ABSTRACT
Utilizing comprehensive administrative data from Norway I investigate long-term birth month effects. I demonstrate that the oldest children in class have a substantially higher GPA than their younger peers. The birth month differences are larger for low-SES children. Furthermore, I find that the youngest children in class are lagging significantly behind their older peers on the educational track, and need more time to reach the same level of earnings.

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1. Introduction
Since most education systems have a single cut-off date for age at school enrollment, the age difference between the youngest and oldest pupils in class is close to one year. A number of studies have shown that this age difference has a significant impact on school performance, not only during the early grades when the age difference is relatively more pronounced, but also persisting into higher grades: The oldest pupils in class outperform their younger peers (see e.g. Bedard and Duhey 2006). If this relative age effect disappears after compulsory school, such age-related performance gaps may be of less importance. On the other hand, if relative age effects persist into adulthood, this may have important implications for adult outcomes and productivity.

In this paper I explore birth month effects on school performance, educational achievement and labor market performance across birth months. Several studies find that the variation in outcomes is larger for boys than girls, in particular on school performance, which may suggest that boys are more receptive to external conditions as relative age in class. For evidence on ‘the greater male variability’, see for example, Baye and Monseur (2016). Empirical evidence also suggest that girls and boys respond differently to peer effects (see e.g. Black, Devereux, and Salvanes 2013), possibly also to peers’ age. I therefore pay special attention to heterogeneous effects across gender. Furthermore, I investigate how birth month effects vary across socioeconomic status. This is important since several studies suggest that higher educated parents to a larger extent allocate more time and better support for the child when school performance drops. For instance, Crawford, Dearden, and Greaves (2011) find that parental investment increases substantially for the youngest relative to the oldest in class at the time when the child enrolls in school. Hence, children from more advantaged families may be less negatively affected of being among the youngest in class.

There are several reasons for why birth month may have an effect on school performance and long-term outcomes. First, age differences in class obviously stem from different ages at school start. If being older and more mature has a positive effect on learning, the oldest in class have an advantage.
when starting school. In accordance with Heckman’s theories on skill accumulation, this initial advantage will not only remain but will also increase over time, since the initially most advantaged pupils progress through the curriculum at a faster rate (Heckman 2006). Second, early tracking in the schooling system may propagate initial maturity differences related to age differences (Bedard and Duhey 2006). Third, the oldest children in class are stronger and more mature, and this relative standing in class may have an effect on self-esteem, aspirations and the child’s social development (Thompson, Barnsley, and Battle 2004). Fourth, since students are evaluated at the same point in time, the oldest pupils in class may outperform their younger peers simply because they are older at the time of assessment. Finally, if birth month has an impact on final grades from compulsory school, this is likely to affect educational achievement and future career, firstly by performance-based tracking into high schools. I do not intend to identify or quantify the effect of any of these mechanisms separately. A potential birth month effect will therefore reflect a mix of these and possibly more mechanisms.

I investigate the birth month effect by utilizing a comprehensive registry database containing demographic information (gender, age, and country of birth) and annual records for education level and earnings for all Norwegians during the period 1992–2003. Personal identifiers allow me to merge the registry data to an educational database containing final grades from compulsory school for the graduating cohorts 2002–2007. Links between parents and children allow for identifying socioeconomic status, here defined as whether the mother is a high school graduate or not. I allow for a non-linear relationship between birth month and outcomes. Outcomes are in all analyses observed at a given point in time. The birth month effect is identified by using ordinary least-squares regression models including birth month dummies. In order to obtain an estimate for effect of age at school start that adjusts for differences in biological at time of observation, I also investigate the birth month effect around the cut-off date for school enrollment.

A potential challenge when comparing outcomes for children born in different birth months is that other characteristics also affecting outcomes may be correlated with birth month. If, for example, more advantaged families time their births to early in the year, then positive outcomes associated with being relatively old in class may be entirely due to parental resources. I deal with this challenge in three different ways. First, the rich dataset allows me to investigate if the estimated birth month effects are robust to controlling for a number of parent and child characteristics. Second, having unique identifiers for parents, the dataset allows me to control for mother fixed effects and identify the birth month effect only between siblings. Third, I investigate directly if parent characteristics are associated with birth month.

I find that the oldest in class perform significantly better in school than their younger peers, in line with existing empirical evidence. The difference in the 10th grade point average (GPA) between the youngest and oldest in class constitutes as much as around 20% of a standard deviation. The birth month effect is of similar magnitude for boys and girls. The effect is robust to controlling for background characteristics. Also when controlling for mother fixed effects I find the same effect, suggesting that the performance gap is not related to parent characteristics associated with birth month. The birth month effect on GPA is more pronounced for low-SES children. This may reflect that parental resources and support may offset the drawback of being relatively young in class.

Observing longer term outcomes, I find that children born early in the year are more likely than their younger peers to proceed directly from to high school after compulsory school and graduate at age 19, and more likely to enroll into college. I also find that they have higher earnings at age 30. Effects on educational achievement are of similar magnitude for boys and girls, but the birth month effects on earnings are more pronounced for boys. When utilizing the discontinuity around the cut-off date for school enrollment, I find that starting school younger has a positive effect on graduating from high school at age 19, but no effect on college enrollment (age 25) or earnings at age 30. All together, this suggest that the advantage of a head start on the educational track and in the labor market is offset by negative effects of being born late in the year.

This study contributes to the literature in two important ways: First, this is the first study to control for fixed unobservable mother characteristics that possibly generate a birth month effects. In this
paper I demonstrate that birth month effects on school performance, high school completion at age 19 and earnings at age 30 are robust to controlling for mother fixed effects. Second, by using two different approaches to identify birth month effects, I reconcile findings from existing literature, and show that although the relatively youngest in class lag behind their older peers, they catch up by the time they reach the same biological age.

The remainder of the paper is laid out as follows: Section 2 provides a theoretical framework and overview of existing literature. Section 3 gives a brief introduction to the Norwegian schooling system. Section 4 describes the empirical strategy and Section 5 describes the data and construction of central variables. Results are presented in Section 6, and Section 7 concludes.

2. Theoretical framework and previous literature

This paper joins an extensive literature on birth month effects. There are several studies investigating how age differences in class affects school performance, and there is convincing empirical evidence for the oldest students to outperform their younger peers. For instance, see Strøm (2004) on Norwegian data; Crawford, Dearden, and Greaves (2011) on British data; Jürges and Schneider (2011), Puhani and Weber (2007), and Mühlenweg and Puhani (2010) on German data. For differential probabilities across relative age of entering academic or high ability tracks, see, for example, Jürges and Schneider (2011). In particular, Bedard and Duhey (2006) find that the oldest pupils in class outperform their younger peers across a large number of countries and different cut-off dates. Interestingly, despite similar effects across countries on test scores at the fourth grade level, they find substantial variation in effects at eighth grade level, and point to the fact that different education structures across countries are likely to have an impact on the relative age effect. For instance, they find substantially smaller age effects for countries practicing performance based promotion to the next grade level and ability based early tracking. The Norwegian education structure, on the other hand, is characterized by substantial rigidity, with few children enrolling into school earlier or later than according to the statutes, social/automatic promotion from one grade level to the next, and no formal tracking before high school.

There is some empirical evidence suggesting that the effects of age at school start is stronger for boys than for girls. Cascio and Schanzenbach (2016) find using US data that the probability of grade retention is significantly lower for relatively old boys than relatively old girls, but there are no gender differences in effects of age at school start on test scores in 8th grade. Regarding socioeconomic status, investigations for the US tend to find stronger birth month effects for advantaged children, but the effects tend to fade away as children progress through school, see Elder and Lubotsky (2009) and Cascio and Schanzenbach (2016). For the UK, Crawford, Dearden, and Meghir (2010) find no differences across socioeconomic status.

The literature on long-term effects of age differences in class is less extensive and also less conclusive. This can partly be explained by different approaches to identify birth month effects. Final grades from compulsory schooling is a ‘one shot’ measure achieved at a given point in time, unadjusted for differences in biological age at time of observation. Longer term outcomes, however, in particular earnings, change and may be observed continuously over the life span. Hence, it is possible to compare outcomes at a given biological ages. Existing literature on long-term effects divides into these two main strands. One strand consists of studies identifying long-term effects of age differences and peer effects within the classroom, that is, between individuals enrolling and graduating from school at the same time, and thereby march in pace from school and into the labor market. The other strand consists of studies identifying the impact of school starting age, and utilizes the discontinuity occurring around the cut-off date for school enrollment.

The following stylized model of earnings differences illustrates how the two approaches capture different mechanisms and consequently lead to different birth month estimates. Obviously, the model is parsimonious and intended only to illustrate some main mechanisms, and is not an attempt at a full count of all potential birth month effects.
Assume that earnings \((E)\) observed at a given point in time is affected by biological age, \(f(A)\); labor market experience (time since graduation), \(h(W)\); age at school start, \(g(\text{SS})\); relative age in class, \(k(R)\); and other individual characteristics that are balanced across birth months. The earnings differential, \(dE\), between individuals with different birth months is:

\[
dE = f(A)dA + h(W)dW + g(\text{SS})d\text{SS} + k(R)dR.\]

The obvious identification challenge is the strong (or even perfect) correlation between \(A\), \(W\), \(SS\), and \(R\). The frequently used approaches to identify the impact of these mechanisms are to compare earnings for individuals \((i)\) within the same school cohort, consequently holding work experience \((W)\) constant; or \((ii)\) at the same biological age, that is, around the cut-off date for school enrollment, holding age \((A)\) constant. The figure below illustrates a timeline of birth months, and shows how different year and month specific school cohorts are compared when utilizing the two approaches. Birth year, \(c\), is defined according to the school cohort and enrollment regulations, which in Norway coincides with the calendar year.\(^5\) The shaded cells refer to the oldest individuals within a school cohort (Group I) and the youngest individuals in two adjacent school cohorts (Group II and Group III). Notably, at a given point in time Group III and Group I are of approximately the same biological age, but Group I start school one year later that Group III.

When comparing individuals within a school cohort, earnings of Group I and Group II are compared \((E_{II} vs E_{I})\), while comparing for a given biological age implies comparing earnings of Group I and Group III \((E_{III} vs E_{I})\). Earnings are observed at the same point in time for all three groups. For simplicity, we assume that the impact of \(A\), \(W\), \(SS\), and \(R\) on earnings is linear. The reduced form effect on earnings, \(dE\), then shows that the two approaches capture the following mechanisms:

\[
dE = 12 f(A) + 12 g(\text{SS}) + 12 k(R) + 0h(W) = 12[g(\text{SS}) + k(R) + f(A)], \quad (i)
\]

\[
dE = 0f(A) + 12 g(\text{SS}) + 12 k(R) - 12h(W) = 12[g(\text{SS}) + k(R) - h(W)]. \quad (ii)
\]

The two equations show that differences in birth month estimates from the two approaches stem from \((i)\) the impact of biological age differences; and \((ii)\) the impact of graduating from compulsory school (and potentially entering the labor market) one year earlier. The latter is particularly likely to have an impact when investigating early-career labor market outcomes. Consequently, the interpretation of the birth month estimates differ substantially across approaches, and the estimates are not directly comparable. Rather, they should be considered as complementary in terms of achieving a more complete understanding of mechanisms leaving imprints on long-term outcomes.

A particularly relevant study reconciling these two approaches and magnifies how they yield different estimates, is Røed Larsen and Solli (2017): Comparing within academic cohorts, the relatively younger have an advantage in early-career years that translates into a disadvantage in late career years. On the other hand, when utilizing the cut-off date comparing across school cohorts, the relatively youngest have an advantage in early-career years since they enter the labor market one year earlier, an advantage that rapidly fades out and is counterbalanced by mechanisms disfavoring the relatively youngest in class.

Other empirical evidence is limited to comparison either within or across cohorts. Comparison within a school cohort include Bedard and Duhey (2006), that find that the youngest children in class have a lower probability of participating in pre-university programs (Canada and US) and are
underrepresented in accredited four-year college enrollments (US). Crawford, Dearden, and Greaves (2013) find that the youngest within an academic cohort is 1.2 percentage points less likely to achieve a degree level qualification, but find no effects on labor market outcomes when investigating earnings on the whole cross-section of individuals aged 25–64. Kawaguchi (2011) finds that the youngest in class has lower educational attainment than the oldest in class, and the effects are particularly strong for males. Observing earnings at age 30–34 he finds that the youngest men within a school cohort have 4% lower earnings than the oldest. Utilizing German data Fertig and Kluve (2005) find no evidence that age differences within a school cohort has an impact on educational achievement.

There are two particularly relevant contributions comparing across cohorts, utilizing the discontinuity around the cut-off date for school enrollment to identify birth month effects. Black, Devereux, and Salvanes (2011) investigate Norwegian registry data, and find no impact on educational attainment. When investigating earnings they find that starting school older has a negative effect on earnings until age 30. This suggests that after the age of 30 the advantage of being older when starting school offsets the disadvantage of having one year foregone labor market experience. Fredriksson and Öckert (2014) investigate Swedish data and find that starting school older increases educational attainment, in particular for females, and for less advantaged children. Investigating prime-age earnings (25–54 years) they find no effects on the full population, that masks strong heterogeneous effects across subgroups: Starting school older has a positive effect for women and a small negative effect for men. Furthermore, they find positive effects on earnings for less advantaged children of starting school older, and negative effect for advantaged children. They argue that while the positive effects are driven by increased labor market participation among individuals likely to be on the extensive margin of the labor market, the negative effects are driven by lower wages due to the later entry into the labor market. Other recent studies investigating the impact of age at school start include Bedard and Duhey (2012) finding a positive effect on earnings of starting school older, and Dobkin and Ferreira (2010) finding positive effects of age at school start on educational achievement, but no effects on labor market performance. The results are similar for males and females.

In order to reconcile these two approaches, I will in this study investigate the impact of birth month on long-term outcomes both within a school cohort and across school cohorts. The investigation of birth month effects across cohorts will provide an estimate that resembles the regression discontinuity effect from existing literature.

3. Institutional settings

An important aspect of Norwegian school policy has been to integrate children with different backgrounds and abilities throughout compulsory school. Equal treatment of all children is presumed to promote social mobility and equal opportunities. There is no ability or performance based group placement of pupils, no tracking of pupils before they enroll in high school at age 16, pupils advance automatically from one grade level to the next independent of performance; and there is no promotion of pupils. Hence, all pupils enrolled into compulsory school the same year are exposed to the same curriculum and classroom teaching.

For the cohorts of this study, the administrative rule for enrollment into school was that all children start school in mid August the calendar year in which they turn seven, and they graduate after nine years when they are 16 years old. Strict enforcement of enrollment regulations together with social promotion to the next grade level implies that individuals born within a given cohort enroll into school at the same time and graduate at the same time.

Non-compliance with enrollment regulations requires an expert assessment stating that the child is too immature to enter school. Non-compliance was around 5% in the late 1960s and dropped to less than 1% in the 1990s. However, the likelihood of being an early or late school enroller is highly associated with birth month: Most deferred children are December borns, and deferred children constitute a substantially larger share of December borns than of the cohort at large. When non-compliance was at its highest, as much as 20% (13) of boys (girls) born in December were deferred. Note
that due to strict enforcement of enrollment regulations and requirements for expert assessment on school ability, there is a negative selection to deferment, and positive selection to early enrollment: Less advantaged children constitute two thirds of deferred children and only one third of children early enrolled.

Compulsory schooling is publicly funded and free of charge for all pupils, and less than 1% of all pupils attend private schools. Pupils generally attend the school designated for the area where they live. All schools adhere to a national standard regarding curriculum and teacher resources and qualifications. Pupils are allocated to classrooms regardless of their characteristics and abilities.

Students apply to high school and acceptance is based on their GPA from compulsory school. Students proceeding directly to high school after compulsory school graduate from high school in June the year they turn 19 years old.

4. Empirical strategy

I intend to identify long-term effects of age differences within the classroom. Notably, such age differences in class may exceed a full year, since some pupils delay school start or enroll earlier than according to the administrative regulations. An obvious challenge to estimating effects of observed school starting age, and age differences within a school cohort, is the likely bias due to selection into such non-compliance with enrollment regulations. A common approach is therefore to utilize birth month as an instrument for age at school enrollment. The effects represent reduced form estimates of the impact of age at school start and age differences within a school cohort, and should be considered a lower bound of the true effect.

In addition to comparing individuals within academic cohorts, that graduate – and potentially enter the labor market – at the same point in time, I will for long-term outcomes also compare individuals across the cut-off date for school enrollment. This is in order to obtain a measure comparable to the discontinuity estimate from existing literature. The two different approaches are in line with the theoretical framework in Section 2.

I specify a flexible functional form in order to allow for non-linear birth month effects, with no structural restrictions on how various mechanisms may generate a birth month effect. The effect of birth month on GPA will be identified by the following equation:

$$\text{GPA}_i = \alpha + \sum_{m=2}^{12} \beta_m \text{BM}_m + \sum_y \mu_y C_i + \sigma X_i + \epsilon_i,$$

(1)

where GPA is the GPA for individual $i$, and BM are dummy variables indicating birth month, $m$. Individuals born in the first month of the school cohort (in Norway January) serve as the reference category. $C_i$ denote (school) cohort fixed effects, and $X_i$ is a vector of background characteristics. The coefficients $\beta_m$ measure the effect on GPA of being born in month $m$ compared to being born in the reference category January.

In order to investigate heterogenous effects across gender and socioeconomic status, I will in some specifications add interaction terms between birth month and gender or socioeconomic status. The regression model is

$$\text{GPA}_i = \alpha + \sum_{m=2}^{12} \beta_m \text{BM}_m + z \sum_{m=2}^{12} \theta_m \text{BM}_m + \sum_y \mu_y C_i + \sigma X_i + \epsilon_i,$$

(2)

where the $z$-terms represent the interaction terms, $z =$ female; high SES. Dummy variables for female and high SES are included in $X$. In this specification $\beta_m$ measures the birth month effect for boys/low SES, and $\theta_m$ the additional birth month effects for girls/high SES. Hence, the total birth month effects for girls/high SES are ($\beta_m + \theta_m$).

The coefficients of interest, $\beta_m$ and $\theta_m$, are reduced form effects, capturing the net effect of all mechanisms of birth month effects. Although the birth month effect is not restricted to be linear, I
expect a trend in the birth month coefficients: If age differences in class has an impact on GPA, it is unlikely to bounce up and down across birth months.

While an individual’s GPA from school does not change over age, the longer term outcomes do. Specifically, while the achieved GPA is unaffected by age of observation, educational outcomes and earnings are likely to be affected by the 11 months age difference between the youngest and oldest in a school cohort when outcome is observed at a given point in time.

In order to obtain an estimate adjusted for this age difference, I include in the regressions on long-term outcomes also individuals born just before the cut-off date for school enrollment, that is, Group III from the theoretical framework in Section 2. Hence, for each school cohort, I estimate effects for 13 consecutive birth months, from December in cohort $c-1$ to December in cohort $c$, with January in cohort $c$ as the reference category. The regression model for long-term outcomes is

$$Y_i = \alpha + \sum_{m=2}^{12} \beta_m BM_i^m + z_i \sum_{m=2}^{12} \theta_m BM_i^m + \beta_D D_i + \theta_D D_i z_i + \sum_y \mu_y C_i + \sigma X_i + \epsilon_i,$$

where $Y_i$ is the outcome for individual $i$ observed at a given point in time and age level. $D_i$ is a dummy variable for individuals born in December ($c-1$), and consequently enrolled into school one year younger. The cut-off estimate $\beta_D$ resembles a regression discontinuity estimate, capturing the difference in outcome between individuals born just before and just after the cut-off date for school enrollment. Hence, $\beta_D$ reflects the long-term impact of starting at and graduating from school one year younger, holding biological age (close to) constant at time of observation. In specifications where interaction terms are included, $\beta_D$ represents the effect of the cut-off estimate for boys/low SES, and the coefficient $\theta_m$ the additional effect for girls/high SES. The remaining variables are similar as in Equation (2).

Notably, for long-term outcomes observed at a given point in time, the birth month coefficients $\beta_m$ also capture the effect of enrolling into school one year earlier or later than according to the enrollment regulations. This is important to keep in mind, since it is mainly children born in December (January) that enroll into school later (earlier) than according to the statutes. For outcomes observed at a given point in time, for example, high school completion at age 19 and earnings at age 30, deferred children lag one year behind their cohort peers, and this will directly affect the estimates. This should carefully be taken into account when interpreting the impact of birth month on longer term outcomes. Deferral will affect also the cut-off estimate $\beta_D$, but in the opposite direction. The estimate should therefore be considered as a lower bound of the true effect. However, estimated effects on having enrolled into college by age 25 are unlikely to be affected by deferment.

In order for birth month to capture the effect of age differences in class, birth month should not be correlated with other characteristics affecting the outcome. For example, if highly educated parents time the birth to a specific season, children born this season may outperform their peers due to parental resources rather than age differences in class. Buckles and Hungerman (2013) find strong evidence on US data for correlation between birth month and parental characteristics that are likely to affect a number of outcomes. In Section 5 Data, I will investigate this directly by investigating parent characteristics across the child’s birth month. Furthermore, I will investigate if the birth month estimates are robust to controlling for a rich set of observable parental characteristics. Finally, adding mother fixed effects to the model controls for all unobservable differences in family background across birth month. Notably, when controlling for mother fixed effects the birth month effect is identified from variation across siblings, which constitutes a limited part of the full sample. In order to compare estimates across models, I conduct the analysis without mother fixed effects also on this limited fixed-effects sample.
5. Data

The association between birth month and long-term outcomes is investigated by utilizing a combination of several official Norwegian registers, prepared and provided by Statistics Norway. The dataset contains records for every Norwegian from 1992 to 2003. Variables include individual demographic information (gender, birth date, and number of children), socioeconomic data (education level and earnings) and employment status (full-time, part-time, and minor part-time). In addition, data on final grades from compulsory school for the graduation cohorts 2002–2007 are available. With unique personal identifiers these can be merged with registry data for information on child and parent characteristics.

In order to capture effects on individuals who have attended school in Norway and who have been exposed to the Norwegian cut-off regulations of school enrollment, immigrants are excluded in all analyses. Notably, I will investigate birth month effects on educational performance, educational attainment and earnings, and the sample will be different in all these analyses depending on data availability. In particular, cohorts included in the analyses depend on age when outcome is observed: I observe outcomes for ages 19–30 years old, and the intention is to identify birth month effects and how these may change over time as the individuals get older. Since birth month effects may also vary across cohorts, for example, due to changes in the schooling system or enforcement of enrollment regulations, ideally I want to observe the same cohorts for all ages. However, data for outcomes from 19 to 30 years old are available only for the 1973 cohort. In order to utilize the large dataset available, I observe outcomes at age 19 for the 1980–1984 cohorts, and outcomes at ages 25 and 30 for the 1969–1973 cohorts. Birth month effects on GPA are observed for the 1986–1991 cohorts, see Table 1.13

5.1. Outcome variables

The data allows for several outcome measures to be constructed. First, I observe the GPA when graduating from compulsory school (9th grade). GPA is constructed as the average of grades in all 10 subjects entered onto the final diploma from compulsory school. Grades are teacher-evaluated and range from 1 (lowest) to 6 (best). In the regressions GPA is standardized to mean 0 and standard deviation 1. Second, I observe if the individual has graduated from high school at age 19, which is the graduation age for individuals ‘marching in pace’, that is, enrolling into school according to the statutes and proceeding to high school directly after compulsory school. Third, I observe college enrollment by age 25. An individual is coded enrolled in college if he/she has completed at least one college exam the calendar year he/she turns 25 (or earlier). Fourth, I observe (log of) earnings at age 30. Earnings are measured as total pension-qualifying earnings reported in the tax registry, and include labor earnings, sick benefits, unemployment benefits, parental leave payments, and pensions. In the earnings analysis individuals with zero earnings are excluded. This sample selection criterion would be problematic if the likelihood of having zero earnings is associated with birth month. In separate regressions (not reported here) I find that the association between zero earnings and birth month is small and insignificant.

5.2. Background characteristics

I use a rich set of family background characteristics. I control for mother and father education level (indicators for high school degree and college education), mother and father’s labor market status

| Table 1. Sample selection criteria and age/timing when observing parent characteristics. |
|---------------------------------------------|---------------------------------|---------------------------------------------|
| Outcome variable                           | Cohorts observed                | Age (year) when parent characteristics are observed |
| Grade point average, GPA (16 yrs)           | 1986–1991                       | 10 years old (1996–2001)                     |
| High school graduation (19 yrs)             | 1980–1984                       | 19 years old (1999–2003)                     |
| College enrollment (25 yrs)                 | 1969–1973                       | 25 years old (1994–1998)                     |
| Earnings (30 yrs)                           | 1969–1973                       | 30 years old (1999–2003)                     |

Note: In analyses of GPA are 617 pupils (0.02%) born in 1985 or 1992 also included in the sample (non-compliers).
(indicator for working at least 30 hours per week), number of siblings (six categories: 0, 1, 2, 3, 4, >=5), and birth order: (six categories: 1, 2, 3, 4, 5, >=6).

The indicator for whether the mother has completed high school is a strong predictor for educational and labor market performance, and will also serve as the measure for socioeconomic status when investigating heterogeneous birth month effects.\textsuperscript{14}

With data available only for the years 1992–2003, background variables cannot be observed at a similar age for all analyses. Background characteristics are observed when the child is 10 years old in the analysis of GPA, and in analyses of long-term outcomes background characteristics are observed the same year as outcome is observed, see Table 1.

If certain parent characteristics that are predictive of the outcome variable are concentrated among children born in specific birth months, the birth month estimates may reflect such differences rather than differences in relative age. In particular, I investigate the birth month distribution of parental marital status; mothers education level (indicator for having completed high school); and mother’s and father’s labor market status (indicator for being full-time employed). In order to investigate distribution of parent characteristics, I employ a similar approach, utilizing Equations (2) and (3) on the same samples as those that enters into the main analyses.

The distribution of family characteristics will be unbalanced across birth month if different families time their births to different times of the year. Furthermore, since parents of children born later in the year are on average somewhat younger than parents of children born early in the year, family characteristics may reflect general trends, for instance the general increase in education level over the last decades. Since the distribution of family characteristics across birth month may change over time, I investigate each of the samples in my analyses separately. Table 2 provides the description of how parent characteristics are distributed across birth month.

I find that the correlation between birth month and several of the parent characteristics is statistically significant. This is particularly the case for older cohorts. For children born prior to 1984 the estimates suggest that those born during early spring and late fall, have more advantageous family characteristics (education level and labor market participation). Although the differences across birth month in general are small, this should be carefully taken into consideration when interpreting the birth month estimates.

This also suggests that the models controlling for mother fixed effects are especially useful. Notably, when adding mother fixed effects to the models, the birth month estimates are identified between siblings, and the relevant samples includes only families with more than one child born during the observation periods. Table 3 reports the corresponding distribution of parent characteristics among families with at least two children born during the observation period. On this smaller sample there are substantially less significantly different parent characteristics across birth months. However, the point estimates still suggest that for older cohorts, children born during early spring and late fall are characterized by somewhat more advantageous family characteristics.

6. Results

I now turn to the main analyses on birth month estimates for long-term outcomes. The estimated birth month coefficients, $\beta_m$, for February to December reflect the incremental effect on outcome of being born in month $m$ as compared to January, which serves as the reference category. Standard errors for regression coefficients are close to constant across birth month, and reported only once for each model. For a visual impression, regression coefficients will be graphically illustrated for some specifications. The cut-off estimate on long-term outcomes reflect the long-term effect of entering and graduating from school one year younger, holding biological age close to constant at time of observation.
Table 2. Distribution of parent characteristics across birth months.

| Panel A: Cohorts 1986–1991 (observed when child is 10 years) | Panel B: Cohorts 1980–1984 (observed when child is 19 years) | Panel C: Cohorts 1969–1973 (observed when child is 25 years) |
|-------------------------------------------------------------|-------------------------------------------------------------|-------------------------------------------------------------|
| Table 4, Models 1, 2, 3 and 6                               | Table 5, Models 1, 2, 3 and 6                               | Table 6, Models 1, 2, 3 and 6                               |
| Observations                                              | Observations                                               | Observations                                               |
| 278,602                                                   | 278,602                                                   | 284,325                                                   |
| Mean                                                      | Mean                                                      | Mean                                                      |
| 0.690                                                    | 0.728                                                     | 0.765                                                     |
| St.dev                                                    | St.dev                                                    | St.dev                                                    |
| 0.462                                                    | 0.445                                                     | 0.424                                                     |

| (1) Married | (2) Mother high school | (3) Mother full time | (4) Father full time | Cut-off | (1) Married | (2) Mother high school | (3) Mother full time | (4) Father full time | Cut-off | (1) Married | (2) Mother high school | (3) Mother full time | (4) Father full time | Cut-off | (1) Married | (2) Mother high school | (3) Mother full time | (4) Father full time | Cut-off |
|----------------|------------------------|----------------------|----------------------|---------|----------------|------------------------|----------------------|----------------------|---------|----------------|------------------------|----------------------|----------------------|---------|----------------|------------------------|----------------------|----------------------|---------|
| **February**   | 0.009*                 | −0.001               | −0.007               | −0.001  | 0.006          | 0.007                  | 0.012*               | −0.001  | 0.002              | −0.003               | −0.003               | −0.004               |
| **March**      | 0.011*                 | 0.002                | −0.006               | 0.005   | 0.008+         | 0.004                  | 0.009+               | 0.004   | 0.003              | −0.002               | −0.002               | 0.001               |
| **April**      | 0.016**                | 0.006                | −0.009*              | 0.009*  | 0.009*         | 0.010*                 | 0.007               | 0.011*  | 0.006              | 0.010**               | 0.006               | 0.007               |
| **May**        | 0.004                  | 0.004                | −0.001               | 0.006   | 0.001          | 0.010*                 | 0.007               | 0.008   | 0.014**             | 0.015**               | 0.014**             | 0.017**             |
| **June**       | 0.001                  | 0.004                | −0.007               | 0.003   | −0.001         | 0.004                  | 0.005               | 0.008   | 0.009*              | 0.014**               | 0.013**             | 0.014**             |
| **July**       | −0.004                 | −0.004               | −0.007               | 0.005   | −0.001         | 0.009+                 | 0.005               | 0.004   | 0.008+              | 0.008+                | 0.006               | 0.009+               |
| **August**     | −0.003                 | 0.008                | 0.000                | 0.000   | −0.006         | 0.009+                 | 0.001               | 0.004   | 0.008+              | 0.004                | 0.012**             | 0.011*               |
| **September**  | −0.011**               | 0.008                | −0.005               | −0.000  | −0.011*        | 0.010*                 | −0.007              | 0.003   | 0.000              | 0.004                | 0.012**             | 0.011*               |
| **October**    | −0.010*                | 0.008+               | −0.010*              | 0.008+  | −0.007         | 0.012*                 | 0.003               | 0.010+  | 0.000              | 0.004                | 0.008+              | 0.015**             |
| **November**   | −0.010*                | 0.008+               | −0.005               | 0.010*  | −0.016**       | 0.010+                 | −0.003              | 0.010*  | 0.003              | 0.011**               | 0.006               | 0.018**             |
| **December**   | −0.015**               | 0.007                | −0.009*              | 0.001   | −0.016**       | 0.012*                 | 0.002               | 0.009+  | −0.001             | 0.012**               | 0.013**             | 0.023**             |
| **st.err.**    | (0.004)                | (0.005)              | (0.005)              | (0.004) | −0.007         | −0.002                 | 0.000               | −0.005  | 0.002              | −0.003               | −0.003               | −0.004               |
| **Ref analyses**|                       |                      |                      |         | (0.005)        | (0.005)                | (0.005)             | (0.005) | (0.004)            | (0.004)               | (0.005)             | (0.005)             |
Table 3. Distribution of parent characteristics across birth months. Mother fixed-effects sample.

| Panel A: Cohorts 1986–1991 (observed when child is 10 years) | Panel B: Cohorts 1980–1984 (observed when child is 19 years) | Panel C: Cohorts 1969–1973 (observed when child is 25 years) |
|------------------------------------------------------------|------------------------------------------------------------|------------------------------------------------------------|
| (1) Married                                                  | (1) Married                                                  | (1) Married                                                  |
| (2) Mother high school                                       | (2) Mother high school                                       | (2) Mother high school                                       |
| (3) Mother full time                                         | (3) Mother full time                                         | (3) Mother full time                                         |
| (4) Father full time                                         | (4) Father full time                                         | (4) Father full time                                         |
| February 0.004 −0.000                                        | 0.007 −0.001                                                | −0.001 0.000 −0.005                                         |
| March 0.001 0.003                                            | 0.012 −0.006                                                | 0.005 0.010 0.013                                           |
| April 0.006 0.006                                            | 0.005 0.010                                                | 0.013 0.011                                                 |
| May −0.003 −0.003                                            | 0.003 −0.004                                                | 0.002 0.004                                                 |
| June −0.008 0.004                                            | −0.002 0.005                                                | 0.001 0.002                                                 |
| July −0.010 −0.001                                           | 0.003 0.004                                                | 0.000 0.003                                                 |
| August −0.008 0.007                                          | 0.001 0.005                                                | −0.003 0.006                                               |
| September −0.008 0.006                                       | −0.015+ −0.007                                              | −0.007 0.005                                               |
| October −0.004 0.013+                                         | 0.003 −0.001                                               | −0.003 0.010                                               |
| November −0.010 0.006                                        | −0.008 −0.006                                               | −0.001 0.004                                               |
| December −0.013+ −0.004                                      | −0.009 −0.004                                               | −0.007 −0.002                                              |
| st.err. (0.006) (0.007)                                      | (0.008) (0.009)                                             | (0.009) (0.009)                                             |

Ref analyses Table 4, Models 4 and 5 Table 5, Models 4 and 5 Table 6, Models 4 and 5

| Observations | 117,180 | 117,180 | 117,180 | 117,180 | 69,359 | 69,359 | 69,359 | 69,359 | 103,109 | 103,109 | 103,109 | 103,109 |
|-------------|---------|---------|---------|---------|--------|--------|--------|--------|---------|---------|---------|---------|
| Mean        | 0.752   | 0.547   | 0.313   | 0.710   | 0.762  | 0.458  | 0.424  | 0.651  | 0.778   | 0.226   | 0.373   | 0.564   |
| St.dev      | 0.432   | 0.498   | 0.464   | 0.454   | 0.426  | 0.498  | 0.494  | 0.477  | 0.416   | 0.418   | 0.484   | 0.496   |
**Table 4. Birth month effects on GPA.**

|          | Model 1          | Model 2          | Model 3          | Model 4          | Model 5          | Model 6          |
|----------|------------------|------------------|------------------|------------------|------------------|------------------|
|          | (Figure 1)       | (Figure 2)       |                  |                  |                  |                  |
| February | −0.001           | −0.001           | −0.002           | −0.001           | −0.016           | 0.006            |
| March    | −0.024*          | 0.003            | −0.023**         | −0.023*          | −0.040**         | −0.016           |
| April    | −0.011           | −0.017           | −0.019*          | −0.015+          | −0.042**         | −0.003           |
| May      | −0.053**         | −0.003           | −0.054**         | −0.052**         | −0.065**         | −0.053**         |
| June     | −0.077**         | 0.015            | −0.069**         | −0.066**         | −0.085**         | −0.066**         |
| July     | −0.126**         | 0.047**          | −0.103**         | −0.111**         | −0.117**         | −0.097**         |
| August   | −0.125**         | 0.010            | −0.120**         | −0.117**         | −0.117**         | −0.114**         |
| September| −0.146**         | 0.009            | −0.141**         | −0.137**         | −0.135**         | −0.130**         |
| October  | −0.172**         | 0.016            | −0.164**         | −0.159**         | −0.161**         | −0.163**         |
| November | −0.201**         | 0.030+           | −0.186**         | −0.179**         | −0.167**         | −0.183**         |
| December | −0.190**         | −0.014           | −0.197**         | −0.191**         | −0.199**         | −0.197**         |
| st.err.  | (0.011)          | (0.016)          | (0.008)          | (0.009)          | (0.013)          | (0.012)          |
| Female   | 0.454**          | 0.462**          | 0.452**          | 0.458**          | 0.462**          | 0.462**          |
|          | (0.012)          | (0.003)          | (0.005)          | (0.005)          | (0.003)          | (0.003)          |
| High SES | 0.312**          | 0.312**          | 0.313**          | 0.313**          | 0.278**          | 0.278**          |
|          | (0.004)          | (0.004)          | (0.006)          | (0.006)          | (0.012)          | (0.012)          |
| Controls | Yes              | Yes              | No               | Yes              | Yes              | Yes              |
| Mother FE| No               | No               | No               | Yes              | No               | No               |
| Interactions |          |                  |                  |                  |                  |                  |
| Observations | 278,602          | 278,602          | 278,602          | 117,180          | 117,180          | 278,602          |
| Adj. R²  | 0.226            | 0.226            | 0.007            | 0.555            | 0.231            | 0.226            |
| Mean     | 0.00             | 0.00             | 0.00             | 0.069            | 0.069            | 0.00             |
| St.dev.  | 1.00             | 1.00             | 1.00             | 0.980            | 0.980            | 1.00             |

Notes: ***, * and + denote significance at 1%, 5%, and 10% level. Cohorts 1986–1991. GPA is standardized to mean = 0 and sd = 1. Reported standard error is approximately constant across birth month coefficients. Model 1 and Model 5 include interaction terms between birth month and ‘Female’ and ‘High SES’, respectively. High SES is defined as mother having completed high school.
6.1. Grade point average

The first outcome is the GPA when graduating from compulsory school (10th grade). Model 1 in Table 4 report regression coefficients for the birth month effect on GPA. Interaction terms between birth month and gender (female) are included in the analysis. Hence, the left hand side column of birth month coefficients reflects birth month effects for boys, and the right hand side column reflects the additional birth month effect for girls. The coefficients are also illustrated in Figure 1. We can see that children born early in the year outperform their younger peers, and the birth month effect on GPA is close to linear: The GPA score of children born in December is 19% of a standard deviation lower than the GPA score of children born in January. From the coefficient for Female, we see that girls on average score 45% of a standard deviation higher than boys. Furthermore, the birth month effect tends to be smaller for girls than boys, but the difference is not statistically significant. The interaction effects on gender will therefore be excluded in the following analyses. Model 2 in Table 4 report the birth month coefficients when interaction effects are excluded from the regression model.

As discussed, if children born early in the year have background characteristics associated with good school performance, the birth month effect may be due to such compositional effects. In Table 4, Model 3, all covariates are dropped from the regression model, and we find that the birth month effect remains nearly constant. In line with Table 2, Panel A, this suggests that the estimated birth month effects are not affected by other unobserved characteristics. Table 4, Model 4, shows that the birth month estimates are robust to adding mother fixed effects to the model. Notably, when controlling for mother fixed effects, the birth month effects are identified only between siblings born during our period of observation. This constitutes less than half of the full sample. In order for birth month estimates to be comparable across models, Model 2 is replicated on this limited fixed effects sample. Results are reported in Model 5. We find that the birth month effects are similar in this smaller sample and the full sample.

In Table 4, Model 6, interaction terms between birth month and socioeconomic status are included. The estimated birth month effects are also illustrated in Figure 2. We find that the birth month effects on GPA are significantly smaller for high SES children. This suggests that high SES parents compensate for children’s disadvantage of being relatively young in class. We also see that high SES children’s GPA score is, on average, 28% of a standard deviation higher.

Figure 1. Birth month effects on GPA, by gender.
Notes: GPA is standardized to mean = 0, standard deviation = 1. Cohorts 1986–1991. N = 278,602. Standard error coefficients = 0.011, approximately constant across birth month estimates. Figure illustrates birth month coefficients in Table 4, Model 1.
6.2. Completing high school at age 19

GPA from compulsory school is likely to have an impact on the motivation to proceed to and complete high school. Empirical evidence suggests that there is a negative association between the dropout rate from high school and GPA: Nearly 75% of all high school students in the lowest GPA-decile from compulsory school do not follow statutory progress in high school, see Byrhagen, Falch, and Strøm (2006). Related to this, it has also been shown that students accepted into their first choice of high school have a lower dropout rate, also after controlling for GPA, see Markussen et al. (2008). I investigate differences across birth months in high school graduation at age 19, which is the statutory graduation age for students proceeding to high school directly after compulsory school.

Table 5, Model 1 report birth month coefficients for boys and girls, respectively, of having graduated from high school at age 19 (see also Figure 3). We can see that boys born late in the year have significantly lower probability of having graduated from high school at this age: December born boys have 7.1 percentage points lower probability of having completed high school at age 19, a difference that constitutes 17% of the average completion rates for boys at this age. The additional birth month effects for girls tend to be smaller, but the difference is statistically significant only for December born children: The disadvantage of being youngest in class is significantly stronger for boys than girls. The interaction effects for gender will be excluded in the following analyses on high school completion, and Model 2 presents the birth month estimates for both gender.

Model 3 demonstrate that the birth month estimates are robust to excluding controls from the model specification. Moreover, when adding mother fixed effects to the model in Model 4, the birth month estimates are nearly unaffected. Re-estimating the model without mother fixed effects on this limited sample provides somewhat smaller estimates, reported in Model 5, but the differences are insignificant.

Model 6 reports estimates for low and high SES children, respectively. The birth month effects for high SES children are even stronger, see also Figure 4, but the differences are mostly not significant.

Birth month effects may reflect that the youngest children within a cohort have an overall lower probability of ever graduating from high school. Alternatively, the birth month effects may reflect that
Table 5. Birth month effects on having completed high school at age 19.

| Month   | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 | Model 6 |
|---------|---------|---------|---------|---------|---------|---------|
|         | (Figure 3) |         |         |         |         | (Figure 4) |
| February| −0.012+ | 0.019+  | −0.002  | 0.002   | −0.001  | 0.007   | 0.002   |
| March   | −0.007  | −0.004  | −0.009+ | −0.008  | −0.028**| −0.008  | 0.001   |
| April   | −0.007  | 0.003   | −0.005  | −0.001  | −0.020+ | −0.002  | −0.004  |
| May     | −0.014* | −0.003  | −0.015**| −0.012* | −0.031**| −0.010  | −0.012+ |
| June    | −0.028**| 0.008   | −0.024**| −0.023**| −0.032**| −0.025**| −0.017**|
| July    | −0.022**| 0.003   | −0.020**| −0.017**| −0.038**| −0.021* | −0.019**|
| August  | −0.029**| 0.002   | −0.028**| −0.026**| −0.018  | −0.019* | −0.031**|
| September| −0.035**| 0.012  | −0.0287**| −0.026**| −0.030**| −0.019* | −0.026**|
| October | −0.028**| 0.005   | −0.0259**| −0.022**| −0.035**| −0.019* | −0.020**|
| November| −0.053**| 0.013   | −0.0461**| −0.043**| −0.047**| −0.041**| −0.042**|
| December| −0.071**| 0.021** | −0.0605**| −0.059**| −0.058**| −0.057**| −0.058**|
| st.err. |         |         | (0.006) | (0.004) | (0.011) | (0.009) |          |
|         |         |         | (0.009) | (0.005) | (0.004) | (0.004) |          |
| Female  | 0.171** | 0.176** | 0.178** | 0.182** | 0.176** | 0.176** |          |
|         | (0.007) | (0.002) | (0.004) | (0.005) | (0.002) | (0.002) |          |
| High SES| 0.081** | 0.081** | 0.086** | 0.091** | 0.091** | 0.126** | −0.030**|
|         | (0.003) | (0.003) | (0.005) | (0.007) | (0.006) | (0.010) |          |
| Cut-off | 0.119** | −0.0111 | 0.113** | 0.113** | 0.126** | −0.030**|          |
|         | (0.006) | (0.009) | (0.004) | (0.005) | (0.006) | (0.010) |          |
| Controls| Yes     | Yes     | No      | Yes     | Yes     | Yes     | Yes     |
| Mother FE| No      | No      | Yes     | No      | No      | No      | No      |
| Interactions| Female |         |         |         |         |         |         |
| Observations | 234,817 | 234,817 | 234,817 | 69,359  | 69,359  | 234,817 |
| Adj. $R^2$ | 0.122  | 0.122  | 0.007   | 0.312   | 0.136   | 0.122   |
| Mean    | 0.515  | 0.515  | 0.515   | 0.514   | 0.514   | 0.515   |
| St.dev. | 0.499  | 0.499  | 0.499   | 0.500   | 0.500   | 0.499   |

Notes: **, * and + denote significance at 1%, 5%, and 10% level. Cohorts 1980–1984. Reported standard error is approximately constant across birth month coefficients. Model 1 and Model 5 include interaction terms between birth month and ‘Female’ and ‘High SES’, respectively. High SES is defined as mother having completed high school.
individuals born late in the year lag behind, for instance by having a higher probability of taking a break from the education track before proceeding to high school, or benefiting from ‘second chance’ possibilities after poor performance in compulsory school. If children born late in the year have a higher probability of enrolling into vocational training this will also be reflected in the

**Figure 3.** Birth month effects on high school completion at age 19, by gender.

Notes: Cohorts 1980–1984. Mean of outcome variable = 0.515. Standard error coefficients = 0.006, approximately constant across birth month coefficients. The outcome variable is constructed as an indicator taking the value 1 if the person had graduated from high school by year end the year he/she turned 19, otherwise 0. N = 234,817. Figure illustrates birth month coefficients in Table 5, Model 1.

**Figure 4.** Birth month effects on high school completion at age 19, by SES.

Notes: Cohorts 1980–1984. Mean of outcome variable = 0.515. Standard error coefficients = 0.006, approximately constant across birth month coefficients. High SES is defined as mother having completed high school. The outcome variable is constructed as an indicator taking the value 1 if the person had graduated from high school by year end the year he/she turned 19, otherwise 0. N = 234,817. Figure illustrates birth month coefficients in Table 5, Model 6.
birth month effects since most vocational trainings require four years. Finally, pupils being deferred at enrollment into primary school will not graduate from high school until the year they turn 20 years old. This is especially relevant for December borns, and is a likely explanation for why the drop in completion rates is so large for December borns. However, the negative trend in completion rates prior to December cannot be explained by children delaying school start, as very few children born in November or earlier in the year delay school start.\textsuperscript{18}

The last row in Table 5 presents the cut-off estimate. In Model 1, the estimate of 0.1189 suggests that boys born just before the cut-off date for school enrollment have a nearly 12% higher probability of having completed high school at the same age as their male peers born just after this cut-off date. The strong effect is as expected, since the outcome is observed four years after the former group graduated from compulsory schooling and only three years after the latter group graduated. There is no significant difference between girls and boys. In Model 6 we find, however, that it is particularly among children from low-SES families that this additional year has an impact on the probability of graduating from high school. A possible reason is that more children from low-SES families are enrolled in vocational tracks rather than academic tracks, which often requires four years to complete.

\subsection*{6.3. College enrollment by age 25}

In Table 6 I investigate birth month effects on enrollment into college, defined as having completed at least one college exam the year he/she turns 25 years (or earlier). In Model 1 we see that boys born late in the year generally have a lower probability of enrolling into college, with December born boys having 1.8 percentage points lower probability than January born boys. The pattern in birth month estimates for girls deviates somewhat from that of the boys, in particular with a strong peak for girls born in April, see also Figure 5. The difference is, however, not statistically significant. When we compare Model 2 to Model 3 we find that birth month estimates, in particular for April, are somewhat sensitive to exclusion of control variables. This suggests that there is some positive selection of parental characteristics associated with April borns in these cohorts. This is in line with the estimates in Table 2, Panel C, which suggested that children born during spring are characterized with more advantageous parent characteristics.

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{figure5.png}
\caption{Birth month effects on having enrolled in college at age 25, by gender.}
\label{fig:birth_month_effects}
\textbf{Notes:} Cohorts 1969–1973. Mean of outcome variable = 0.29. Standard error coefficients = 0.005, approximately constant across birth month coefficients. The outcome variable is constructed as an indicator taking the value 1 if the person had completed at least one college exam at year end the year he/she turned 25, otherwise 0. N = 284,325. Figure illustrates birth month coefficients in Table 6, Model 1.
\end{figure}
Such differences in parent characteristics will be controlled for when adding mother fixed effects to the model. Results are reported in Model 4, where we can find little evidence for birth month effects on college enrollment. Notably, we find the same results in Model 5, which replicates the analysis without mother fixed effects on this limited sample. Moreover, in both Models 4 and 5, even if statistically insignificant, the size of point estimates still suggest that April born individuals have higher enrollment rates than their peers.

Finally, from Model 6 we find that the birth month effects is stronger for high-SES children, see Figure 6. The difference in estimates between high and low SES is, however, not statistically significant. We find a similar April peak for low-SES individuals as we did for girls.

The last row in Table 6 provides the cut-off estimates. The only significant estimate is for high-SES children, who are more likely to have enrolled into college if they enter school at a younger age than low-SES children. We find no overall effect on college enrollment, even if those born just before the cut-off date graduated from compulsory schooling one year earlier. This is consistent with findings in Black, Devereux, and Salvanes (2011) on Norwegian data.

Summing up, analyses on educational achievement suggest that children born late in the year are systematically lagging behind on the educational track, but catch up with their older peers over time.

6.4. Earnings at age 30

In Table 7 I investigate the birth month effects on (log of) earnings at age 30. Individuals without earnings are excluded from the sample. In Model 1 we see a clear trend that men born late in the year have substantially lower earnings than men born early in the year: Men born in December have on average 4% lower earnings than January born males. There is no statistically significant difference across gender, but the estimates for female suggest a less clear association between birth month and earnings for women, see also Figure 7. The estimates are robust to exclusion of controls (see Models 2 and 3) and inclusion of mother fixed effects (Model 4). In Model 6 we find that there is no significant difference across socioeconomic strata, see also Figure 8.
Table 6. Birth month effects on having enrolled in college at age 25.

|       | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 | Model 6 |
|-------|---------|---------|---------|---------|---------|---------|
|       | (Figure 5) |         |         |         |         | (Figure 6) |
| February | 0.001   | -0.010  | -0.004  | -0.006  | 0.001   | -0.002  |
| March   | 0.001   | -0.006  | -0.002  | 0.002   | 0.001   | 0.007   |
| April   | 0.006   | 0.005   | 0.005   | 0.012** | 0.009   | 0.014*  |
| May     | -0.006  | 0.003   | -0.004  | 0.002   | 0.006   | 0.007   |
| June    | -0.010+ | 0.010   | -0.005  | -0.002  | -0.005  | -0.003  |
| July    | -0.011* | 0.003   | -0.010* | -0.008+ | -0.012  | -0.005  |
| August  | -0.011+ | -0.004  | -0.013** | -0.011* | -0.003  | -0.012+ |
| September | -0.014* | -0.004  | -0.016** | -0.014** | -0.005  | -0.007  |
| October | -0.014* | 0.003   | -0.013** | -0.008+ | -0.001  | -0.007  |
| November | -0.022** | 0.004  | -0.020** | -0.015** | -0.014+ | -0.013+ |
| December | -0.018** | -0.001  | -0.018** | -0.015** | -0.006  | -0.010  |
| st.err. | (0.005) | (0.008) | (0.004) | (0.004) | (0.008) | (0.006) |
| Female  | 0.081** | 0.081** | 0.082** | 0.081** | 0.081** |         |
| (0.006) |         |         |         |         |         |         |
| High SES| 0.111** | 0.111** | 0.1094** | 0.116** |         |         |
| (0.003) |         |         |         |         |         |         |
| Cut-off | 0.003   | -0.003  | 0.001   | -0.002  |         | -0.003  |
| (0.005) |         |         | (0.004) | (0.004) |         | (0.004) |
| Controls | Yes     | Yes     | No      | Yes     | Yes     | Yes |
| Mother FE | No      | No      | Yes     | No      | No      | No |
| Interactions | Female |         |         |         |         | High SES |
| Observations | 284,325 | 284,325 | 284,325 | 103,109 | 103,109 | 284,325 |
| Adj. R2  | 0.135   | 0.135   | 0.002   | 0.353   | 0.145   | 0.135   |
| Mean    | 0.290   | 0.290   | 0.290   | 0.274   | 0.274   | 0.290   |
| St.dev. | 0.454   | 0.454   | 0.454   | 0.446   | 0.446   | 0.454   |

Notes: **, * and + denote significance at 1%, 5%, and 10% level. Cohorts 1969–1973. College enrollment is defined as having completed at least one college exam. Reported standard error is approximately constant across birth month coefficients. Model 1 and Model 5 include interaction terms between birth month and ‘Female’ and ‘High SES’, respectively. High SES is defined as mother having completed high school.
Table 7. Birth month effects on log earnings at age 30.

|       | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 | Model 6 |
|-------|---------|---------|---------|---------|---------|---------|
|       | (Figure 7) |         |         |         |         | (Figure 8) |
| February | −0.007 | 0.012 | −0.001 | 0.002 | 0.006 | −0.004 | −0.008 | 0.028 |
| March   | −0.018⁺ | 0.005 | −0.016* | −0.009 | −0.044** | −0.021⁺ | −0.013 | −0.008 |
| April   | −0.018⁺ | 0.004 | −0.016* | −0.013 | −0.012 | −0.014 | −0.019* | 0.009 |
| May     | −0.021⁺ | 0.024 | −0.009 | −0.002 | −0.007 | −0.010 | −0.007 | −0.010 |
| June    | −0.016 | 0.012 | −0.010 | −0.006 | −0.035⁺ | −0.029* | −0.009 | −0.005 |
| July    | −0.022* | 0.009 | −0.018* | −0.015⁺ | −0.020 | −0.020 | −0.019* | 0.005 |
| August  | −0.026* | 0.022 | −0.015⁺ | −0.009 | −0.030⁺ | −0.031* | −0.018⁺ | 0.011 |
| September | −0.035** | 0.010 | −0.030** | −0.025** | −0.035⁺ | −0.031* | −0.032** | 0.006 |
| October | −0.027* | −0.004 | −0.030** | −0.026** | −0.035⁺ | −0.032* | −0.028** | −0.007 |
| November | −0.040** | 0.017 | −0.032** | −0.024** | −0.037* | −0.040** | −0.033** | 0.003 |
| December | −0.040** | 0.027⁺ | −0.027** | −0.021⁺ | −0.038⁺ | −0.036** | −0.028** | 0.005 |
| st.err. | (0.011) | (0.016) | (0.008) | (0.008) | (0.0178) | (0.0131) | (0.009) | (0.018) |
| Female  | −0.474** | −0.464** | −5.000** | −4.899** | −0.464** |
| High SES | 0.039** | 0.039** | 0.038** | 0.038** | 0.036** |
| (0.005) | (0.005) | (0.007) | (0.005) | (0.003) |
| Cut-off | 0.007 | −0.011 | 0.002 | −0.000 | −0.001 | 0.011 |
| Controls | Yes | Yes | No | Yes | Yes | Yes |
| Mother FE | No | No | Yes | No | No | No |
| Interactions | Female | High SES |
| Observations | 272,038 | 272,038 | 272,038 | 94,891 | 94,891 | 272,038 |
| Adj. R² | 0.093 | 0.093 | 0.010 | 0.173 | 0.103 | 0.093 |
| Mean | 7.641 | 7.641 | 7.641 | 7.635 | 7.635 | 7.641 |
| St.dev. | 0.859 | 0.859 | 0.859 | 0.854 | 0.854 | 0.859 |

Notes: **, *, and + denote significance at 1%, 5%, and 10% level. Cohorts 1969–1973. Reported standard error is approximately constant across birth month coefficients. Model 1 and Model 5 include interaction terms between birth month and ‘Female’ and ‘High SES’, respectively. High SES is defined as mother having completed high school.
As for educational achievement, individuals having delayed enrollment into school lag one year behind their cohort peers. One year less labor market experience is likely to have a significant impact on earnings, particularly as early in the career as at age 30. Since deferment mainly applies to individuals born late in the year, it is particularly the December estimates that would be affected by late school enrollment. However, particularly for men the birth month effect is close to linear and does not only apply to individuals born very late in the year, which suggests that delayed school enrollment and less labor market experience is not the sole explanation for the birth month effect.

**Figure 7.** Birth month effects on log earnings at age 30, by gender.
Notes: Cohorts 1969–1973. Standard error coefficients = 0.011, approximately constant across birth month coefficients. The outcome variable is constructed as log of earnings the calendar year he/she turns 30. N = 272,038. Figure illustrates birth month coefficients in Table 7, Model 1.

**Figure 8.** Birth month effects on log earnings at age 30, by SES.
Notes: Cohorts 1969–1973. Standard error coefficients = 0.009, approximately constant across birth month coefficients. High SES is defined as mother having completed high school. The outcome variable is constructed as log of earnings the calendar year he/she turns 30. N = 272,038. Figure illustrates birth month coefficients in Table 7, Model 6.
The cut-off estimates in the last row of Table 7 shows that there are no earnings differences between individuals born just before and after the cut-off date for school enrollment. This suggests that the advantage of an additional year of labor market experience for the former group is counter-balanced by a negative effect of being born late in the year. Such negative effects may for instance be the younger age at school start, and the relative standing (age and maturity) in class throughout school. The finding is in line with Black, Devereux, and Salvanes (2011) which also uses Norwegian registry data.

7. Conclusion

There is a strong and close to linear effect of birth month on GPA: The oldest pupils in class perform significantly better than their younger peers. The birth month effect is particularly strong for low-SES children, possibly reflecting that parental resources and support may offset the drawback of being relatively young in class. Observing longer term outcomes, I find that children born late in the year, especially boys, have a significantly lower probability than their older peers in completing high school at age 19, and are less likely to be enrolled into college by age 25. Finally, I find that individuals born late in the year, in particular men, have significantly lower earnings at age 30 than those born early in the year. The birth month effects on GPA, high school completion and earnings are robust to controlling for mother fixed effects.

When comparing individuals around the cut-off date for school enrollment, we find that starting school younger increases the likelihood for completing high school by the exact age of 19, suggesting that December born individuals lag behind their older peers but catch up over time. Similarly, starting and graduating from school one year younger has no impact on earnings observed at the exact age of 30. All together the results suggest that the youngest in class need an additional year on the education track and in the labor market to catch up with their older peers. Hence, the advantage of a head start on the educational track and in the labor market, appears to be offset by negative effects of being born late in the year, possibly related to the experience of being a low performer in school during important formative years in childhood and adolescence. There is no significant difference in this overall effect on long-term outcomes across gender or socioeconomic status.

Long lasting effects on educational achievement and early-career earnings of age differences within the classroom suggest that the strict enrollment regulations systematically discriminate against the relatively youngest. Given the Norwegian schooling system’s strong focus on promotion of equal opportunities for all children, it should be noted that the relative age effect on GPA is particularly strong for low SES children. Hence, the young low-SES children face disadvantages along two dimensions.

Non-compliance with enrollment regulations in flexible education systems as, for example, the US, have been shown to reinforce inequality between socioeconomic strata by positive selection into deferment: Red-shirting (late enrollment) is by far most common in affluent communities, where parents are more aware of the advantage of being relatively old in class. On the other hand, in countries with more rigid enrollment regulations, as in Norway, the practice of expert assessment on maturity and abilities generates a negative selection into deferment. Relaxing the enrollment regulations by allowing more of the most immature children to delay school start by one year may therefore be a step towards providing more equal opportunities for all children.

Notes

1. Although tracking or ability based streaming is not practiced in the Norwegian schooling system, it can be argued that allowing the weakest students to fall progressively behind their stronger peers is also a kind of streaming, see Bedard and Duhey (2006).

2. There is no formal tracking into high schools in Norway, but since students apply and get accepted into different high schools based on the grade point average from compulsory school, there is in practice a performance based tracking.
3. Crawford, Dearden, and Greaves (2014) find that the vast majority of relative age effects on tests results in school are driven by the biological age difference. Black, Devereux, and Salvanes (2011) find similar results when investigating relative age effects on IQ scores.

4. Note that finding similar relative age effects across different cut-off dates excludes the possibility that performance gaps are due to health differences associated with season of birth.

5. This implies that if the cut-off date for school enrollment were August 1, month = 1 are individuals born in August. When the cut-off date for school enrollment is January 1, month = 1 refers to individuals born in January, and month = 12 refers to individuals born in December.

6. Since 2004, schools have been entitled to develop more flexible groups also based on abilities.

7. In 1997 compulsory schooling was extended to 10 years, and enrollment age changed to 6 years old. However, all individuals in the sample enrolled in school before 1997.

8. See Table A1 in Appendix for compliance rates (own calculations based on official data from Statistics Norway).

9. Among deferred children 55% were born in December and 20% born in November.

10. With individual data available on age at school enrollment, I could have adjusted the estimates for the proportion non-compliers by doing a 2SLS. Such data are unfortunately not available to me, and I cannot estimate the first stage relationship. Except for the reduced form estimates to be somewhat smaller since they are unadjusted for non-compliance, the interpretation of reduced form and 2SLS estimates are similar.

11. Since several cohorts enter into each analyses, this implies that some December born individuals are represented twice in the sample: As December (c-1) and December (c). All birth month estimates, $\beta_m$, are unaffected by the inclusion of the cut-off estimate, $\beta_D$.

12. Due to the one month age difference between those born in December and the subsequent January, $\beta_D$ will deviate somewhat from a conventional discontinuity estimate. The February to December birth month estimates will, however, indicate how much we should expect this cut-off estimate to differ from a regression discontinuity estimate.

13. Data for the graduation cohorts 2002–2007 are available. Among these pupils a total of 1.5% enrolled in school earlier or later than statutory enrollment age. These are included in the analytical sample. Observing GPA for graduation cohorts implies that the sample selection criterion deviates slightly from the remaining analysis where birth cohort is the selection criterion.

14. In regressions not reported here I find that defining socioeconomic status by the whether the father holds a high school degree, or by setting the education threshold to college education has no effect on the estimated effects.

15. For the sake of comparison, moving a student from a low-quality school to a high-quality school is found to improve the student’s GPA with a similar magnitude as the January–December difference, see Fiva and Kirkebøen (2011).

16. In regressions not reported here, I find no birth month effect on the small subsample of girls having a mother holding a Master’s degree.

17. Pupils failing in compulsory school, have the opportunity to add an extra year of schooling between compulsory school and high school.

18. In regressions not reported here, the birth month effects of having graduated at age 20 are somewhat smaller than those reported here, but the negative trend is similar.

19. In regressions not reported here, I find a similar pattern when earnings are measured linearly rather than logarithmic. I also find a similar pattern if including those with no earnings in the sample.

20. Early enrollers score on average 25% better on GPA than deferred children.

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References

Baye, A., and C. Monseur. 2016. “Gender Differences in Variability and Extreme Scores in an International Context.” Large-Scale Assessments in Education 4 (1): 1–16. doi:10.1186/s40536-015-0015-x
Bedard, K., and E. Duhey. 2006. "The Persistence of Early Childhood Maturity: International Evidence of Long-run Age Effects." The Quarterly Journal of Economics 121 (4): 1437–1472.

Bedard, Kelly, and Elisabeth Duhey. 2012. "School-entry Policies and Skill Accumulation Across Directly and Indirectly Affected Individuals." Journal of Human Resources 47 (3): 643–683.

Black, S., P. Devereux, and K. G. Salvanes. 2011. "Too Young to Leave the Nest? The Effects of School Starting Age." Review of Economics and Statistics 93 (2): 455–467. doi:10.1162/REST_a_00081

Black, S., P. Devereux, and K. G. Salvanes. 2013. "Under Pressure? The Effect of Peers on Outcomes of Young Adults." Journal of Labor Economics 31 (1): 119–153. doi:10.1086/666872

Buckles, K., and D. M. Hungerman. 2013. "Season of Birth: Old Questions, New Answers." Review of Economics and Statistics 95 (3): 711–724. doi:10.1162/REST_a_00314

Byrhagen, K. N., T. Falch, and B. Strøm. 2006. "Frafall i videregående opplæring: Betydning av grunnskolekarakterer, studieretning og fylke." [High School Dropout: The Impact of GPA], SØF-rapport nr. 8/06.

Cascio, E., and D. Schanzenbach. 2016. "First in the Class? The Education Production Function." Education Finance and Policy 11 (3): 225–250. doi:10.1162/EDFP_a_00191

Crawford, C., L. Dearden, and E. Greaves. 2011. "Does When You are Born Matter? The Impact of Month of Birth on Children’s Cognitive and Non-Cognitive Skills in England." IFS Briefing Note: BN 122, Institute of Fiscal Studies/ Nuffield Foundation.

Crawford, C., L. Dearden, and E. Greaves. 2013. "The Impact of Age within Academic Year on Adult Outcomes." IFS Working Paper W13/07.

Crawford, C., L. Dearden, and E. Greaves. 2014. "The Drivers of Month-of-birth Differences in Children’s Cognitive and Non-cognitive Skills." Journal of the Royal Statistical Society: Series A 177: 829–860. doi:10.1111/jrss.a12071

Elder, T., and D. Lubotsky. 2009. "When you are Born Matters: The Impact of Date of Birth on Educational Outcomes in England." IFS Working Paper W10/06.

Dobkin, C., and F. Ferreira. 2010. "Do School Entry Laws Affect Educational Attainment and Labor Market Outcomes?" Economics of Education Review 29 (1): 40–54. doi:10.1016/j.econedurev.2009.04.003

Elder, T., and D. Lubotsky. 2009. "Kindergarten Entrance Age and Children’s Achievement: Impacts of State Policies, Family Background and Peers." Journal of Human Resources 44 (3): 641–683. doi:10.1353/jhr.2009.0015

Fertig, M., and J. Kluve. 2005. "The Effect of Age at School Entry on Educational Attainment in Germany." IZA discussion paper no 1507.

Fiva, J., and L. J. Kirkeboen. 2011. "Information Shocks and the Dynamics of the Housing Market." Scandinavian Journal of Economics 113 (3): 525–552.

Fredriksson, P., and B. Ockert. 2014. "Life-cycle Effects of Age at School Start." The Economic Journal 124: 977–1004. doi:10.1111/ecoj.12047

Heckman, J. 2006. "Skill Formation and the Economics of Investing in Disadvantaged Children." Science 312 (5782): 1900–1902. doi:10.1126/science.1128898

Jürges, H., and K. Schneider. 2011. "Why Young Boys Stumble: Early Tracking, Age and Gender Bias in the German School System." German Economic Review 12 (4): 371–394. doi:10.1111/j.1468-0475.2011.00533.x

Kawaguchi, D. 2011. "The Effect of Age at School Entry on Education and Income." Journal of the Japanese and International Economies 25 (2): 64–80. doi:10.1016/j.jjie.2009.02.002

Markussen, E., M. W. Frøseth, B. Lødding, and N. Sandberg. 2008. "Bortvalg og kompetanse." Rapport 13/2008. NIFU STEP.

Mühlenweg, A. M., and P. A. Puhani. 2010. "The Evolution of the School-Entry Age Effect in a School Tracking System." Journal of Human Resources 45 (2): 407–438. doi:10.1353/jhr.2010.0020

Puhani, P. A., and A. M. Weber. 2007. "Does the Early Bird Catch the Worm? Instrumental Variable Estimates of Early Educational Effects of Age of School Entry in Germany." Empirical Economics 32: 359–386. doi:10.1007/s00181-006-0089-y

Røed Larsen, E., and I. F. Solli. 2017. "Born to Run Behind. Persisting Relative Age Effects on Earnings." Labour Economics. doi:10.1016/j.labeco.2016.10.005.

Strøm, B. 2004. "Student Achievement and Birthday Effects." Working paper, Department of Economics, NTNU.

Thompson, A. H., R. H. Barnsley, and J. Battle. (2004). "The Relative Age Effect and the Development of Self Esteem." Educational Research 46 (3): 313–320. doi:10.1080/0013188042000277368