are finally able to allocate their time at will so that differences in social attitudes become manifest leading to the results that we document in our data.

Our results contribute to the literature in several directions. First, we produce evidence suggesting that a correct understanding of the long-term consequences of early life events requires the analysis of both the mechanics of skill formation and the interaction of such a process with the endogenous choices on the allocation of time and effort. Given the recent emphasis on early policy intervention (Carneiro and Heckman, 2003; Cunha and Heckman, 2007b; Heckman and Masterov, 2007), we believe this to be a very relevant issue. Second, our findings support the idea that lowering the age of school-entry as well as school-leaving might increase the efficiency of the school system, by focusing on an age interval with higher returns to human capital investment (Lutz and Skirbekk, 2005; Mayer and Knutson, 1999). Finally, although relative age effects cannot be completely eliminated, as one will always be either younger or older than his/her peers, merely revising the rules of class formation can, at least, reduce relative age differences in the school environment and, thus, potentially promote equality of later outcomes. For example, school cohorts could be defined by semester instead of year of birth, so that the maximum age difference between (regular) students in a school class would be reduced from 11 to 5 months. Given the almost complete randomness of birth dates, this simple policy can be applied without additional costs whenever the school cohort is currently divided into more

[3]The survey covers several countries but, for comparison with our Bocconi data, we limit our analysis to the Italian sample.

than just one class.[4] It should be noticed, though, that our main evidence on academic performance is not enough to justify such a policy, which can be rationalized only in the presence of long-term psychological effects of relative age, as in Thompson et al. (2004) and in Dhuey and Lipscomb (2006).

Finally, external validity is an obvious concern with our analysis of Bocconi students. We address this issue with a series of robustness checks, where we show that the month-of-birth distribution in our sample is comparable to what is observed in the general population. Moreover, given that our data include an excellent measure of cognitive ability (the admission test score), we are able to control for selection along this dimension (up to functional form variations), which is, theoretically, the most worrisome. However, if concerns with external validity remain, our results are still important as they document the functioning of age effects among elite groups.

The paper is organized as follows. Section 2 describes our data and the institutional details of both the Italian school system and Bocconi University. Section 3 briefly clarifies the conceptual framework and the empirical strategy. Section 4 presents the main results on relative age effects at university. Section 5 contains a series of robustness checks. Section 6 provides additional evidence that helps rationalizing our results with the previous findings in the literature. Section 7 concludes.

2 Data and institutional details

The Italian educational system is such that most students turn 19 during their freshman year at university.[5] The typical pupil would, in fact, start primary school in September of the year she turned 6. Primary school lasts 5 years, unless the student fails one (or more) grades. At the end of fifth grade all students take an exam to obtain their primary school certificate. The next schooling level is a 3-year junior high school, which also ends with a national exam. Primary and junior-high schools are both compulsory and completely homogeneous with no differentiation in curricula.[6]

After junior-high school, students can voluntarily continue their studies at one of the several different types of high schools (lyceums, technical or vocational schools), which normally last 5 years.[7] Thus, unless a student enrolled early in primary school and/or failed one (or more) grades during her educational track, she would normally enroll at university the year she turns 19. Importantly, students are never streamed by ability in any school level. If anything primary and secondary school classes are formed either completely randomly or with the objective of maintaining a rather uniform distribution of family background, ethnicity, gender and other key characteristics both across and within classes.[8]

[4]Notice that such a policy does not necessarily maximize average performance but it might still be desirable if the social objective function is aimed at guaranteeing equality of opportunities.

[5]As we discuss later in this section, the main data used in our analysis include students born between 1976 and 1979. The school system described in this section is the one pupils born in these years were subject to. The system has been modified since then, with the most important change occurring in 1999, when compulsory schooling was increased by one year. None of the students in our data is affected by this change.

[6]Generally, the pre-1999 legal requirement imposes all pupils aged between 6 and 14 to attend school. However, students can satisfy the requirement by either passing the junior-high school final exam (thus even before they turn 14) or by having attended at least 8 years of full-time schooling as they turn 14.

[7]Some technical institutes offer 3- or 4-year degrees. However, only students graduating from 5-year high schools can enroll at university. Students who want to go to high school cannot not be refused a place (at least within the public system) regardless of their previous school performance.

[8]In educational systems where students are streamed into classes on the basis of observed performance already at the very initial stages of their academic careers, early differences in childhood development are perpetuated over a long

Our data come from the administrative archives of Bocconi University, a private and selective institution of higher education that specializes in Economics and Management. The database covers all students enrolled between 1995 and 1998, whose distribution of birth months is described in Table 1.[9] The first column shows the year of actual enrollment at Bocconi while in the second column we report the year of birth for the *regular* students in each cohort, where we define *regular* students those who turn 19 during the (calendar) year of enrollment. The third column shows the fraction of such students in each cohort, while the following columns report the fraction of *older* and *younger* students, i.e. students who were older or younger than 19 when they enrolled. In the remaining of the paper we will call these students *late* and *early enrollees*, respectively.

[TABLE 1 ABOUT HERE]

Regular students represent on average about 86% of a cohort. Older students are typically those who failed one or more grades in their previous educational tracks and some (few) students who enrolled at Bocconi after having enrolled at a different university and then changed their minds.

Younger students are normally those who entered school early. In fact, parents do have some limited freedom in deciding when exactly to enroll their children in primary school. Compulsory schooling laws require pupils to start attending school on September of the calendar year in which they turn 6. As a consequence, parents cannot postpone school entry after age 6 but they can have their children progress faster by enrolling them directly in grade two (or higher) at age 6. In fact, the law does not specify which grade students should enroll at entry and school principals were given some discretionary power to admit students directly into higher grades.[10] Hence, the typical pattern that led to early schooling in our cohorts was one in which the pupil attended preparatory classes at age 5 during her last year in kindergarten and apply to enter directly into the second grade in primary school at age 6. Although some public primary schools offered these types of preparatory classes, such schools were very few due to cost restrictions and, in most cases, parents relied on private, often religious, institutions. Admission was subject to the discretion of the school principal, who, in most cases, required the student to sit a simple math and reading test. Normally, schools were reluctant to allow children born after March (or April, at most) to enter school early.

These features of the legal setting differentiate Italy from many other countries, like the USA, where parents are allowed to postpone school entry by several years after the minimum legal age.

[FIGURE 1 ABOUT HERE]

Figure 1 shows the distribution of student types (regular, older and younger) by month of birth. As it is evident, many of the children who could reasonably hope to enter school early did so. The fraction of younger students is as high as 30% among the January born and it declines rapidly for

period of time. In fact, the oldest pupils typically end up in the highest tiers (i.e. the classes of the best performing students) simply because at very young ages they are substantially more developed (Allen and Barnsley, 1993). This type of mechanism has been documented to be very important in sports, where a large fraction of professional players are indeed born in the earliest months of the year (Barnsley, Legault, and Thompson, 1992; Dudink, 1994; Helsen, van Winckel, and Williams, 2005).

[9] The most complete version of our data covers all students enrolled from 1989 to 2004. We exclude the earlier cohorts because data on the admission tests are not available. Moreover, we also limit the sample to cohorts with at least 80% of students who have completed their degrees, thus leading to our focus on the 1995-1998 freshmen.

[10] Although this issue was not formally regulated, it was very uncommon to admit a new student directly into a grade higher than 2.

students born in the later months of the year. In Section 3 we discuss the implications of the presence of younger students for the identification of our parameters of interest.

Table 2 describes the distribution of month of birth within the regular students in each cohort. The bimodal pattern of birth months (with local maxima in May and September) is consistent with what is known from research on the seasonality of births on the overall population (Rizzi and Dalla Zuanna, 2007).

[TABLE 2 ABOUT HERE]

Eventually, we end up working with a sample of 6,237 students.[11] The university's administrative archives contain detailed data about the entire academic history of these students, including entry test scores, high school results and a set of family background variables (place of residence and income). In Table 3 we report descriptive statistics for these variables, breaking up the sample into late enrollees, regular students and early enrollees. Additionally, since one of our empirical strategies compares the youngest and the oldest individuals within each cohort of regularly enrolled students, Table 3 further separates regular students into those born in January, those born between February and November and those born in December.[12]

The numbers in Table 3 already show that the youngest students (namely, those born in December and the early enrollees) tend to perform slightly better in terms of final graduation mark and in all subjects (but foreign languages) compared to the other categories.[13] Moreover, if one focuses on regular students only, the differences in academic performance between students born in January and students born in December are significant at conventional statistical levels (apart from the average grades in foreign languages and history). Interestingly, all pre-university performance indicators show the same patter: younger students do better at high school and also at the admission test. However, these earlier differences are never statistically significant. Consistently with the interpretation that they are mostly re-takers, late enrollees do appear to perform worse than all other groups, both in university and in high school.

[TABLE 3 ABOUT HERE]

3 Conceptual framework

In order to clarify our approach and compare it with the rest of the literature, it is useful to start with a simple education production function where schooling s_i (i.e. time spent in education), absolute age age_i, age at school entry $age0_i$ and relative age $ageR_i$ interact to produce some measurable academic outcome y_i (a grade) for a generic student i:

$$y_i = \beta_0 + \beta_1 s_i + \beta_2 age_i + \beta_3 age0_i + \beta_4 ageR_i + \beta_5 X_i + \beta_6 H_i + \epsilon_i \tag{1}$$

[11] The few drop-outs and missing values lead to a loss of about 8% of the original observations.

[12] Although in the main text we present results based on month of birth, all our findings are confirmed when we measure age in days. However, Bocconi does not allow us to distribute the exact day of birth to external users and therefore only results produced using information on month and year of birth can be replicated by external researchers.

[13] Exams are graded on a scale 1 to 30, with 18 being the minimum pass grade and graduation marks range from 66 (pass) to 110. Such a peculiar grading scale comes from historical legacy: while in primary, middle and high school students were graded by one teacher per subject on a scale 0 to 10 (pass equal to 6), at university each exam was supposed to be evaluated by a commission of three professors (11 for the graduation defense), each grading on the same 0-10 scale, the final mark being the sum of these three. Hence, 18 is pass and 30 is full marks. Apart from the scaling, the actual grading at Bocconi is performed as in the average US or UK university.

where X_i and H_i are set of observable and unobservable individual characteristics, respectively. ϵ_i is a random error term generated either by measurement error or by idiosyncratic shocks to performance. For simplicity, we assume a linear functional form for equation 1 and we abstract from complementarities between the inputs of the education production process.

We define $ageR_i$ as absolute age relative to the age of the oldest regular student, i.e. $ageR_i$ is equal to zero for regular students born in January and it increases or decreases with each month of age. For example, a student born in March of her regular enrollment year would have $ageR_i = -2$ and a student born in December of her regular enrollment year would have $ageR_i = -11$. Similarly, a student who is born in February and enrolls in school one year in advance would have $ageR_i = -13$, while a student who is born in April, enrolls regularly in school at age 6 but then fails one grade and enters Bocconi one year later than normal would have $ageR_i = 4$.

Even in this simple formulation, the identification of equation 1 is extremely problematic because of both collinearity and endogeneity. First of all, since $s_i = age_i - age0_i$ it is impossible to separately identify β_1, β_2 and β_3. Additionally, also age_i and $ageR_i$ are usually perfectly collinear (unless students change cohort), so that even β_4 is not identified separately from the other parameters. Secondly, since parents normally have some degree of freedom in deciding when their children should start school, age of school entry $age0_i$ (and consequently also age_i and $ageR_i$) is likely to be correlated with the unobservable individual traits H_i, thus inducing endogeneity. Notice that, in our specific case, ability, the one characteristic that is usually thought to be the source of endogeneity, is observable (i.e. it is one of the variables in X_i). However, H_i still includes other variables, such as motivation or parenting style, that may be correlated with $age0_i$ and, thus, impede identification.

Perhaps the most common strategy used to address this complex identification problem consists of comparing students born just across a fixed cut-off date for school enrollment (Elder and Lubotsky, 2008; McEwan and Shapiro, 2008). In the Italian setting, this would be equivalent to comparing students born on December 31st, who are the youngest in their cohort, with those born on January 1st, who are the oldest in their cohort (unless they enter school early).

However, even in its simplest formulation, this popular strategy does not allow to separately identify the parameters in equation 1, as it compares children who have the same absolute age but different relative ages and different ages at school entry. Moreover, depending on when and how the outcome y_i is measured, absolute age might also vary at the time of testing, despite its being constant at birth. Additionally, cohort (or class) effects would further complicate the matter. Some more recent papers exploit geographical variation in cut-off school entry dates across regions (Crawford et al., 2007) or countries (Bedard and Dhuey, 2006) as an additional source of identification. Obviously, these studies rest on the assumptions made on country or region unobservables and their interactions with the various age effects.[14]

In their recent book Angrist and Pischke (2009, pag. 6) cite the specific identification problem of equation 1 as one that cannot be solved. Consistently with this interpretation, we do not intend to identify the various parameters in equation 1. We rather estimate a composite age effect and we exploit the unique features of our data, where we observe both academic performance and a very good measure of ability and we have information on other activities from the ISAS surveys, to investigate the role of the various inputs of the education production function in the determination of such a

[14]To the extent that we will use variation across Italian provinces in our analysis, a similar concern applies to our approach as well. An underlying assumption of our identification strategy requires the timing of births to be uncorrelated with province-level unobservables. Compared to other studies (Bedard and Dhuey, 2006; Crawford et al., 2007), however, we can argue that all the institutions are kept constant across Italian provinces (at least formal institutions). Additionally, the exact source of variation for our instrument is at the level of the interaction of provinces and years of birth.

composite parameter.

Additionally, we do not adopt the common approach of comparing students born across the cut-off date because it requires making comparisons across cohorts, which, in our setting, are subject to a variety of different environmental factors, such as different teachers and professors, different exam texts and formats. In fact, the cut-off date strategy is typically combined with the use of standardized tests to measure performance, which are more likely to be comparable across cohorts (Crawford et al., 2007; Elder and Lubotsky, 2008; McEwan and Shapiro, 2008).

Eventually, we concentrate on the estimation of the following equation:

$$y_i = \alpha_0 + \alpha_1 ageR_i + \alpha_2 X_i + \alpha_3 H_i + u_i \tag{2}$$

which is the equivalent of equation 1 where we excluded age_i and $age0_i$ from the set of explanatory variables. Moreover, since s_i is constant within cohorts in our sample (and X_i always includes a full set of cohort dummies), the parameter α_1 is a composition of the effects of absolute age, relative age and age at school entry.[15] We still label α_1 as the effect of relative age but merely for coherence with the definition of $ageR_i$. Hence, we do not attempt to solve the collinearity of the various age effects in equation 1 but we still need to address endogeneity.

One way to describe the issue is to define the variable of interest $ageR_i$ as follows:

$$ageR_i = m_i + f(m_i, X1_i, H1_i) + v_i \tag{3}$$

where m_i is an indicator for the calendar month of birth (e.g. 0=January, 11=December) and $f(\cdot)$ is a function that adjusts the age of late and early enrollees. So, if i is a early (late) enrollee, $f(m_i, X1_i, H1_i) < 0$ (> 0) otherwise, if i is a regular students, $f(m_i, X1_i, H1_i) = 0$. Since the choice to enter school early/late and the likelihood of failing a grade somewhere in one's school career depend on various observable and unobservable characteristics, so does the function $f(\cdot)$, whose arguments $X1_i$ and $H1_i$ potentially include some or all of the variables in X_i and H_i. Moreover, for the reasons discussed in Section 2 and as shown in Figure 1, the option of entering school early was essentially available only to children born in the first few months of the year, so m_i also enters the determination of $f(\cdot)$. v_i is an additional random shock to relative age that captures some special cases of students who, for random reasons, enroll at an age that is different from the norm.

Equations 2 and 3 clarify the identification problem: since the variables in $H1_i$ are unobservable and potentially overlap with those in H_i, the simple OLS estimator of the coefficients of equation 2 is likely to be inconsistent.

The usual solution to this type of identification problem is instrumental variables. Recall that the conditions for a valid instrument are three: (i) exogeneity, i.e. the instrument(s) should be uncorrelated with the error term of the main equation (u_i in equation 2, in our setting), once conditioning on the other control variables; (ii) relevance, i.e. the instrument(s) should be correlated with the endogenous variable(s) (conditional on the controls) and such correlation should be strong enough to avoid concerns with weak instruments (Staiger and Stock, 1997); (iii) monotonicity, i.e. the sign of the (conditional) correlation between the instrument(s) and the endogenous variable should be constant across the population of interest (generally, it does not matter whether it is positive or negative (Imbens and Angrist, 1994)). The third condition (monotonicity) is often overlooked but it turns out

[15]If schooling s_i is interpreted as actual taught material, then it is indeed constant within cohort for all students in our sample. However, if s_i is intended as mere schooling time, than it does vary for the few re-takers, who repeated the same grade one or more times and, thus, spent more time in school although they were taught the same material.

to be important in our setting.

In fact, casual inspection of equations 2 and 3 may suggest that the calendar month of birth m_i is a valid instrument for $ageR_i$ in equation 2. The almost complete randomness of the distribution of birth months guarantees that m_i satisfies the exogeneity assumption.[16] At the same time, such a variable does not enter directly the determination of academic performance but it clearly correlates with $ageR_i$, thus satisfying the second condition for a valid instrument. Bedard and Dhuey (2006) adopt this approach (instrumenting $ageR_i$ with a function of m_i) to identify the parameters of an equation similar to 2 for fourth and eight graders.[17]

As already mentioned, though, identification through instrumental variables also requires monotonicity, i.e. the behavior of all units in the sample should be affected by changes in the instrument in the same direction (Imbens and Angrist, 1994). In our context, this means that being born in an earlier month than the one in which one was actually born, should lead to the same behavioral change in the endogenous variable $ageR_i$ for all students in our sample. Put it differently, monotonicity fails if some students would have entered school early if there were born in an earlier month, while others would have postponed it (similarly for being born later).[18]

Unfortunately, this is precisely what happens in our data. Figure 1 shows that being born in an early month of the year increases the probability of entering school early, hence the correlation between m_i and $ageR_i$ is positive in this subpopulation (approximately until $m_i \leq 3$), the higher the calendar order of one's month of birth the lower one's relative age. This is due to the possibility offered to Italian parents to send their children to school earlier if they are born in the early months of the year.

For all the other students, i.e. those born in the mid and late months, the correlation between month of birth and relative age is negative. This is obvious for regular students, for whom $ageR_i = -m_i$, while the same Figure 1 suggests that being born in a late month slightly increases the likelihood of late enrollment. Table A.1 in Appendix A presents results that confirm this intuition.[19] For robustness and comparison with Bedard and Dhuey (2006), we have produced results instrumenting $ageR_i$ with m_i, finding that the instrument is indeed non monotonic and obtaining a set of IV estimates that are very similar to our OLS (results are not reported for brevity but are available from the authors upon request).

For these reasons, we take a different approach and we use the number of private pre-schools in one's province of origin (relative to the size of one's same birth cohort in the province of origin) as an instrument for relative age.[20] More formally, for a generic student born in province p and in year

[16]One may question this assumption if parents try to target the actual month of birth for reasons related to work, parental care or even directly to school entry. However, since conception and pregnancy still are largely stochastic events, it is unclear whether such targeting can go beyond the seasonal frequency.

[17]For comparison with Bedard and Dhuey (2006), note that they define their instrument as "assigned age" or $-m_i$ in our terminology.

[18]Notice that the presence of non-compliers does not necessarily affects monotonicity. The instrument may have no effect on the behavior of some units (the non-compliers) but it should not have effects of opposite signs across units, which is what makes monotonicity fail.

[19]Bedard and Dhuey (2006) are more concerned with endogeneity due to grade retention (which leads to late enrollment, in our terminology) than with early schooling. Moreover, they seem to believe that the parents of children born on the left side of the cutoff date (those born in December in our setting) would "hold them out of school so that they enter kindergarten a year late (who are positively selected)" (page 1442). Figure 1 shows that in our setting early school entry is the most important source of selection and the descriptive statistics in Table 3 suggest that early enrollees are positively selected. In general, it is unlikely that the relationship between relative age and month of birth is monotonic in all the cases considered in Bedard and Dhuey (2006).

[20]We define the province of origin as the province where the student attended high school. Very similar results are

b our instrument is defined as follows:

$$z_{pb} = \frac{priv\_schools_p}{births_{pb}} \tag{4}$$

where $priv\_schools_p$ is the number of private pre-schools in province p and $births_{pb}$ is the total number of births in province p and year b, i.e. the size of the birth cohort in the province. In terms of the empirical framework described in equations 2 and 3, we impose a standard exclusion restriction and we assume that our instrument is included in $X1_i$ and excluded from X_i.

The idea is that the supply of places in preparatory courses offered by private pre-schools is limited and it adjusts sluggishly to changes in the size of the potential demand. Hence, the likelihood of early enrollment is enhanced by the availability of such preparatory courses.[21] The validity of such an instrument, particularly its exogeneity, rests on an argument about initial conditions. We acknowledge the fact that private pre-schools locate in areas with high potential demand, which might, in turn, be related to the prevalent parental background in the area (both in terms of economic resources and educational awareness). However, since such location choices are subject to numerous frictions (real estate investments, hirings, licensing), they cannot respond to current changes in potential demand and will be based on past realizations (and possibly expectations, which are merely functions of past realizations).[22]

The exogeneity of our instruments might be questioned on the basis of at least two arguments. First, since pre-schools are generally known to have positive effects on future learning (Berlinski, Galiani, and Manacorda, 2008; Berlinski, Galiani, and Gertler, 2009), having access to a large supply of places in such schools improves students outcomes regardless of when they start school. Similarly, a particularly large birth cohort in one's province may generate negative crowding effects on learning. The richness of our data allows us to address these concerns by including in our set of controls X_i either the student's high school grade or the entry test score or both. Unless the pre-school and the crowding effects are such that they only emerge at university, which is highly unlikely, this should be enough to maintain (conditional) exogeneity of z_{pb} in equation 2. Additionally, our standard set of controls includes a full series of dummies for one's region of origin but we can also introduce province of origin's dummies, at the cost of loosing conventional statistical significance in a few cases, given that for several provinces we only observe very few students.

A second reason of concern for the exogeneity of our instrument is geographical mobility, as parents may move across provinces in search of locations with a more convenient supply of such courses. The traditional limited mobility of Italian families guarantees that this is a minor concern. For example, in our data 91% of the students attend high school in the same province where they were born.

There are on average 0.2 private schools per 100 children by province in our data with a standard deviation of 0.06 and with a slightly higher incidence in the northern regions of the country (0.22) than in the center and the south (0.13). In order to understand the functioning of our instrument, Table 4 presents a brief analysis of the relationship between relative age and the incidence of private pre-schools. In our later analysis we will devote particular attention to the comparison of results

obtained using the province of birth. We simply choose the variable with the fewer missing values.

[21]One caveat with our instrument comes from data limitations. In fact, we only have information on private schools currently recognized by the government and it is impossible to reconstruct which ones were already active before the year 2000. We are told by officials at the Ministry of Education that turnover of schools is very limited.

[22]Notice that this is argument is very similar to those used to justify the use of the initial stock of migrants as an instrument for current migration, as in Altonji and Card (1991) or in Card (2001) and Card (2005).

obtained with and without conditioning on entry test scores, our measure of cognitive ability. For this reason, also Table 4 presents results produced under such two alternative specifications (in Panel A and Panel B) and, similarly to what we find in the following sections, results are only marginally different.

In the first column we report the actual first stage regression of our IV strategy, which indicates that the instrument strongly affects relative age, as the availability of one additional private pre-school reduces relative age by approximately 2 months. In the second column of Table 4 we run the same regression restricting the sample to regular students only and we show that the instrument has no power in this subpopulation, consistently with the interpretation that the instrument affects the likelihood of early schooling.

In the last two columns we directly explore the relationship between the instrument and the probability of early (column 3) and late enrollment. Results show that, indeed, one is more likely to enroll early at university when there are more private pre-schools in one's province of origin and relative to the size of one's birth cohort in the province. Column 4 shows that also the likelihood of late enrollment is affected by our instrument but in the opposite direction, thus maintaining monotonicity. We interpret this result in the light of the fact that often the same private institution offers courses at various school levels and, in particular, remedial classes for grade re-takers. Hence, the presence of private schools in one's province reduces the likelihood of late enrollment at university.[23] Notice, however, that the effect in column 3 is much stronger than that in column 4.

The analysis of Table 4 clearly shows that, although our instrument does satisfy the monotonicity assumption, it also affects different sub-populations differently and, thus, it necessarily identifies only a local effect. There certainly are many students, particularly those born in the middle months of the year, whose relative age is unaffected by changes in the incidence of private schools. For this reason we complement our analysis by presenting both the OLS and the IV results and also by producing simple estimates of the comparison between the youngest (born in December) and the oldest (born in January) within each cohort of regular students. We return on the local interpretation of our results in Section 4.

[TABLE 4 ABOUT HERE]

4 Relative age effects at university

In this section we present our main estimates of the relative age effects among Bocconi students. Following our discussion in Section 3, we estimate equation 2 under three different specifications: OLS, IV, and OLS on the restricted sample of regular students only. In this last case we replace $ageR_i$ with month of birth dummies and we compare the youngest January-born with the oldest December-born. i.e. students who were born 11 months apart. Such age difference amounts to 4-5% of total biological age at the time of university attendance (19 to 23 years of age). For comparison purposes, in all other specifications we also divide relative age $ageR_i$ by 11, so that all coefficients measure the difference in the outcomes between students born 11 months apart and can be directly compared.

Our data allow us to look at a wide set of academic outcomes so that y_i can be the student's GPA or a specific exam result but also her final graduation mark. The set of controls X_i includes a gender dummy, high school grades, dummies for the type of high school (academic or technical

[23] We also have data on private primary and secondary schools but including these in the instrument set reduces efficiency, probably because of the high correlation between the incidence of these various types of schools (0.98).

and religious or not religious), family income, a dummy for residence outside the province of Milan (which is where Bocconi is located), cohort and region (of residence) dummies as well as a set of indicators for the particular degree chosen.[24] We will also look at how the estimated effects change when we augment the set of controls with our measure of cognitive ability, the entry test score. Unless otherwise indicated, the standard errors are clustered at the same level of variation of our instrument. i.e. by cells identified by the interaction of province of residence and year of birth (there are over 450 such cells in our data). For consistency we maintain the same clustering also in the OLS regressions, where it is not obviously needed.

Table 5 reports our main results. In panel A we look at the effect of relative age on graduation marks and our OLS estimate indicates that younger students outperform their older mates by about 0.6% for each 11 months of age difference. When we estimate this effect using our IV strategy, the coefficient increases to 3.3%. The difference between the OLS and the IV estimates can be attributed to various factors, particularly to the fact that the IV may estimate the effect on a very specific sub-population.

Specifically, the IV age effect estimated in Table 5 is identified by the group of compliers to our instrument, i.e. students born in an early month of the calendar year who were induced to enter school early by the large supply of preparatory classes and students born in the same months who did not enter school early for lack of such preparatory classes. It is probably correct to think that the compliers in our analysis are relatively higher income and higher ability, as private pre-schools are costly. It is always hard to speculate about the exact locus of the distribution of the treatment effect that is identified by an IV estimator but, in this case, a obvious concern would be that our results differ from those in previous studies (Bedard and Dhuey, 2006; Crawford et al., 2007; Mayer and Knutson, 1999) simply because they are obtained with different instruments.

To try and rule out such a concern, consider the situation that would seem the most obvious based on previous results and suppose that pure age effects were positive for everyone due to differences in cognitive development. Heterogeneity of the effects is generated exclusively by different endogenous responses to one's age. The youngest, who are disadvantaged by their relative age, would like to compensate with other resources and one might expect the most able and the richest to be able to do so more effectively. Similarly, the most able and the richest among the oldest students, who are advantaged by their age, would be able to exploit such an advantage more than their less able and poorer mates (as long as there are complementarities among the inputs of the learning process). Hence, in general the local effect estimated on the richest and most able students should, if anything, be more positive than the average effect, given than, if both groups face the same production/learning function and the same cost of effort/investment, the youngest should not be able to more than offset the original disadvantage and the additional investment made by the oldest. To further investigate this issue, in unreported results we replicated our main IV estimates (column 2, Table 5) for different subgroups of ability and family income and we found that the estimated relative age effect remains negative in all cases.[25]

Additionally, one may find surprising to see that the IV estimator is larger than the OLS. In fact, if the endogeneity of relative age in equation 2 were driven by the early enrollees being more

[24] In the period covered by our data, Bocconi offered 6 types of bachelor degrees with different specializations. The most popular ones were management (with acronym CLEA) and economics (CLEP). A third option was a more academic version of the BA in economics (DES). Other programs specialized in financial markets (CLEFIN), public administration (CLAPI), law and economics (CLELI).

[25] Specifically, we found that the estimated effect is very similar across income groups and larger among the low ability. Results are available from the author upon request.

able and the late enrollees being less able (as suggested by the descriptive statistics in Table 3), one would expect the IV estimate to be smaller than the OLS. Notice, however, that in our data ability is observable and, although in Table 5 we do not condition on the entry test score, the student's high school leaving grade apparently already captures a lot of the variation in ability. In fact, when we exclude from the set of controls all possible measures of ex-ante ability (i.e. both the test score and the high school grade and type) the IV estimate decreases substantially to 2.4%. Apparently, the bias that is corrected by our the IV strategy seems to be generated by other, less obvious, unobservables, like motivation or parenting styles, and it is difficult to have a prior about the direction of such a bias.

In column 3 we restrict the sample to regular students only and we replace relative age with a dummy for the birth months between February and November and one for students born in December. Since the omitted category is January, the coefficient on this last dummy measures the difference in performance between the youngest and the oldest among the cohort of regularly enrolled students. The estimated effect indicates an advantage of approximately 0.8% in favor of the youngest born in December. The dummy for the months between February and November is also positive - equal to about 0.3% - but not statistically significant. Given an average graduation mark of approximately 102 over 110 in the entire population, our estimates imply that the difference between the youngest and the oldest students in a cohort is on average about 1 grade point, or 0.13 of a standard deviation.

[TABLE 5 ABOUT HERE]

In the lower panel (panel B) of Table 5 we look at a different outcome, namely the average grade over the exams of the first and second academic years, when students take (almost) exclusively compulsory courses. While the effect on graduation mark also captures a variety of students' endogenous choices (elective courses, dissertation supervisor, et.), the average grade in the first two academic years should reflect actual performance more directly. Results indicate that relative age effects on this measure of performance are very similar to those estimated in panel A.

One important feature of our data is the availability of both measures of academic achievement and of cognitive ability for the same students. In Table 6 we replicate our main results augmenting the set of controls with the entry test score as a measure of cognitive ability.

[TABLE 6 ABOUT HERE]

Interestingly, conditioning on ability does not significantly change the estimated relative age effects, whose absolute value decreases only by approximately 10%. We will return to a more detailed analysis of entry test scores in Section 6.1, however, the results in Table 6 already suggest that differences in cognitive ability are only one of the channels through which age differences influence academic performance and, perhaps, not the most important.

In Table 7, we explore how relative age effects vary over the course of the students' university lives. To do this, we compute the average grade in the exams taken in each academic year, pooling the fourth year together with any subsequent one.[26] This leads to a dataset with 4 observations for each student. The regressions in Table 7 pool all observations together and interact relative age and the month-of-birth dummies with indicators for the academic year (the errors are clustered at the individual level). The dependent variable is the log average grade in each course year.

[26] A good fraction of students (about 10% in our data) graduate after the official duration of the degree (4 years for all but one program). Late graduation is a well-known problem of the Italian university system, see Garibaldi, Giavazzi, Ichino, and Rettore (2007) for an analysis of this phenomenon on our same data.

[TABLE 7 ABOUT HERE]

The results indicate that the effect already emerges fully in the first year and it remains unchanged for the entire academic career of the student. The estimates for the first academic year are entirely comparable to those reported in Table 5 and 6.

The results presented so far show that relative age has a significant effect on overall performance but our data also allow to look at specific subjects. In Table 8 we categorize courses by subject on the basis of the department that is responsible for organizing and teaching the course. In order to exclude any potential bias due to students self-selecting themselves into elective courses, we consider (the log of) the grade obtained in the first exam taken in each subject, which is always compulsory, and run separate regressions for each of them.

[TABLE 8 ABOUT HERE]

In each column of the table we report the results for a specific subject while the four panels (A to D) show different specifications. We concentrate only on our two preferred specifications - the IV and the OLS restricted to the sample of regular students - and we show results obtained both with and without the entry test score as a control variable.

We find that relative age effects are important in all the subjects that we consider, although the estimates are not significant at conventional statistical levels in some specifications and for some subjects. The strongest and most robust effects are in economics and mathematics&statistics. For economics we find a difference of about 1.5% to 3.8% for each 11 months of age in favor of the youngest students. For mathematics&statistics the effect is of the order of 1% to 2.5%. Similarly to what emerged from the comparison of Tables 5 and 6, the inclusion of the test score in the control set influences the results only very marginally.

Our finding that the strongest effect is concentrated in the most quantitative subjects (economics and mathematics&statistics), which are also the subjects that students indicate in their evaluation questionnaires as those with the heaviest workload, is consistent with our interpretation that youngest students spend more time studying (see Section 6.2). The results of Table 8 are confirmed also when differences in the degree of grade dispersion across subjects are taken into account, either by normalizing the dependent variables or by computing standardized coefficients.

[FIGURE 2 ABOUT HERE]

We conclude this section with the results in Figure 2, that shows the estimated relative age effects for each single month of birth and for some selected outcomes, namely graduation mark, the average grade in the exams of the first two academic years and the grade obtained in the first exam in economics and mathematics&statistics. The effects are reported in absolute levels, so that on the vertical axis one can read the (conditional) average of the dependent variable for each month of birth. For convenience we limit our attention to a restricted group of late and early enrollees, namely those born from October of the year preceding the regular one to March of the following year.

As expected, students older than normal (those born between October and December of year $t-1$) perform worse. In fact, these students typically enroll late because they failed one or more grades in previous school levels (primary, junior-high or high school). Consistently with the descriptive evidence presented in Table 3, the small number of late enrollees leads to very wide confidence intervals around the estimated mean outcomes. Also, the conditional mean outcomes of the early enrollees are higher than for the other students, but such difference does not appear to be statistically significant, especially when compared with the youngest regular students.

5 Robustness checks

In this section we provide additional evidence to exclude some simple mechanical explanations of the effects estimated in Section 4. First (Section 5.1), we document that the process of selection into Bocconi does not play a major role in generating our results. Second, (Section 5.2), we check that our estimates are robust to conditioning on season of birth.

5.1 Selection at entry in Bocconi

Bocconi University is a highly selective institution in Italy and it also specializes exclusively in Economics and Management.[27] Admission is subject to a formal assessment of the quality of the candidate based on both high school records and the result of the admission test score. Additionally, tuition fees are more expensive than in competing Italian public universities. Thus, the students in our sample are clearly a selected group, both on ability and on family background, and our results may not generalize to the population of Italian university students. In particular, our finding that the youngest students perform better might be generated by such students being less likely to either apply to Bocconi or, conditional on submitting an application, to pass the entry exam. Bedard and Dhuey (2006) show that Canadian (British Columbia) and US students who are the youngest in their cohorts are, indeed, less likely to enroll in college.

Notice that the second of these selection processes (i.e. the entry exam) is fully observable in our data because we have information on both candidates who passed and those who failed. Hence, conditioning on the entry test score, like in Table 6 or in panels B and D of Table 8, already purges our results from such a potential selection bias.

In Table 9 we pursue this argument even further and we replicate our main results allowing for a more flexible specification of the role of the entry test score. Specifically, we concentrate on a few selected outcomes (graduation mark, the average grade in the exams of the first two academic years and the grade obtained in the first exam in mathematics&statistics) and we condition on dummies for the quintile distribution of entry test scores. For comparison purposes we also report the main results that we obtained in Table 5 or Table 8 and we find that the estimated relative age effects change only minimally.

[TABLE 9 ABOUT HERE]

The process that leads only some students to apply to Bocconi is a more serious concern, as one might be worried that that the self-selection that generates the students' applications might work differently for students born in different months. For example, if the youngest students, indeed, do worse in school, only the very best of them would actually submit an application to Bocconi. Notice, however, that such a differential self-selection would lead to equalizing the performance of students within the same cohort and only under very peculiar assumptions it may be able to generate the effects that we document in Section 4.[28]

Nevertheless, in Figure 3 we provide some suggestive evidence that the self-selection of students into Bocconi is relatively homogeneous across months of birth. Specifically, we compare the distribution of month of birth of Bocconi students with that of the population of all Italians in the same cohorts, as computed from the official census.

[27] Only very recently, a degree program in law has been introduced.

[28] Notice also that any process that is driven merely by ability should already be taken care of by our estimates that condition on the entry test score.

[FIGURE 3 ABOUT HERE]

The upper panel of Figure 3 describes the relative distribution of month of birth for students who took the entry test at Bocconi in the years 1995 to 1998 (a bar taller than 1 indicates that the percentage of students born in that month is higher among Bocconi applicants than in the population, within the same cohorts). Although there is some variation, Bocconi does not seem to attract particularly older or younger students. The bottom panel of Figure 3 focuses on students who have been eventually admitted at Bocconi. Similarly to the upper panel, the relative incidence of students born in any month is never statistically different from 1 and there seems to be no indication of a trend towards older or younger students being more likely to enroll at Bocconi.

Due to the anonymization procedures, in the official census data the information on the month of birth cannot be combined with education or other individual characteristics, hence we cannot distinguish between graduates and non graduates. However, we obtain very similar results when we use other data sources to compute the distribution of month of birth for the population. For example, we used survey data from the Italian sample of the European Community Household Panel (ECHP), which allows us to exclude individuals who never attended college but at the cost of reducing the size of the sample. We also replicated Figure 3 using only observations in the top quintile of the income distribution obtained from the complete tax records for the fiscal year 2004, so as to focus on a sub-population that is likely to include a majority of college graduates. In all cases the general message of Figure 3 is confirmed.[29]

The evidence in this section also answers some obvious questions about the external validity of our analysis. The concern would be that the relationship between month of birth and academic performance might be different for Bocconi students, compared to the entire population. If Bocconi students were selected by month of birth, only a section of that relationship would be visible in our data, thus making it impossible to generalize. Hence, selection by month of birth is one of the, admittedly many, treats to external validity and perhaps one of the most obvious and important. The evidence in Table 9 and Figure 3 suggest that this type of selection bias is not major.

In any event, even if our results could not be generalized, they are still important as evidence of the functioning of age effects among elite groups.

5.2 Season of birth effects

In Table 10 we perform a further robustness check. Several previous studies documented statistically significant differences in various outcomes between children born in different seasons of the year (Buckles and Hungermann, 2008; Wilson, 2000). Usually, such differences, especially as far as health outcomes are concerned, are explained with environmental, biological and medical factors, like weather conditions and temperature at the time of gestation or birth. These factors are known to affect the health conditions of newborn children, such as birth weight and height.

In our analysis, the comparison of students born in January and December should not be affected by season of birth effects, given that both are winter months. However, for robustness and comparison, Table 10 reports estimates of relative age effects conditional on season of birth for our students.[30] Like in Figure 2 and Table 9, we consider only a set of selected outcomes.

[29]These alternative versions of Figure 3 are available from the authors upon request.

[30]We define seasons exclusively on the basis of months so that results can be replicated by external researchers. Namely, December, January and February are coded as winter; March, April and May as spring; June, July and August as summer; September, October and November as autumn.

[TABLE 10 ABOUT HERE]

Since our identification approach essentially exploits variation in age that is partially collinear to variation in the date of birth, our results might in principle be driven by systematic time trends in meteorological conditions that favor the youngest, i.e. those born more recently.[31] To make our specification robust to this particular issue, we include among the control variables a full set of interactions between season of birth and year of birth dummies.

The estimates of Table 10 show that relative age effects remain statistically significant also in this more sophisticated specification. Furthermore, while the OLS point estimates are largely unchanged (both in column 1 and columns 3) the IV now suffers from weak instrument because the set of season and cohort effects takes out a lot of variation from the excluded variable, whose F-test in the first stage regression drops to 5.42. Reassuringly, though, the estimated relative age differences always favor the youngest students. As far as the season effects are concerned, students born in the spring (the reference season in our specification) seem to be slightly advantaged as compared to their mates, especially in mathematics&statistics.

6 Why do relatively younger students perform better?

The evidence that we presented in the previous sections contrasts with what many other authors have found when focusing on younger students. Bedard and Dhuey (2006), for example, show significant positive age effects among Italian 8th graders. In terms of our conceptual framework from Section 3 this corresponds to estimating a positive α_1, while in our data we find the opposite.[32] In this section we investigate two possible explanations that may not only rationalize our results but also reconcile them with previous findings.

The first explanation is a combination of early learning and progression over the age-profile of cognitive development. Although there still is some controversy on this issue, several studies (Fredriksson and Ockert, 2005; Goodman and Sianesi, 2005; Skirbekk, 2005; Skirbekk et al., 2004) have shown that going to school earlier improves later outcomes. At the same time, the medical and psychological literature documents that, just like physical strength, cognitive abilities first develop and then deplete with age, with the turning point for the average person being probably in the early twenties (Jones, 2005; Salthouse et al., 2004). Hence, in the early stages of childhood development the effect of older students being more mature probably dominates the benefits of early learning. Later, such an advantage fades out and possibly reverses, thus leading to the observed better performance of the youngest students in the cohort.

Again, we can use equations 1 and 2 from Section 3 to formalize such an argument. A positive effect of early schooling implies that $\beta_3 < 0$ in equation 1. For young children in primary school, such an effect is more than offset by the fact that older pupils are cognitively more developed ($\beta_2 > 0$) and, since individual ability is usually unobservable, this leads to a $\alpha_1 > 0$. Later on at university, while the early schooling effect persists, differences in cognitive ability flatten out (or even reverse) and we estimate a negative α_1.

Given that in our data we observe a very good measure of cognitive ability, we will be able to explore the validity of such an interpretation. In particular, in Section 6.1 we show that younger

[31] When we focus on regular students only, variation in relative age is, indeed, perfectly collinear to variation in dates of birth.

[32] Note that many studies focus on estimating the effect of early schooling, i.e. $age0_i$. However, given the collinearity issues that we discussed in Section 3, this can be equivalently interpreted in terms of relative age.

students do marginally better at the entry test. However, we already know from the results in Tables 6 and 9 that, when we include the entry test score in our set of control variables, the estimated relative age effect on academic performance changes only marginally. We interpret this last finding as suggesting that there must be (at least) another channel through which relative age affects academic outcomes.

Hence, we also explore a second possible explanation in Section 6.2. Several psychological studies (Dhuey and Lipscomb, 2006; Thompson et al., 2004) document the important role of relative age differences in the development of personality traits that favor the oldest pupils in a group. According to these studies, the youngest students in a cohort, who have likely been the smallest kids in their reference groups at early ages, should be less socially active and, hence, spend more time on studying, as predicted by a simple model of optimal time allocation. In terms of equation 1 this implies that $\beta_4 < 0$, i.e. relatively older students exert less effort and perform worse. In our interpretation this particular effect emerges only at university and it is irrelevant at younger ages because it is only in college that one gets full control of one's time. Using data from a novel survey we find evidence of relative age differences in social behavior and (using the PISA study) we also document that the youngest in a cohort devote more time to studying, which eventually leads them to achieve better academic results.

6.1 Relative age differences in cognitive ability and academic performance

Table 11 explores the existence of relative age effects in cognitive ability in our Bocconi data by analyzing students' results in the admission test. Such a test was - and still is - meant to measure ability rather than actual knowledge and was designed by professional educational psychologists. It includes several different sections, such as reading comprehension and problem solving, and it is taken by all students on exactly the same date and location.

[TABLE 11 ABOUT HERE]

Similarly to Table 5, in Table 11 we report results from various specifications. In column 1 we estimate relative age effects in the entry test by simple OLS, in column 2 we apply the IV strategy that we discussed in Section 3 and, finally, column 3 restricts the sample to regular students. The dependent variable is the logarithm of the test score. Results are very consistent with our analysis in Section 4 and show a modest but significant advantage of about 0.9-1.5% for each 11 months difference in favor of the youngest students, depending on the specification. In this case, the OLS and IV results are highly comparable.

[TABLE 12 ABOUT HERE]

In Table 12 we analyze in details the different sections of the test for some more recent cohorts, namely for students who applied to Bocconi in the years 2000, 2001 and 2002. These cohorts were administered a newer version of the test which consists of 8 sections and results have been recorded separately for each of those sections: reading comprehension, spatial and perceptive abilities, computer use, mathematical reasoning, verbal relations, logics of images, verbal patterns and general culture. In Appendix B we present a brief description of the actual content and questions in each of these 8 sections. The breakdown of test scores by section is not available for students in the 1995-1998 enrollment cohorts.

Note that two of the sections refer directly to skills that come mostly from the accumulation of previous knowledge, namely computer use and general culture. In Table 12 we do not report results for general culture but we do present the estimates for computer use as well as for all the other sections that are meant to directly measure different types of cognitive abilities. In all columns the dependent variable is the standardized test result, so that the estimated coefficients can be readily compared across test areas. The two panels of Table 12 present results based on two different specification: in the upper panel (Panel A) we show the IV estimates, while in the lower panel (Panel B) we report the simple comparison between regular students born in January and regular students born in December.

We start in column 1 with the overall test score, which is a weighted average of the results in the single sections, where the estimated effect indicates that being younger by 11 months of age leads to a significant advantage of approximately 0.1 of a standard deviation. This effect increases to 0.14 in Panel B, where we concentrate on regular students and we compare those born in December with those born in January. Also, students born in the middle months of February to November show a considerable 0.08 advantage over the oldest January-born.

The following columns (2 to 8) present results for the different test sections (excluding only general culture). All the point estimates indicate a relative advantage of the youngest over the oldest students in the cohort, however such differences are rarely statistically significant in panel A and only in three sections of panel B: spatial perception, computer use and logics of images.

These results suggest that cognitive ability as measured at age 19 is subject to mild relative age differences, while our interpretation of the effect on computer use is more in line with the psychological mechanism that we discuss below. Students with less active social lives also have more time to spend on other things, such as using a computer, an activity that does not necessarily require interacting with others.

6.2 Relative age differences in social behavior

Relative age might also affect academic outcomes through effort. The sketch of a simple model of the efficient allocation of time/effort to different sets of activities may help understanding our argument. Assume that students obtain utility from both academic performance y and other social activities z (for expositional simplicity, let us omit subscripts):

$$U = U(y, z) \tag{5}$$

where we assume that the partial derivatives with respect to both arguments are positive and decreasing (no assumption is needed on the cross derivative).

Both y and z are produced using two inputs, skills (η or ζ) and effort (e). Cognitive skills (η) enter the production function of y and social skills or personality traits (ζ) influence the level of z. Effort is measured as time devoted to studying or socializing and it is constrained to a total amount normalized to 1. Under these assumptions, the production functions of y and z can be written as follows:

$$y = y(e, \eta) \tag{6}$$
$$z = z(1 - e, \zeta) \tag{7}$$

where we assume that, for both functions, the partial derivatives are all positive and decreasing and the cross derivatives are also positive, capturing the idea that better cognitive or social skills increase the return to time/effort in the corresponding activities (studying or socializing).

Students choose the level of e that maximizes U according to the following first order condition:

$$U_1(y, z)y_1(e, \eta) = U_2(y, z)z_1(e, \eta) \tag{8}$$

where $U_1(\cdot)$ is the derivative of U with respect to its first argument and similarly for $y_1(\cdot)$ and $z_1(\cdot)$.

Next, in order to understand the role of relative age, we need to make assumptions about how η and ζ evolve with age. Our results in the previous Section 6.1 suggest that, for the students in our age range, η is relatively constant within cohorts. On the other hand, the studies that we discussed earlier on (Dhuey and Lipscomb, 2006; Thompson et al., 2004), indicate that ζ is higher for older students, due to psychological relative age effects at young ages that perpetuate over time. Alternatively, it is also plausible to assume that the pattern of development of some social skills, especially in the sexual and affectivity area, is particularly steep around 19-20 years old, so that differences in ζ across students of different ages within the same cohort may arise even in the absence of psychological relative age effects.

Given the complementarities in the production function of z and according to equation 8, older students with higher ζ would exert less effort e and, thus, perform worse than their younger mates, who have lower ζ.

We take this simple prediction to the empirical test using data from the Italian sample of the International Survey on Affectivity and Sex (ISAS).[33] This is an internationally comparable survey of first and second year university students that collects information on various aspects of their social and sexual lives. The Italian data are collected from a sample of 23 public universities selected at random among all those that offer degrees in economics and/or statistics (47 in total). During the academic year 2000-2001 a lecture in one first or second year compulsory course in either economics or statistics was selected. At this lecture the students were distributed the questionnaires. They were asked to fill them and seal them into anonymous envelopes so as to guarantee privacy. These procedures allowed to obtain almost non-existent non-participation rates and non-response rates that are never above 15% for the most delicate questions. For a detailed description of the survey see Billari, Caltabiano, and Dalla Zuanna (2007).

Unfortunately, in the ISAS data we do not know the actual year of enrollment at university and therefore we cannot compute relative age in the same manner as in the Bocconi data. For this reason we concentrate exclusively on the most frequent birth cohort (1981), which accounts for over 40% of all observations, and we simply compare students born in different months of the year. Under the assumption that these students enrolled as freshmen in the academic year 2000-2001, this strategy is analogous to the comparison of the youngest and the oldest regular Bocconi students. We will not be able to apply our IV strategy on the ISAS data.

[TABLE 13 ABOUT HERE]

In Table 13 we report some descriptive statistics. The first set of variables describes some features of social behavior. About one fourth of all students are not engaged in any regular sport activity during the school year. This percentage is slightly higher for the December-born individuals and slightly lower for the older January born. A similar patter can be detected also for the other indicators about discos and sexual intercourse. Particularly this last set of variables shows a marked trend

[33]The ISAS survey was conducted within a project by the University of Padua and the Max Planck Institute for Demographic Research.

towards more active sexual lives for the oldest students in the cohort. About 66% of the January-born individuals are in a stable relationship at the time of the interview, as compared to about 50% among the younger December-born. Also, 59% of the oldest students in the cohort have already had their first sexual experience at age 20, while the same percentage is only 50% for their youngest mates. This difference is reflected in the average monthly frequency of sex intercourse, which is coded to zero for those students who have not yet had their first experience. Differences in this variable across birth months remain strong also within students who have already had their first sexual experience.[34] The remaining variables describe other demographic characteristics of the sample.

[TABLE 14 ABOUT HERE]

In Table 14 we use these data to analyze differences in various aspects of social behavior between the oldest and the youngest students in the cohort. For the reasons that we discussed in Section 2, we concentrate exclusively on one birth cohort (1981) and we simply compare students born in different months of the year.

In the first column of Table 14 we look at sport activity. The dependent variable is a dummy equal to 1 if the respondent answers never to the following question: *"During the school year, do you practice any sport or physical activity?"*. The other possible answers are *sometimes*, *often* and *very often* and are all coded to zero in our right-hand-side variable. The model is estimated using a probit specification and conditioning on a large set of controls: gender, high school grade, dummies for region of birth and region of the university, home-town size, dummies for mother's and father's education, a dummy for students living on their own.

The estimated effect of being born in December is not significant, although the sign of the coefficient is positive and increasing over the calendar year of birth (0.045 for February to November and it doubles to 0.083 for December), suggesting that younger individuals are more likely to do little sport. We obtain very similar results in column 2 for another aspect of social behavior. The dependent variable is coded 1 for students who answer *never* to the question *"Do you go to clubs or other places where you can dance?"*.

The last three columns of Table 14 explore love and sexual behaviors. In column 3 we run a linear regression of the self-reported mean number of monthly sexual intercourses on our month-of-birth dummies and the usual set of controls. The estimates show a very large effect with the youngest students in the cohort having on average 1.2 fewer intercourses than their oldest mates. This is about 35% over the average of approximately 3 and corresponds to almost 20% of a standard deviation. This result is confirmed (and actually reinforced) in column 4, where we restrict the sample only to those students who already had their first sexual intercourse, suggesting that our findings cannot be explained by a profile of sexual development that is particularly steep around the age of 19 and 20.

Finally, in the last column of Table 14 we explore the probability of being in a stable love relationship at the time of the interview. Here, we also find a very strong and significant effect of the youngest students being 18 percentage points less likely to be in such relationship over an average of approximately 60%.

[34] The original question reads: *"How often have you had sexual intercourse during the last three months?" Possible answers are: never, less than once a month, once a month, two or three times a month, once a week, two or three times a week, four or five times a week, almost every day*. Based on self-reported interval-coded answers we construct a continuous estimated frequency of intercourses taking the mid point of each interval. Results are robust to alternative specifications.

To the extent that these differences in social behavior also reflect differences in the allocation of time and effort between studying and other activities, our results support the interpretation that relative age effects in psychological development are a powerful determinant of differences in academic outcomes. Unfortunately, we do not have information on both social activity and time allocation for the same sample of students. However, the Programme for International Student Assessment (PISA) does collect information on time allocation. The PISA is a well known database constructed by the OECD that contains information on standardized tests administered to comparable samples 15-year-old students in a large number of countries (57 in the most recent 2006 edition).

[TABLE 15 ABOUT HERE]

In Table 15 we use the data from the Italian 2003 PISA survey to analyze relative age effects in the amount of time students allocate to self-studying at home. As in most of our previous analysis, we focus exclusively on regular students and we regress the number of hours devoted to self-studying at home on month of birth dummies and a set of controls.

Consistently with our suggested interpretation, we do find that the youngest students in the cohort devote more time to doing their homework. This finding is confirmed also when we break down the total number of hours by subject. The December-born students appear to spend more time on their mathematics and language homework, while the effect is not significant for science. The estimates in Table 15 suggest that, already at age 15, the youngest students in a cohort spend more time studying at home and thus, possibly, less time on other activities, like sports or socializing. To the extent that these differences are due to psychological relative age effects, they are likely to expand as people grow older and gain more and more control over the allocation of their time.

7 Conclusions

In this paper we document that relative age effects are still present at the age of university attendance and such effects favor of the youngest students within a given cohort. This contrasts with the results of most previous studies that looked primarily at earlier schooling stages and typically found better outcomes for the oldest students.

We produce these findings using an identification strategy that takes into account the potential endogeneity of age at school entry by means of an instrumental variable based on the availability of private pre-schools in the students' province of birth. Furthermore, we use a very homogeneous group of students that operate in the same exact institutional setting and for whom we observe a very detailed set of characteristics, many of which are unavailable in more standard datasets.

Exploring data on cognitive entry test and a survey of social behaviors of first-year university students, we produce additional evidence that help rationalize our results according to two mechanisms. On the one hand, the flattening of differences in cognitive development over time within cohort, coupled with early learning effects, can easily explain our results and reconcile them with the previous findings in the literature. Moreover, the youngest students also appear to have less active social lives and, thus plausibly devote more time to studying. This argument is consistent with results from psychological studies, showing that being the youngest in a reference group slows down the development of personality traits, like self-esteem and leadership.

Our results have important implications for the study of cognitive development and show that the mechanical evolution of abilities over the life cycle interacts with endogenous individual choices about the allocation of time and effort. Moreover, such interaction involves both cognitive and non-cognitive skills and attitudes. In a policy perspective, the most commonly discussed options focus on the advantages and disadvantages of lowering the age of school entry. Our results support the idea that lowering school entry age might indeed improve performance, however such an intervention cannot eliminate relative age differences and their implications. Rather, if the policy objective is guaranteeing equal opportunities to everybody, relative age differences - which we show to be an important source of later inequality in outcomes - should be limited. In principle, achieving this goal is relatively easy, at least as far as the schooling environment is concerned. For example, the rules of class formation could be redefined by conditioning students in a class to be at most 6 months apart in terms of biological age.

Implementing this type of policy is straightforward and costless, other than in some very special cases, for example when there are only very few students in a school grade. One may also think of changing the actual definition of school grades, by having a grade for each semester instead than for each year. This alternative policy option, however, might require additional inputs in the education production process (smaller class sizes, more teacher, et.).

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Figures

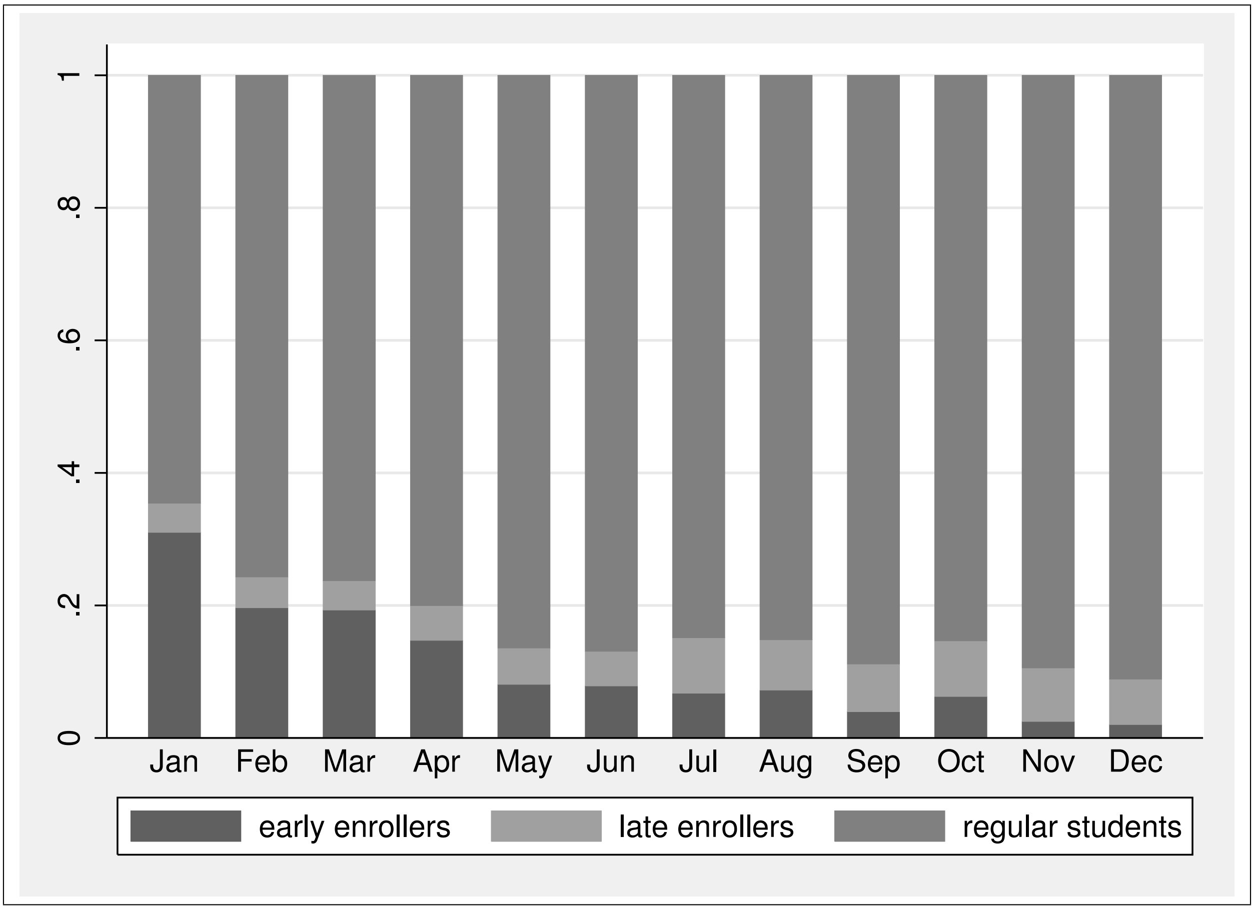


Figure 1: Distribution of student types by month of birth

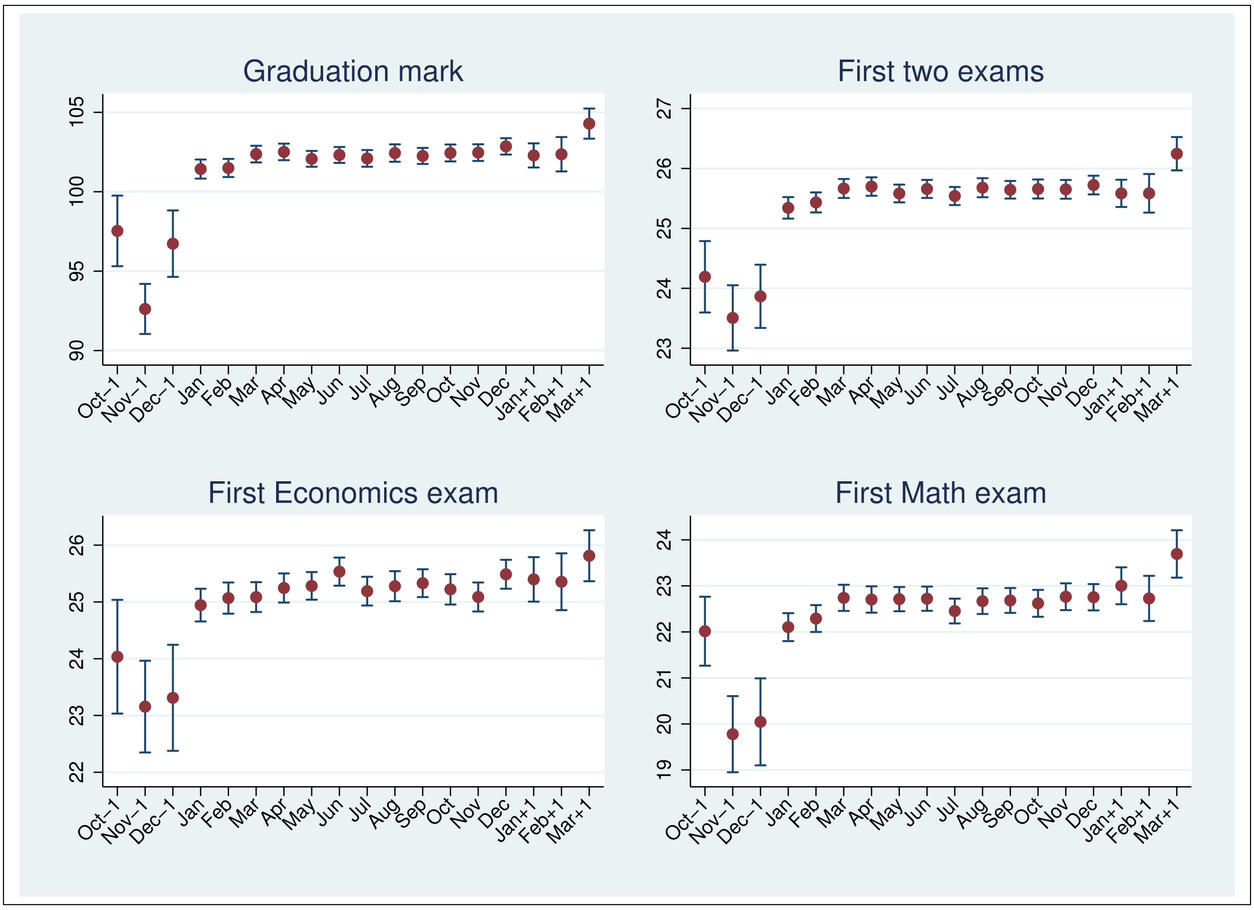


Figure 2: Conditional academic performance by month of birth

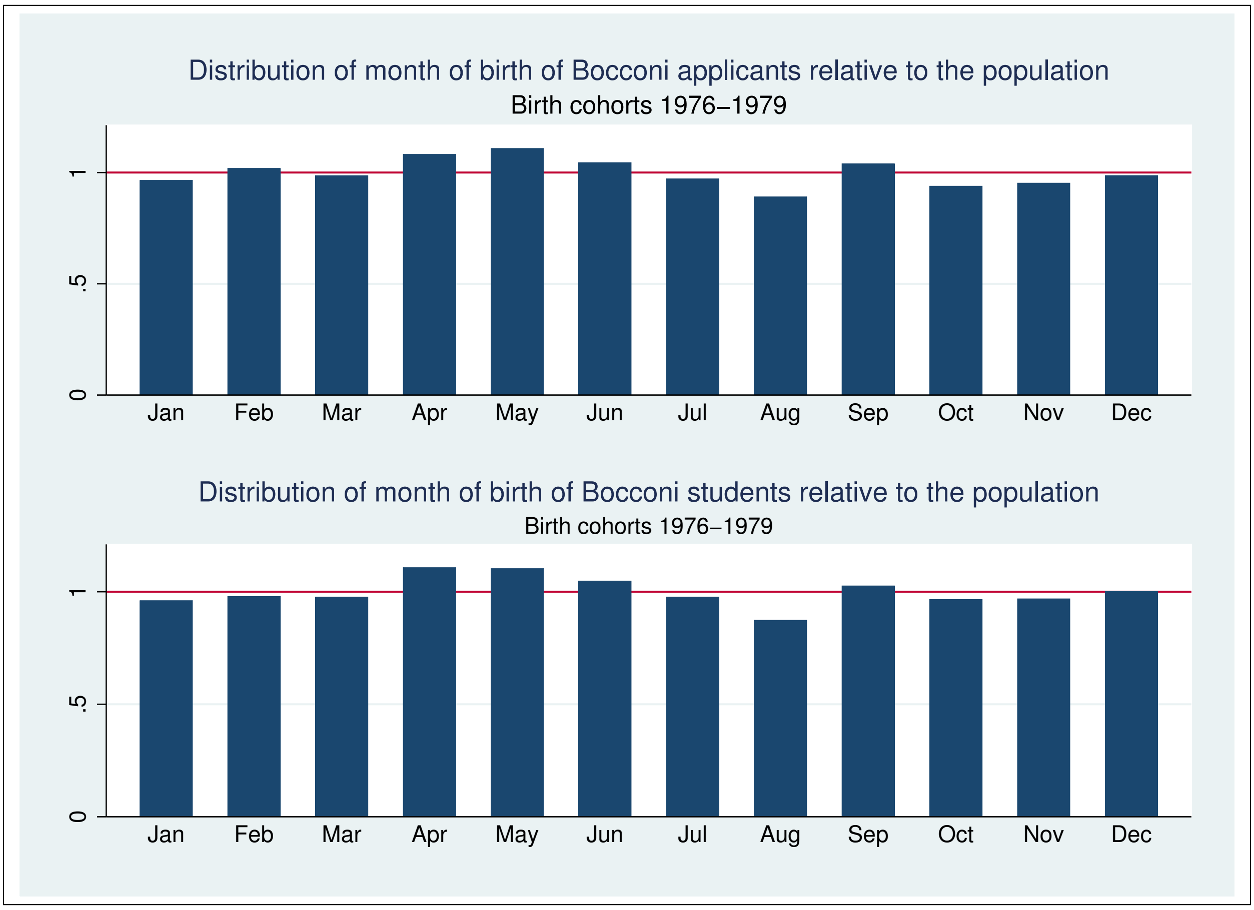


Figure 3: Relative distributions of month of birth

Tables

Table 1: Distribution of student births by cohort

year of first enrollment	typical year of birth	share of *regular* students	share of *older* students	share of *younger* students
1995	1976	0.837	0.069	0.108
1996	1977	0.857	0.059	0.106
1997	1978	0.882	0.047	0.093
1998	1979	0.861	0.044	0.123
	Total	0.857	0.045	0.121

Table 2: Month-of-birth distribution by cohort

	Year of first enrolment				
	1995	1996	1997	1998	Total
January	0.066	0.062	0.074	0.058	0.065
February	0.073	0.074	0.068	0.066	0.070
March	0.084	0.076	0.083	0.076	0.080
April	0.087	0.081	0.086	0.089	0.086
May	0.107	0.109	0.092	0.114	0.105
June	0.106	0.091	0.094	0.100	0.098
July	0.085	0.091	0.075	0.092	0.086
August	0.073	0.083	0.078	0.082	0.079
September	0.093	0.082	0.093	0.094	0.090
October	0.065	0.085	0.080	0.085	0.080
November	0.078	0.079	0.083	0.075	0.079
December	0.084	0.088	0.093	0.069	0.083
Total	1.00	1.00	1.00	1.00	1.00

Table 3: Descriptive statistics of Bocconi data

Variable	Late enrollees mean	Late enrollees (s.d.)	January mean	January (s.d.)	February to November mean	February to November (s.d.)	December Mean	December (s.d.)	Early enrollees mean	Early enrollees (s.d.)	Total mean	Total (s.d.)
Graduation mark[a]	95.74	(7.17)	101.49	(7.63)	102.25	(7.31)	102.83	(6.93)	102.96	(7.36)	101.93	(7.47)
Average grades by subject[b]:												
management	25.18	(1.88)	26.50	(2.05)	26.69	(1.89)	26.83	(1.82)	26.79	(1.98)	26.60	(1.94)
economics	24.12	(2.42)	25.80	(2.48)	26.03	(2.44)	26.14	(2.34)	26.26	(2.43)	25.93	(2.47)
math	22.29	(2.41)	23.78	(2.93)	24.09	(2.93)	24.34	(2.89)	24.40	(3.05)	24.01	(2.94)
history	26.27	(3.00)	27.50	(2.79)	27.51	(2.59)	27.70	(2.36)	27.69	(2.58)	27.47	(2.63)
foreign languages	25.94	(2.77)	27.61	(2.14)	27.56	(2.21)	27.52	(2.20)	27.60	(2.14)	27.46	(2.27)
law	23.89	(2.39)	25.43	(2.42)	25.57	(2.39)	25.82	(2.20)	25.91	(2.38)	25.51	(2.42)
Specialization:												
public administration	0.02	-	0.07	-	0.05	-	0.06	-	0.06	-	0.05	-
management	0.71	-	0.59	-	0.60	-	0.54	-	0.56	-	0.60	-
financial markets	0.08	-	0.09	-	0.09	-	0.09	-	0.10	-	0.09	-
law & economics	0.13	-	0.12	-	0.12	-	0.14	-	0.11	-	0.12	-
economics	0.05	-	0.07	-	0.09	-	0.10	-	0.12	-	0.09	-
economics & social sciences	0.02	-	0.07	-	0.06	-	0.06	-	0.05	-	0.06	-
High school results[c]	57.45	(29.03)	59.68	(33.11)	57.80	(35.06)	61.53	(32.75)	55.34	(37.68)	57.88	(34.76)
Admission test score[d]	68.23	(6.41)	70.71	(7.54)	71.39	(7.56)	71.39	(7.55)	71.81	(7.86)	71.21	(7.56)
Time to graduation[e]	24.34	(4.46)	22.09	(4.11)	21.96	(3.92)	21.80	(3.71)	21.93	(3.86)	22.09	(3.99)
Type of high school												
lyceum	0.66	-	0.79	-	0.75	-	0.75	-	0.81	-	0.76	-
technical-professional school	0.29	-	0.20	-	0.23	-	0.24	-	0.14	-	0.22	-
foreign school	0.05	-	0.01	-	0.01	-	0.01	-	0.05	-	0.02	-
1=female	0.28	-	0.42	-	0.44	-	0.45	-	0.39	-	0.42	-
1=resident outside Milan[f]	0.42	-	0.56	-	0.61	-	0.61	-	0.75	-	0.61	-
Family income (log)7	7.58	(4.85)	10.26	(1.01)	10.30	(1.15)	10.27	(1.26)	7.86	(4.88)	10.29	(1.15)
1=highest income bracket[g]	0.23	-	0.18	-	0.18	-	0.24	-	0.23	-	0.19	-
Number of students	377		337		4,437		436		650		6,237	

[a] Maximum = 110; pass = 66.

[b] Maximum = 30; pass = 18.

[c] Summary evaluation of high school performance, including final grade and marks in selected courses during the last two years. Range 0-100.

[d] Range 0-100. Average over various sections (reading comprehension, problem solving, computer use, et.)

[e] Time between September of the year of first enrolment and the graduation date (measured in quarters).

[f] Dummy = 1 if residence of the family of origin is outside the province of Milan.

[g] As recorded on the first year of registration. For students in the highest income bracket the actual income is not recorded.

Table 4: First stage regressions

Dependent variable:	Relative age[a]		1=early enrollees	1=late enrollees
	all students	regular students		
	[1]	[2]	[3]	[4]
PANEL A				
private pre-schools	-2.044***	-0.158	1.052***	-0.659***
per 100 children[b]	(0.402)	(0.113)	(0.214)	(0.215)
Observations	6,237	5,210	6,237	6,237
PANEL B				
private pre-schools	-2.042***	-0.155	1.051***	-0.659***
per 100 children[b]	(0.403)	(0.113)	(0.215)	(0.215)
(log) admission test score[c]	-0.098	-0.120**	0.041	0.002
	(0.075)	(0.052)	(0.047)	(0.035)
Observations	6,237	5,210	6,237	6,237

[a] Relative age is zero for students born in January of the regular cohort year and increases or decreases with each month of age.
[b] Number of registered private pre-schools in the province of residence over size of the birth cohort.
[c] Range 0-100. Average over various sections (reading comprehension, problem solving, computer use, et.). All regressions are estimated by OLS and include the following set of controls: gender, high school results, residence outside Milan, family income, dummies for academic year, high school type, regional dummies, cohort dummies and a constant. Standard errors in parentheses (clustered by province-birth year cells). * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 5: Relative age and academic performance

	OLS	IV	OLS Regular students
	[1]	[2]	[3]
PANEL A: dependent variable is *(log) graduation mark*[a]			
Relative age (/11)[b]	-0.006***	-0.033***	-
	(0.001)	(0.011)	
1= born February to November	-	-	0.003
			(0.003)
1= born December	-	-	0.009**
			(0.004)
Observations	6,237	6,237	5,210
F-test of excluded instruments	-	25.79	-
PANEL B: dependent variable *(log) average grade in the first and second academic years*[c]			
Relative age (/11)[b]	-0.005***	-0.040**	-
	(0.002)	(0.015)	
1= born February to November	-	-	0.005
			(0.003)
1= born December	-	-	0.009*
			(0.004)
Observations	6,237	6,237	5,210
F-test of excluded instruments	-	25.79	-

[a] Maximum = 110; pass = 66.

[b] Relative age is zero for students born in January of the regular cohort year and increases or decreases with each month of age.

[c] Exam grades range from 18 (pass) to 31 (full marks with honors).

All regressions include the following set of controls: gender, high school results, residence outside Milan, family income, dummies for academic year, high school type, regional dummies, cohort dummies and a constant. Standard errors in parentheses (clustered by province-birth year cells). * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 6: Relative age, ability and academic performance

	OLS	IV	OLS Regular students
	[1]	[2]	[3]
PANEL A: dependent variable is *(log) graduation mark*[a]			
Relative age (/11)[b]	-0.006***	-0.032***	-
	(0.001)	(0.011)	
1= born February to November	-	-	0.003
			(0.003)
1= born December	-	-	0.008*
			(0.004)
(log) admission test score[c]	0.081***	0.078***	0.087***
	(0.009)	(0.009)	(0.011)
Observations	6,237	6,237	5,210
F-test of excluded instruments	-	25.69	-
PANEL B: dependent variable *(log) average grade in the first and second academic years*[c]			
Relative age (/11)[b]	-0.004**	-0.039***	-
	(0.002)	(0.014)	
1= born February to November	-	-	0.004
			(0.003)
1= born December	-	-	0.008*
			(0.004)
(log) admission test score[c]	0.129***	0.125***	0.136***
	(0.013)	(0.013)	(0.015)
Observations	6,237	6,237	5,210
F-test of excluded instruments	-	25.69	-

[a] Maximum = 110; pass = 66.
[b] Relative age is zero for students born in January of the regular cohort year and increases or decreases with each month of age.
[c] Range 0-100. Average over various sections (reading comprehension, problem solving, computer use, et.).
[d] Exam grades range from 18 (pass) to 31 (full marks with honors).
All regressions include the following set of controls: gender, high school results, residence outside Milan, family income, dummies for academic year, high school type, regional dummies, cohort dummies and a constant. Standard errors in parentheses (clustered by province-birth year cells). * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 7: Relative age effects over time

	OLS	IV	OLS Regular students
	[1]	[2]	[3]
Relative age (/11)[a]	-0.006***	-0.033**	-
	(0.002)	(0.012)	
1= born February to November $[F\_N]$	-	-	0.003
			(0.003)
1= born December $[Dec]$	-	-	0.009**
			(0.004)
Relative age$\times$[ac. year $= 2$]	0.000	0.000	-
	(0.000)	(0.000)	
Relative age$\times$[ac. year $= 3$]	0.000	0.000	-
	(0.000)	(0.000)	
Relative age$\times$[ac. year ≥ 2]	0.000	0.000	-
	(0.000)	(0.000)	
$[F\_N] \times$ [ac. year $= 2$]	-	-	-0.000
			(0.000)
$[F\_N] \times$ [ac. year $= 3$]	-	-	0.000
			(0.000)
$[F\_N] \times$ [ac. year ≥ 4]	-	-	-0.000
			(0.000)
$[Dec] \times$ [ac. year $= 2$]	-	-	-0.000
			(0.000)
$[Dec] \times$ [ac. year $= 3$]	-	-	-0.000
			(0.000)
$[Dec] \times$ [ac. year ≥ 4]	-	-	-0.000
			(0.000)
Observations	24,794	24,794	20,713

[a] Relative age is zero for students born in January of the regular cohort year and increases or decreases with each month of age.

In all columns the dependent variable is the average grade in each academic year (i.e. there are 4 observations for each student). Exam grades range from 18 (pass) to 31 (full marks with honors). All regressions include the following set of controls: gender, high school results, residence outside Milan, family income, dummies for academic year, high school type, regional dummies, cohort dummies, academic year dummies and a constant. Standard errors in parentheses (clustered at the level of the individual student). * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 8: The effect of relative age on first grades by subject areas[a]

	Management	Economics	Mathematics & statistics	Foreign language	Law
	[1]	[2]	[3]	[4]	[5]
PANEL A: IV estimates					
Relative age (/11)[b]	-0.021	-0.038**	-0.026***	-0.019*	-0.024*
	(0.015)	(0.016)	(0.009)	(0.011)	(0.012)
Observations	6,237	6,237	6,237	6,237	6,237
PANEL B: IV estimates, controlling for entry test score					
Relative age (/11)[b]	-0.009	-0.036**	-0.025***	-0.018*	-0.023*
	(0.006)	(0.016)	(0.009)	(0.011)	(0.012)
(log) admission test score[c]	0.120***	0.139***	0.097***	0.072***	0.097***
	(0.012)	(0.016)	(0.010)	(0.012)	(0.012)
Observations	6,237	6,237	6,237	6,237	6,237
PANEL C: Month of birth using only regular students					
1= born February to November	0.004	0.005	0.002	-0.002	-0.002
	(0.004)	(0.005)	(0.004)	(0.004)	(0.005)
1= born December	0.008*	0.016**	0.009**	-0.003	0.007
	(0.004)	(0.007)	(0.004)	(0.005)	(0.006)
Observations	5,210	5,210	5,210	5,210	5,210
PANEL D: Month of birth using only regular students, controlling for entry test score					
1= born February to November	0.003	0.004	0.002	-0.003	-0.002
	(0.004)	(0.005)	(0.004)	(0.004)	(0.005)
1= born December	0.007	0.015**	0.008*	-0.003	0.006
	(0.006)	(0.007)	(0.004)	(0.005)	(0.006)
(log) admission test score[c]	0.127***	0.152***	0.103***	0.080***	0.111***
	(0.013)	(0.017)	(0.010)	(0.013)	(0.013)
Observations	5,210	5,210	5,210	5,210	5,210

[a] Defined according to the department responsible for organizing and teaching the subject. The dependent variable is the log of the grade obtained in the first exam taken in each subject area, which ranges from 18 (pass) to 31 (full marks with honors)

[b] Relative age is zero for students born in January of the regular cohort year and increases or decreases with each month of age.

[c] Range 0-100. Average over various sections (reading comprehension, problem solving, computer use, et.).

All regressions include the following set of controls: gender, high school results, residence outside Milan, family income, dummies for academic year, high school type, regional dummies, cohort dummies and a constant. Standard errors in parentheses (clustered by province-birth year cells). * significant at 10%; ** significant at 5%; *** significant at 1%

Table 9: Relative age, ability and academic performance

	(log) graduation mark[a]		(log) average grade in the first two years[c]		(log) first Math/Stat grade[c]	
	[1]	[2]	[3]	[4]	[5]	[6]
Panel A: IV estimates						
Relative age (/11)[b]	-0.025**	-0.023**	-0.039***	-0.037**	-0.038*	-0.035*
	(0.011)	(0.011)	(0.015)	(0.014)	(0.021)	(0.021)
Quintiles dummies of entry test scores:						
1=2nd quintile	-	0.002	-	0.007***	-	0.006*
		(0.002)		(0.002)		(0.004)
1=3rd quintile	-	0.010***	-	0.014***	-	0.014***
		(0.003)		(0.003)		(0.004)
1=4th quintile	-	0.017***	-	0.021***	-	0.022***
		(0.003)		(0.003)		(0.004)
1=5th quintile	-	0.021***	-	0.036***	-	0.039***
		(0.003)		(0.004)		(0.006)
Observations	6,237	6,237	6,237	6,237	6,237	6,237
Panel B: Month of birth using only regular students						
1= born February to November	0.003	0.002	0.004	0.004	0.005	0.004
	(0.003)	(0.003)	(0.003)	(0.003)	(0.006)	(0.006)
1= born December	0.008**	0.008*	0.009*	0.008*	0.016*	0.015*
	(0.004)	(0.004)	(0.004)	(0.004)	(0.006)	(0.006)
Quintiles dummies of entry test scores:						
1=2nd quintile	-	0.003	-	0.011***	-	0.007*
		(0.003)		(0.002)		(0.004)
1=3rd quintile	-	0.013***	-	0.018***	-	0.013***
		(0.003)		(0.003)		(0.004)
1=4th quintile	-	0.019***	-	0.025***	-	0.026***
		(0.003)		(0.004)		(0.004)
1=5th quintile	-	0.023***	-	0.039***	-	0.041***
		(0.003)		(0.005)		(0.006)
Observations	5,210	5,210	5,210	5,210	5,210	5,210

[a] Maximum = 110; pass = 66.

[b] Relative age is zero for students born in January of the regular cohort year and increases or decreases with each month of age.

[c] Exam grades range from 18 (pass) to 31 (full marks with honors).

All regressions include the following set of controls: gender, high school results, entry test score, residence outside Milan, family income, dummies for academic year, high school type, regional dummies, cohort dummies, the full interactions of season dummies and year of birth and a constant. Standard errors in parentheses (clustered by province-birth year cells). * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 10: Relative age, season of birth and academic performance

	OLS	IV	OLS Regular students
	[1]	[2]	[3]
Dependent variable: (log) graduation mark[a]			
Relative age (/11)[b]	-0.006*	-0.246	-
	(0.003)	(0.184)	
1= born February to November	-	-	-0.004
			(0.005)
1=born December	-	-	0.008*
			(0.003)
1=winter	-0.023	-0.023	-0.014***
	(0.021)	(0.048)	(0.005)
1=summer	-0.021	-0.027	-0.004
	(0.013)	(0.031)	(0.005)
1=fall	-0.029	-0.166*	-0.007
	(0.013)	(0.107)	(0.005)
Observations	6,237	6,237	5,210
Dependent variable: (log) average grade in the first two years[c]			
Relative age (/11)[b]	-0.006*	-0.431	-
	(0.003)	(0.273)	
1= born February to November	-	-	-0.003
			(0.005)
1= born December	-	-	0.008*
			(0.004)
1=winter	-0.001	-0.001	-0.018*
	(0.024)	(0.072)	(0.006)
1=summer	-0.016	-0.027	-0.008***
	(0.017)	(0.050)	(0.007)
1=fall	-0.017	-0.261	-0.010*
	(0.017)	(0.159)	(0.004)
Observations	6,237	6,237	5,210
Dependent variable: (log) first Math/Stat grade[c]			
Relative age (/11)[b]	-0.007	-0.477*	
	(0.005)	(0.348)	
1= born February to November			-0.001
			(0.009)
1= born December			0.015**
			(0.006)
1=winter	-0.052**	-0.051	-0.001
	(0.020)	(0.071)	(0.009)
1=summer	-0.056*	-0.068	-0.010*
	(0.030)	(0.063)	(0.006)
1=fall	-0.040*	-0.309	0.010
	(0.023)	(0.203)	(0.009)
Observations	6,237	6,237	5,210

[a] Maximum = 110; pass = 66.

[b] Relative age is zero for students born in January of the regular cohort year and increases or decreases with each month of age.

[c] Exam grades range from 18 (pass) to 31 (full marks with honors).

All regressions include the following set of controls: gender, high school results, entry test score, residence outside Milan, family income, dummies for academic year, high school type, regional dummies, cohort dummies, the full interactions of season dummies and year of birth and a constant. Standard errors in parentheses (clustered by province-birth year cells). * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 11: Relative age and admission test scores

Admission years:	1995-1998		
	OLS	IV	OLS Regular students
	[1]	[2]	[3]
Relative age (/11)[a]	-0.010***	-0.015**	-
	(0.002)	(0.007)	
1 = born February to November	-	-	0.005
			(0.004)
1 = born December	-	-	0.009**
			(0.005)
Observations	12,426	12,426	9,490
F-test of excluded instruments	-	22.26	-

[a] Relative age is zero for students born in January of the regular cohort year and increases or decreases with each month of age.
[b] January=0, December=11.
The dependent variable is the log of the individual entry test score. All regressions include the following set of controls: gender, high school results, residence outside Milan, dummies for high school type, regional dummies, cohort dummies and a constant. Standard errors in parentheses (clustered by province-birth year cells). * significant at 10%; ** significant at 5%; *** significant at 1%

Table 12: Month of birth and admission test by areas

Admission years:	2000-2002							
	Overall result	reading compreh.	spatial perception	computer use	math reasoning	verbal relations	logics of images	verbal patterns
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
PANEL A: All students - IV estimates								
Relative age (/11)[a]	-0.156**	-0.045	-0.060	-0.131*	0.012	-0.122	-0.084	0.012
	(0.072)	(0.087)	(0.090)	(0.079)	(0.072)	(0.081)	(0.088)	(0.083)
Observations	10,231	10,231	10,231	10,231	10,231	10,231	10,231	10,231
F-test excl. instr.	20.27							
PANEL B: Regular students only								
1 = born February	0.082*	0.041	0.072	0.104**	0.022	0.023	0.008	0.031
to November	(0.045)	(0.047)	(0.057)	(0.050)	(0.045)	(0.046)	(0.042)	(0.049)
1 = born December	0.140**	0.081	0.121*	0.178***	0.031	0.041	0.102**	0.077
	(0.056)	(0.059)	(0.064)	(0.061)	(0.058)	(0.058)	(0.051)	(0.061)
Observations	7,619	7,619	7,619	7,619	7,619	7,619	7,619	7,619

[a] Relative age is zero for students born in January of the regular cohort year and increases or decreases with each month of age.
The dependent variable is the normalized test score of the overall test (column 1) or of each section (columns 2 to 8). See the appendix for a description of the content of each test section.All regressions include the following set of controls: gender, high school results, residence outside Milan, dummies for high school type, regional dummies, cohort dummies and a constant. Standard errors in parentheses (clustered by province-birth year cells). * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 13: Descriptive statistics of ISAS data

	January		February to November		December		Total	
Variable	mean	(s.d.)	mean	(s.d.)	mean	(s.d.)	Mean	(s.d.)
Social behavior								
1=no sport[a]	0.22	-	0.25	-	0.27	-	0.25	-
1=no discos[b]	0.12	-	0.11	-	0.14	-	0.11	-
1=stable relationship[c]	0.66	-	0.60	-	0.50	-	0.60	-
1=ever had sex[d]	0.59	-	0.58	-	0.51	-	0.58	-
monthly frequency of sexual intercourse	3.44	(6.29)	3.16	(5.62)	1.84	(4.13)	3.06	(5.56)
monthly frequency of sexual intercourse (> 0)	7.20	(7.48)	6.65	(6.57)	5.07	(5.57)	6.58	(6.58)
Background characteristics								
1=female	0.57	-	0.59	-	0.60	-	0.60	-
1=lives with parents	0.81	-	0.72	-	0.68	-	0.72	-
High school grade[e]	83.13	(13.34)	84.72	(11.77)	83.15	(11.79)	84.47	(11.89)
Father's education								
secondary	0.46	-	0.42	-	0.45	-	0.43	-
tertiary	0.16	-	0.17	-	0.21	-	0.17	-
Mother's education								
secondary	0.48	-	0.42	-	0.39	-	0.42	-
tertiary	0.16	-	0.14	-	0.18	-	0.15	-
Number of students	124		1,551		162		1,837	

[a] Dummy coded 1 for students who answer "never" to the following question: *During the school year, do you practice any sport or physical activity?*
[b] Dummy coded 1 for students who answer "never" to the following question: *Do you go to clubs or other places where you can dance?*
[c] Dummy coded 1 for students who have a steady relationship at the time of the interview.
[d] Dummy coded 1 for students who answer "yes" to the following question: *Have you ever had sexual intercourse?*
[e] Range 0-100.

Table 14: Month of birth and social behaviour

	1=no sport[a]	1=no discos[b]	monthly sex frequency[c]	Monthly sex frequency (> 0)[d]	1=current relationship[e]
Estimation method	probit	probit	OLS	OLS	probit
mean of dep. variable	0.24	0.11	3.06	6.60	0.59
	[1]	[2]	[3]	[4]	[5]
Month of birth					
1= born February to November	0.045	-0.072	0.184	-0.626	-0.160
	(0.139)	(0.159)	(0.544)	(0.977)	(0.153)
marg. effect	0.007	-0.013	0.184	-0.626	-0.062
1= born December	0.083	0.076	-1.223*	-2.588**	-0.460**
	(0.177)	(0.198)	(0.629)	(1.204)	(0.188)
marg. effect	0.011	0.014	-1.223*	-2.588**	-0.181**
Observations	1,689	1,690	1,647	810	1,319

[a] Dummy coded 1 for students who answer ”never” to the following question: *During the school year, do you practice any sport or physical activity?*

[b] Dummy coded 1 for students who answer ”never” to the following question: *Do you go to clubs or other places where you can dance?*

[c] Coded to zero for students who have never had sexual intercourse.

[d] Students who have never had sexual intercourse are excluded. Dummies for home-town size are omitted to increase sample size.

[e] Dummy coded 1 for students who have a steady relationship at the time of the interview.

Additional controls: gender, high school grade, dummies for region of birth and region of the university, home-town size, dummies for mother’s and father’s education, dummy for students living on their own. The sample is restricted to regular students only. Robust standard errors in parentheses. The marginal effects are computed at the average of the explanatory variables. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 15: Hours of self studying at home - PISA 2003 (Italy)

	total time	science	By subject: mathematics	language
	[1]	[2]	[3]	[4]
1= born February to November	0.215	0.013	0.055	0.102**
	(0.148)	(0.046)	(0.048)	(0.050)
1= born December	0.418**	0.027	0.119*	0.157**
	(0.195)	(0.062)	(0.064)	(0.064)
Observations	16,149	16,405	16,385	16,462

Additional controls: gender, dummies for father and mother education; foreign born dummy; second generation dummy; school type dummies. The sample is restricted to regular students only. The dependent variable is the self-reported number of hours dedicated to self-studying at home. Robust standard errors in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

Appendix A. Additional results

In an 2SLS setting, the monotonicity assumption cannot be normally tested. Nevertheless, it is still possible to show that it fails by providing evidence that the sign of the coefficient on the excluded instrument in the first stage regression changes across subgroups. In Table A.1 we provide such evidence for month of birth (m_i in the terminology of Section 3) as an instrument for relative age ($ageR_i$), using the same data of Section 4.

In column 1 we report what would be the first stage regression on the entire sample and we find that the coefficient on the instrument (the calendar order of birth month) is negative and highly significant. In columns 2, 3 and 4 we replicate the same regression for different subgroups: students born between January and March (column 1), students born between April and September (column 2) and students born between October and December (column 3). Interestingly, the instrument has a positive, although not significant, coefficient for the first group and it turns negative for the other groups, increasing in absolute value for students born in the latest months of the year.

These results clearly show that the calendar order of birth month as an instrument for relative age violates monotonicity. In fact, students born before April have the opportunity to enter school early and their probability of doing so increases if they are born early in the year, which is what leads to the positive coefficient. Most of the others are regular students, for whom relative age is mechanically negatively related to month of birth.

The estimates in columns 5 and 6 confirm this intuition. In these columns we report the results of two simple linear probability models where the explanatory variables are the same as before and the dependent variable is an indicator for being a early (column 5) or a late (column 6) enrollee. Results show that being born late in the year reduces the likelihood of entering school early while it increases the likelihood of being delayed during the school track.

Table A.1: Relative age and month of birth

Dependent variable:	Relative age[a]				1=early enrollee	1=late enrollee
Sub-population:	all students	born before Apr.	born btw Apr.-Sept.	born after Sept.	all students	all students
	[1]	[2]	[3]	[4]	[5]	[6]
Calendar order of birth month[b]	-0.063***	0.002	-0.063***	-0.081***	-0.022***	0.003***
	(0.002)	(0.016)	(0.004)	(0.013)	(0.001)	(0.001)
Observations	6,237	1,531	3,300	1,406	6,237	6,237

[a] Relative age is zero for students born in January of the regular cohort year and increases or decreases with each month of age.
[b] January=0, December=11.
All regressions are estimated by OLS and include the following set of controls: gender, high school results, residence outside Milan, family income, dummies for academic year, high school type, regional dummies, cohort dummies and a constant. Robust standard errors in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

Appendix B. Brief description of the attitudinal entry test

The test, in its 1995-1998 version, includes 8 sections. The total score is the sum of the scores obtained in each section. Below we report one sample question for each of the 8 sections. The number in brackets next to section's name indicates the maximum score that is obtained by answering correctly to all the questions in the section.

1. **Reading comprehension (20)**

   Sample question. *Franz Joseph was crowned Emperor of Austria following the Austrian crisis of 1848, on the abdication of his uncle Ferdinand I and the renunciation of his father, the Archduke Franz Karl […].*

   Questions: *Franz Joseph was crowned Emperor of Austria following: a) the death of the Archduke Franz Karl; b) the renunciation of his uncle Ferdinand II; c) the abdication of his mother; d) the Austrian crisis of 1848; e) the death of his mother.*

   Answer. d).

2. **Spatial perception abilities (20)**

   Sample question. *In the following table you find five Original sequences on the left and five Copies on the right. You have to identify which copy or copies are not identical to the originals.*

qzbafjnioacrirceijyy	-------*A*-------	*Qzbafjnioacrirceijyy*
cdefgiouuuimqsyankgi	-------*B*-------	*Cdefgiouuuimqsyhnkgi*
rtsqlaqueapuiuelusgo	-------*C*-------	*Rtsqlaqueapsiuelusgo*
ahmpzjyioankuuliesay	-------*D*-------	*Ahmpzjyioankuuliesay*
mcuvryalduhjyrofeozn	-------*E*-------	*Mcuvryalduhjyrofeozn*

   Answer. *C and B*

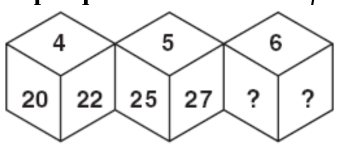
3. **Computer use (15)**

   Sample question. *Which of the following Microsoft Office software would you use to open a file named 'students.mdb': a) MS Word; b) MS Excel; c) MS Powerpoint; d) MS Access.*

   Answer. *d) MSAccess.*

4. **Math reasoning (20)**

   Sample question. *Look at the following figure:*



   Which of the following pairs of numbers should go where the question marks are placed: a) 30-32; b) 15-17; c)30-28; d) 50-52; e) 35-40?

   Answer. *a) 30-32*

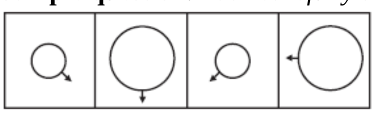
5. **Verbal relations (20)**

   Sample question. *Which of these words is not similar to the others? Genoa, Turin, Vienna, Milan, Venice.*

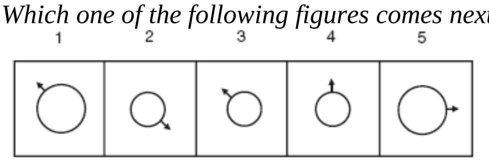
   Answer. *Vienna, since it is the only non Italian city.*

6. **Logics of images (10)**

   Sample question. *Look carefully at the following sequence:*



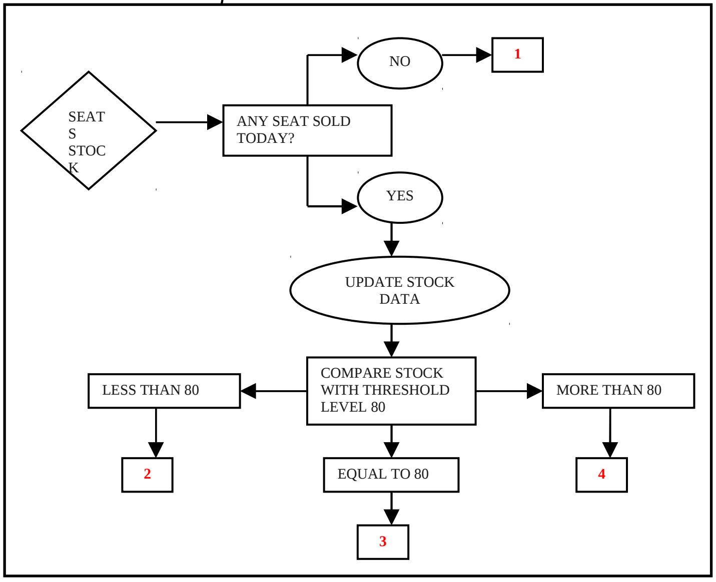
   Which one of the following figures comes next in the above sequence?



Answer. *The third figure. In fact, in the original sequence small and large figures alternate and rotate by 45° at each step.*

7. Verbal and logical patterns (10)

Sample question. *A retailer who sells seats wants to have in stock enough seats to be able to satisfy her clients' requests at all times. She decides to always have at least 80 seats in stock. If there are more than 80 seats in stocks, she does not file a new order to the producer. When there are exactly 80 seats in stocks, she files a regular order to the producer. When there are less than 80 seats in stock, she files an urgent order to the producer. At the end of each day, the retailers counts the seats in stock and decides whether to submit a new order and of which type (regular or urgent). Now, look at the diagram below and, according to the above description, indicate what action the retailer should take at each numbered square.*



Answer. *1 = no action; 2 = submit urgent order; 3 = submit order; 4 = no action*

8. General knowledge (15)

Sample question. *Where does the Gulf Stream originate from? a) from the Gulf of St. Lawrence; b) from the Gulf of California; c) from the Gulf of Mexico; d) from the Hudson Bay; e) from the Indian Ocean.*

Answer. *c) from the Gulf of Mexico.*