Economics H195B

Possible Causes and Implications of Seasonality of Birth

Carmen Ng

Faculty Advisor: Professor Michael Jansson

Abstract: The seasonality of births has been demonstrated by researchers time and time again. In this paper, we analyze possible future implications for children born in different months, and whether there are advantages to conscious decision-making in the timing of births. More specifically, we investigate this in the framework of kindergarten cutoff dates, and discover that there do indeed seem to be future educational and economic benefits in being one of the older students in a class.

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Introduction and Purpose

Contrary to intuition, it has been well-established that seasonality of births is indeed an existing phenomenon. Many possible factors could make childbearing more convenient, desirable, or probable during certain times of the year. Researchers have explored a plethora of plausible explanations – biological, climatic, cultural, etc. However, these factors are not the result of conscious decision-making.

It is possible that couples deliberately plan the timing of giving birth in hopes of eventually benefiting their children. Does month of birth have future implications for social adeptness, educational attainment, or economic success? Do people born in certain months fare better in the long run? If so, is this a result of innate characteristics that babies born in these months possess? Such a theory is close to impossible to corroborate since inherent traits are difficult to measure and compare.

If birth month does seem to have future implications, another possible hypothesis is that birth seasonality might be a consequence of kindergarten cutoff dates. In England and Wales, a child's age on September 1 determines when the child enters school. Studies on children in the United Kingdom have shown that September-born babies tend to fare better than their August-born counterparts, and it has been suggested that children would be better off if their parents strategically choose their birth months to miss cutoff dates for school admission, thereby making them the oldest in their class. [1]

Parents might choose to have their children born a little before or a little after school admission cutoff dates for two diametrically opposite reasons. Some parents, perhaps those who subscribe to findings similar to those in [1], might believe that children who are older than their peers tend to do better in school, especially at younger ages. Other parents might want to give their children an earlier start. Significant behavioral, educational, and economic differences could possibly be the result of school-starting age relative to peers. The purpose of this study is to investigate such possibility.

Data and Variables

The two datasets used in this investigation are the Early Childhood Longitudinal Study – Kindergarten (ECLS-K), conducted by the Institute of Education Sciences, and the National Longitudinal Survey of Youth 1997 (NLSY97), conducted by the Bureau of Labor Statistics. Longitudinal data in the studies allow us to follow the same group of subjects for a number of years.

The ECLS-K focused on the early school experiences of more than 21,000 young children. The ECLS-K sample consisted of kindergarteners in 1998 – 1999, and the survey documented this cohort's schooling experience up to the eighth grade. [2] We use the NLSY97 to capture a different set of educational experiences. The NLSY97 followed a sample of American youths between the ages of 12 and 16 (as of December 31, 1996) from 1997 to 2010. Following a cohort of this age range allows us to trace these respondents from their educational years to their transition into the workforce. This survey has a sample size of about 9000. [3]

It would have been ideal to use one longitudinal survey to follow the same one group from kindergarten to the workforce, but unfortunately, such a dataset does not seem to exist. Nevertheless, these two datasets combined should provide us with an understanding of children's life experiences from about five years of age to twenty-five. Though both surveys have variables covering a variety of characteristics, those of most interest to us are attitudes, education, and employment. A full list of variables used is in the appendix.

Existence of Birth Seasonality

Though the existence of birth seasonality does not necessarily prove that conscious decision-making is an underlying cause of this phenomenon, it is imperative to confirm such existence before performing any further analysis. Figure 1 displays the number of births in each month using data from the ECLS-K. Purely from eyeballing the dot plot, it seems obvious that the distribution is not uniform. To test this statistically, a chi-square test for goodness of fit is performed, by comparing the observed birth counts in the ECLS-K sample in each calendar month with the expected counts based on a uniform distribution, after adjustment by the number of days in each month. [4] For this chi-square test, the p-value is 6.154×10^{-7}, indicating that it is highly unlikely for the lack of uniformity in the empirical data to have been due simply to chance. Drawing the same graph (Figure 2) and applying the same test which yields a p-value of 1.753×10^{-4}, we draw a similar conclusion for the NLSY97 respondents.

Figure 1: Births in Each Month (ECLS-K)

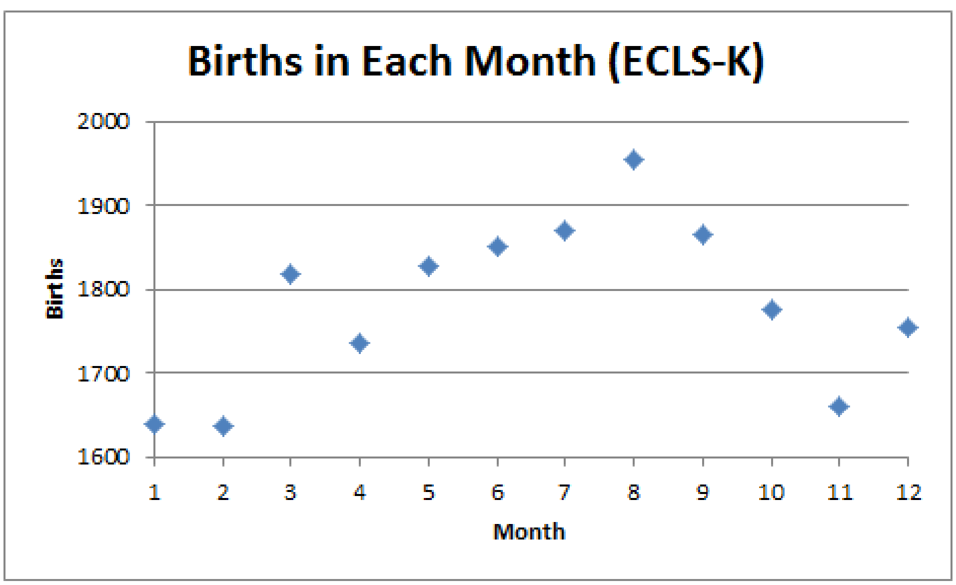
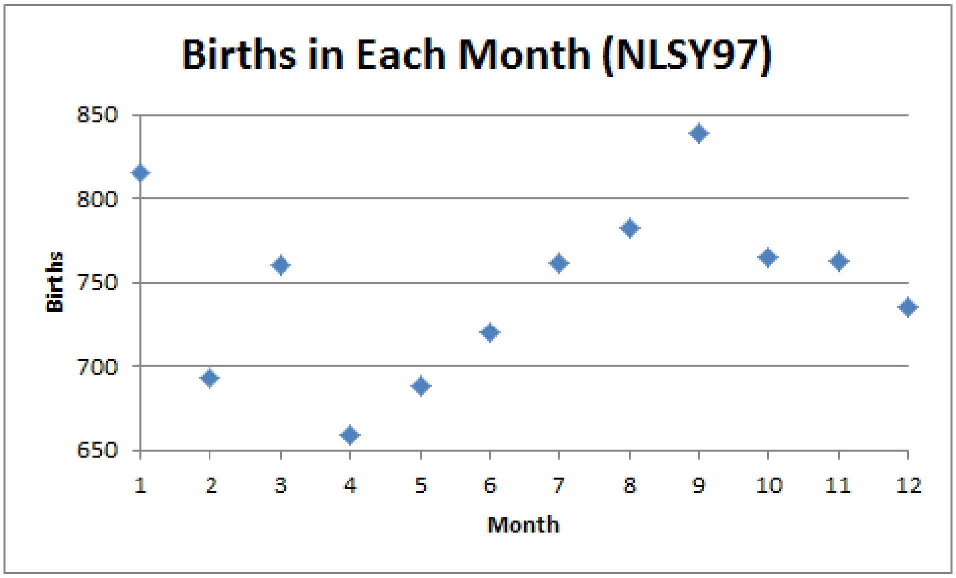


Figure 2: Births in Each Month (NLSY97)



Since the presence of seasonality seems very likely in both datasets, we proceed with more in-depth analysis. We would now like to explore whether month of birth might have any impact on the social, educational, and working aspects of our subjects' lives. If we see significant results, it means that birth month does have correlation with a person's progress in life, and that parents might have a good reason to carefully choose the month of giving birth. We would then ask the following: Do our seasonality patterns line up with this conscious decision-making, or are there other stronger driving forces?

ECLS-K Analysis of Variables

The ECLS-K conducted mathematics, reading, general knowledge, and science tests on its subjects. Seven tests in mathematics and reading (Periods 1 through 7), four in general knowledge (Periods 1 through 4), and three in science (Periods 5 through 7) were given. It should be noted that the periods are not equally spaced. Periods 1 and 2 were in the fall and spring of kindergarten, Periods 3 and 4 were in the fall and spring of first grade, Period 5 was in the spring of third grade, Period 6 was in the spring of fifth grade, and Period 7 was in the spring of eighth grade. For each subject test and each period, we conduct an analysis of variance (ANOVA) to statistically assess the differences in means between our birth-month groups. [4] Figure 3 shows the p-values of the ANOVA tests.

Figure 3: ANOVA P-Values for Test Scores from Various Academic Subjects

	Mathematics	Reading	General Knowledge	Science
Period 1	< 2.2e-16	< 2.2e-16	< 2.2e-16	N/A
Period 2	< 2.2e-16	1.227e-12	< 2.2e-16	N/A
Period 3	2.834e-11	1.281e-05	6.006e-06	N/A
Period 4	< 2.2e-16	2.115e-08	7.178e-12	N/A
Period 5	8.502e-06	1.564e-05	N/A	6.416e-05
Period 6	0.02796	0.0883	N/A	0.02076
Period 7	0.1176	0.1235	N/A	0.04199

The general pattern for the mathematics and reading tests is that the p-value increases with each successive period. It starts out at less than 2.2×10^{-16} in the first period and shows a generally increasing trend until it becomes insignificant toward the later periods, based on a significance level of 5%. The exception to this monotonic increasing behavior is from the third to the fourth periods for both academic subjects. In the ECLS-K, the third period had a lot of missing observations for reasons that were not documented, and this lack of data might be the reason for the seeming anomaly.

The p-values from the general knowledge tests show similar patterns to those of the mathematics and reading tests for the first four periods (the only available periods), and the p-values from the science tests also show similar patterns to those of the mathematics and reading tests for the final three periods (the only available periods). The only difference is that the Period 7 p-value for science still makes it under the five percent cutoff at 0.042.

ANOVA points to the conclusion that test results were not the same for children born in different months. It is interesting that the p-values in the analyses for all these academic subjects, for the most part, are monotonic increasing. This would suggest that the effect of birth month started off very prominently and eventually wore off.

The previous analyses look individually at each academic subject and each period. Now, we turn to testing all of the periods together for each academic subject. While we are trying to investigate whether the month of birth has any effect on test scores, it is obvious that the testing period (positively correlated with age) could also have an effect. The children are expected to have higher scores as they learned and gained more skills in these subjects. The data that we use are the IRT (Item Response Theory) Scale Scores in the ECLS-K, which allow for the measurement of gain in achievement over time. Figure 4 displays the weighted means and standard deviations of IRT Scale Scores for the reading test, which were calculated by the Institute of Education Sciences.

Figure 4: Weighted Means and Standard Deviations of Reading IRT Scale Scores

	Weighted Mean	Standard Deviation
Period 1 Reading IRT Scale Score	35.47	9.86
Period 2 Reading IRT Scale Score	46.52	13.88
Period 3 Reading IRT Scale Score	52.73	16.93
Period 4 Reading IRT Scale Score	77.07	23.70
Period 5 Reading IRT Scale Score	125.70	28.57
Period 6 Reading IRT Scale Score	148.67	26.85
Period 7 Reading IRT Scale Score	167.24	28.03

We need a different test to take into account two factors – the month of birth and the period of testing. However, a typical two-way ANOVA will not work since our samples were not independent. Each child repeatedly took these tests. As a result, we use repeated-measures ANOVA. [5]

For both mathematics and reading, we run longitudinal tests across the seven periods. Due to the demand on computing resources in performing repeated-measures ANOVA, we are not able to do this for the entire dataset. Instead, we take a systematic sample of the dataset, and use all observation numbers divisible by three. Even after extracting a sub-sample, we still have a sample size of about 7000 with more than 30,000 test scores to work with for each academic subject.

The results from the mathematics and reading tests are quite similar, and as expected. Both the period and birth-month factors are statistically significant, with p-values of under 0.0001. Interaction plots are depicted below (Figures 5 and 6) to visually display the interaction between the two factors. The rather parallel lines in both figures suggest that certain months consistently produce higher or lower means on these mathematics and reading tests, and that the effect of birth months does not seem to vary across periods.

Figure 5: Interaction Plot of Birth Months and Average Mathematics Scores

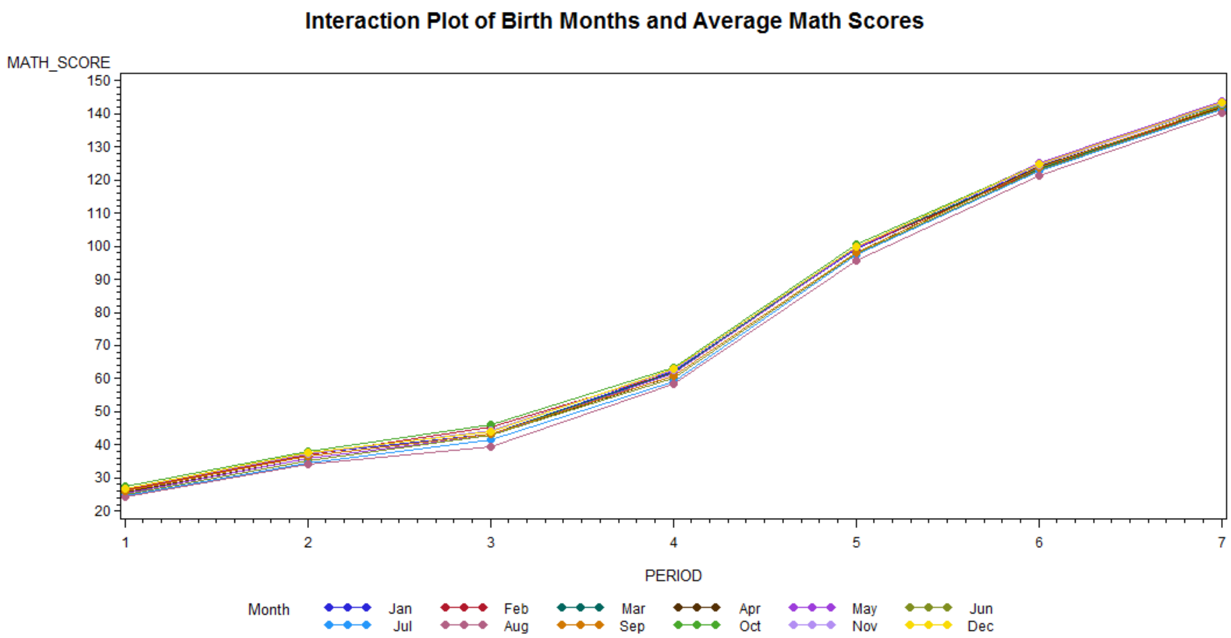
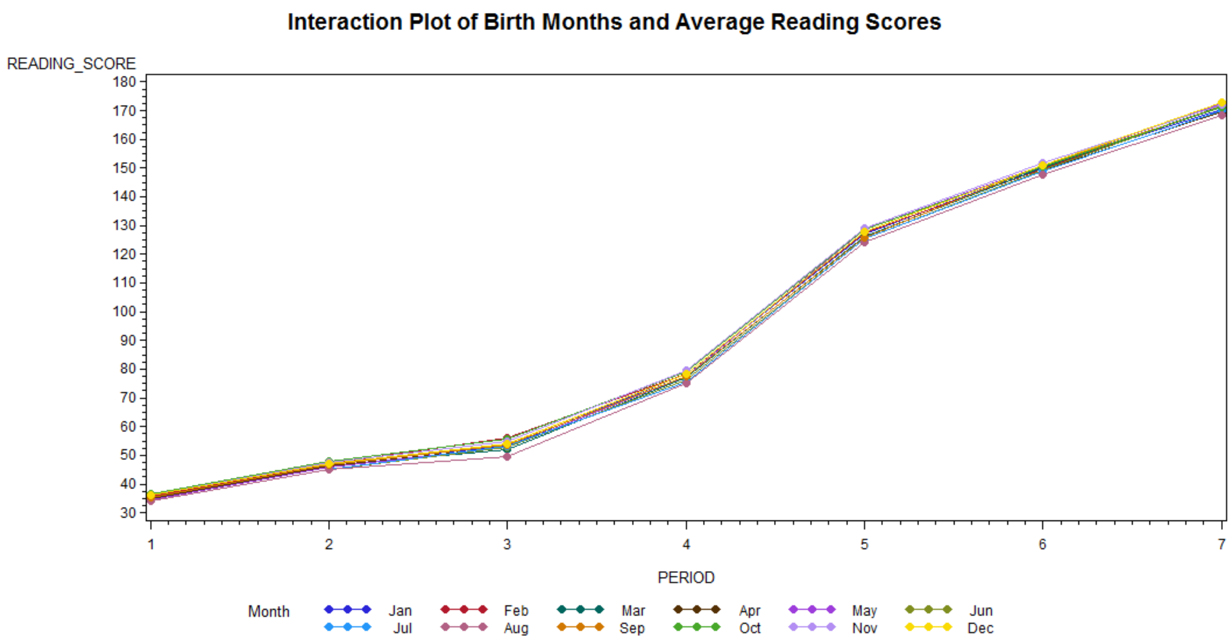


Figure 6: Interaction Plot of Birth Months and Average Reading Scores



We also look into a variable on emotional behavior in the ECLS-K. Because the variable is categorical, we use chi-square testing for independence to see if the two factors (birth month and the variable that we are testing) are independent. [4]

Parents were asked whether they had any concerns about their children's "overall emotional behavior, such as anxiety or depression" in Periods 5 through 7. The p-values for these tests (0.1427, 0.7965, and 0.8414) are not significant in any period. It would have been more telling and helpful in our investigation if this question had been asked at a younger age, before any possible effect had worn off.

NLSY97 Analysis of Variables

Eighth grade and high school grades were recorded by the NLSY97. It would have been interesting to look at each high school year separately, but unfortunately, the survey only asked for average grades in high school. ANOVA on eighth grade and high school grades register statistically significant results at the five percent significance level (Figure 7), meaning that month of birth does appear to have an effect on school performance.

It is surprising that eighth grade and high school grades register as significant, when the ECLS-K analysis performed on various academic subjects reveals that the effect of birth month seemed to have worn off by Period 7 (spring of eighth grade). Since our NLSY97 and ECLS-K samples are large, we expect them both to be fairly representative of the sampling frame, which is the general American population within the specific age ranges. Of course, we need to remember that we are looking at two different groups of people and different survey methodologies.

Since ANOVA testing with grades in grade 8 and high school indicates statistical significance, it seems natural to expect standardized testing scores to give similar results. Using ACT and SAT scores, we perform similar analyses. Interestingly, analyses of these scores give p-values much higher than 0.05. What could be a reasonable explanation for this? The aforementioned kindergarten cutoff date theory suggests that being a younger student in a class is not advantageous. However, there is a major difference between grades and standardized testing, such as the SAT and ACT. Grades are intended to measure how much a student has learned over the course of a schooling period, while tests such as the ACT and SAT attempt to gauge aptitude, as the name “Scholastic Aptitude Test” implies. Innate aptitude is an inborn quality, not something that is acquired through years of education. We asked earlier whether babies born in certain months possess some innate characteristics. Perhaps these results lend credence to a negative answer with respect to innate aptitude.

Figure 7: ANOVA P-Values for Grades and Standardized Testing

8th Grade Grades	0.04813
High School Grades	0.03632
ACT Score	0.5681
SAT Score	0.2741

In the NLSY97, "total income from wages and salary" was asked annually from 1997 to 2010. When we test income as the dependent variable separately for each year, birth month is a significant factor all for years except 2010, with some years registering extremely significant results (Figure 8). This seems to imply that the effect of birth month still persists in working years. It is interesting to note that the 2009 ANOVA p-value, while under 0.05 at 0.039, is still very high compared to that of the prior years. Could there be a reasonable explanation for an increase in p-values in later years, besides statistical distortions? Since the NLSY97 is a longitudinal study, subjects are older in the later years. We could, once again, be seeing a wearing off effect.

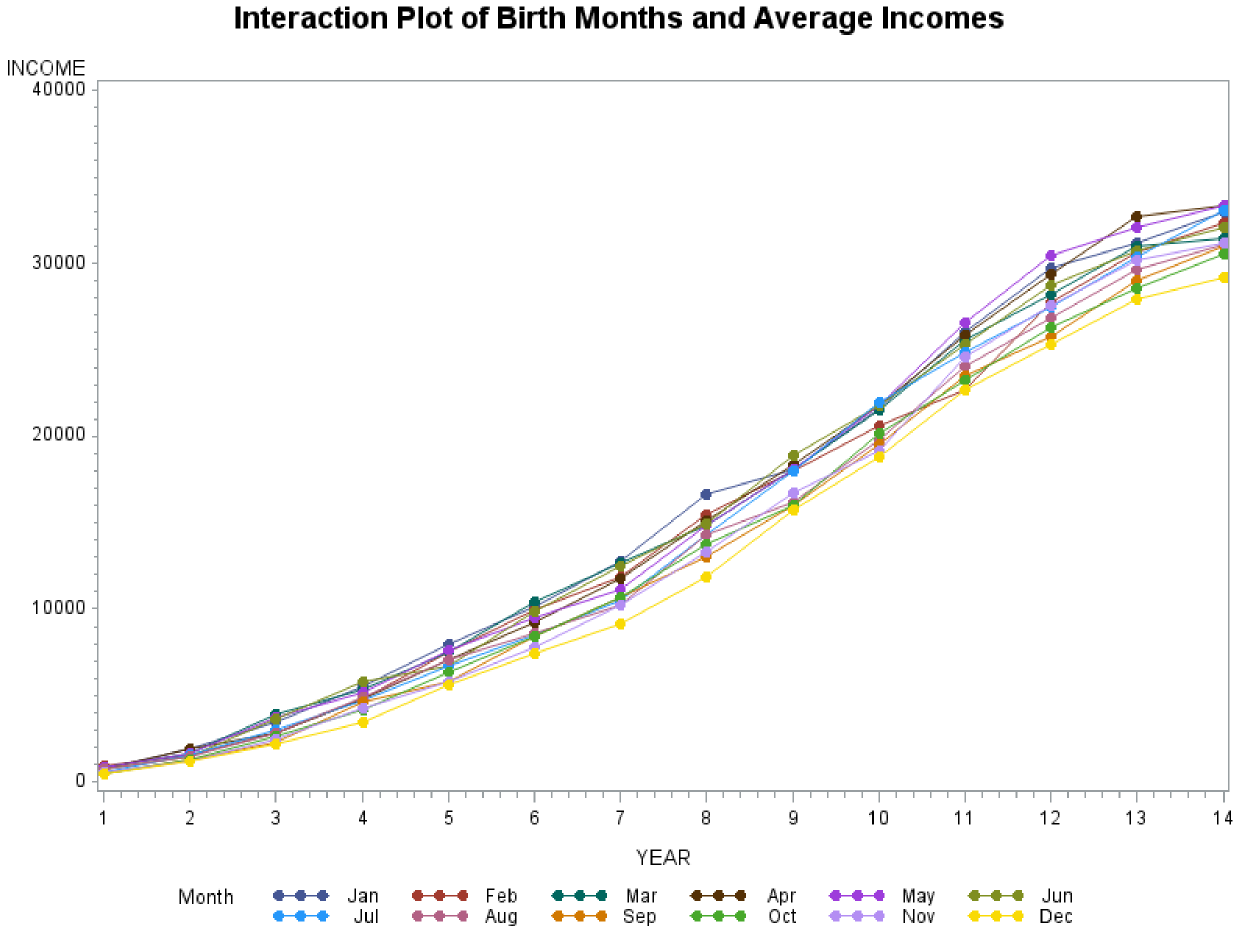
Another point of note is that, in our study based on ECLS-K data, the difference in academic performance seemed to have worn off in middle school. Why did it seem to reappear at the beginning of this income analysis, to be followed by another wearing off? Here is a possible explanation. In 1997, all of the subjects were between 12 and 17 years of age. Some were beginning their working careers, perhaps working part time while in middle school or high school. If students were at the same grade level, there could be up to a one-year difference in age between the oldest and youngest of them. The older ones would tend to have some advantage, especially if the work was physically demanding. But this should wear off as they establish themselves in the workforce, as seen in the ANOVA results. If this is so, then it is another manifestation of the birth-month effect.

Figure 8: ANOVA P-Values for Income

1997	2.965e-05
1998	0.0004726
1999	5.879e-07
2000	1.618e-05
2001	5.449e-07
2002	1.43e-06
2003	3.087e-08
2004	1.472e-05
2005	0.001384
2006	0.00241
2007	0.009011
2008	0.0002751
2009	0.03941
2010	0.2144

Additionally, we perform a longitudinal analysis, as we did for the ECLS-K data. The results of the repeated-measures ANOVA are extremely significant, with both our year and income factors having p-values of less than 0.0001. Figure 9 is an interaction plot, demonstrating the effect of birth month on income over the years. As the relatively parallel lines show, the general pattern did not change much through the years.

Figure 9: Interaction Plot of Birth Months and Income



Again, as we did for our ECLS-K emotional behavior categorical variable, we turn to chi-square testing for independence. Because it is not statistically sound to have fewer than five expected counts in a cell for too many cells, we collapse some of the categories together. In making such modifications, we lose some information, but we also gain statistical validity.

The NLSY-97 asked respondents how often they communicated with their best friends. We collapse the seven possible responses into three – communicate every day, communicate at least once a week (but less often than every day), and communicate fewer than once a week. Chi-square testing produces a p-value of 0.0204, indicating that it is likely that month of birth has some effect on people's social behaviors. Similarly, we collapse the ten possible responses for how close respondents are to their best friends into just three. The p-value here is 0.1476, not significant at a significance threshold of 0.05. These results render it difficult to draw any strong conclusion.

Conclusions So Far

Our combination of ECLS-K and NLSY97 results are a bit all over the place. From the ECLS-K analysis, it seems that the effect of birth month on academic tests slowly faded away as these schoolchildren got older. However, we witness significance again with eighth grade and high school grades, using data from the NLSY97. These are seemingly contradictory results. With the NLSY97 dataset, we also see that the mean incomes for the twelve birth months are likely to not be the same. However, if the birth-month effect was diminishing in our ECLS-K analysis, why was it appearing again in both the later years of schooling and the workforce? A plausible explanation for income differences was provided in the previous section. Whereas the birth-month effect on education seems to exist in both the ECLS-K and NLSY97 datasets, the wearing off effect seems inconsistent in them.

We also have mixed results for our behavioral variables. However, all of the variables used to test social behavior were asked at older ages, where the birth-month effect might have already faded. As we proceed, we will only look at the academic and economic aspects of these individuals' lives.

Extension of Analysis – School Cutoff Dates

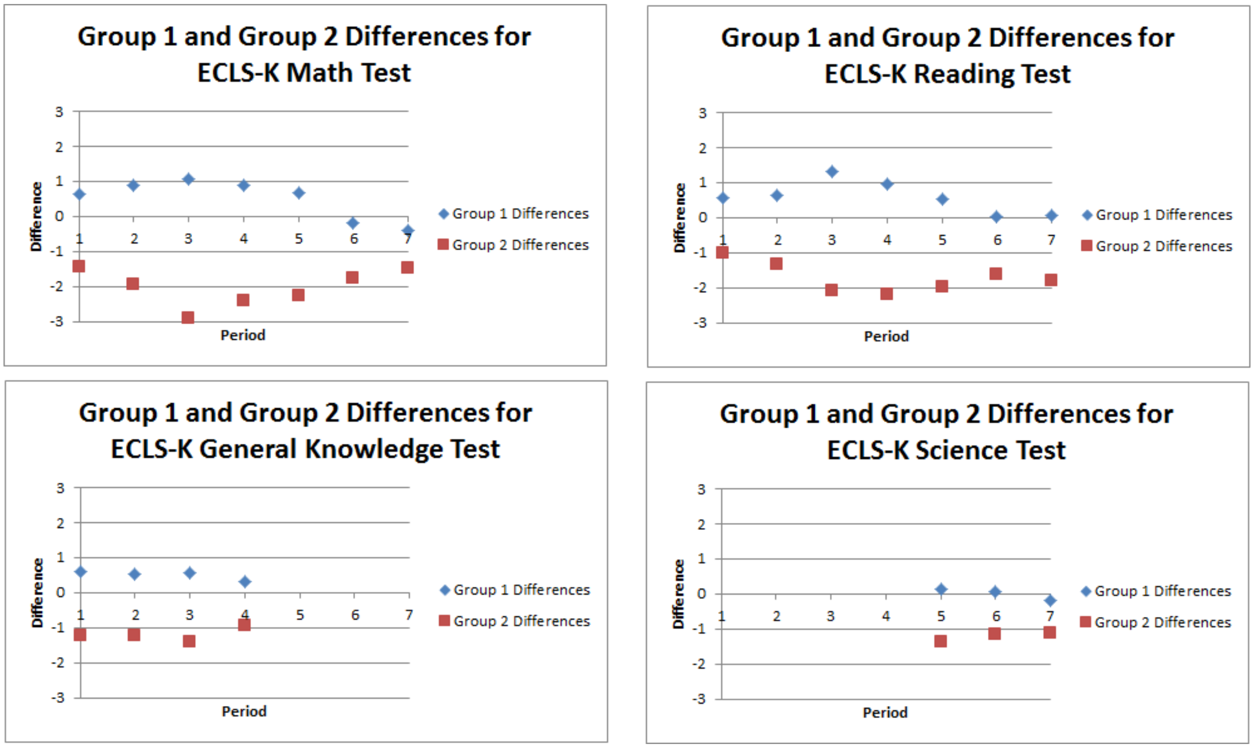
In this section, we attempt to analyze the differences that we saw previously. If it is true that older children perform better than their younger classmates, then we expect that those born right after a kindergarten cutoff date have more educational and economic success. On the other hand, if an early start is beneficial, we would see the opposite – those born right before a cutoff date would have the advantage.

For the NLSY97 and ECLS-K, we unfortunately do not have access to the respondents' locations, due to confidentiality issues. Instead, we take a less accurate, yet still effective, approach. We have kindergarten cutoff dates for all states in 1975, 1990, and 2005. [6] The NLSY97 cohort falls between 1975 and 1990, and the ECLS-K between 1990 and 2005. For 1975, 1990, and 2005, almost all states had kindergarten cutoff dates between August 31 and January 1. The exceptions to this were Alaska (August 15 in 2005), Delaware (January 31 in 1975), Idaho (August 16 in 1990), Indiana (July 1 in 2005), Missouri (July 1 in 1990 and August 1 in 2005). Out of all fifty states, these were the only five that had kindergarten cutoffs outside the August 31 to January 1 range, and they were not nearly the most populous. Moreover, their cutoff dates were not too far off this range.

If the theory that being an older child in one's class puts one at an advantage, we would expect the January/February-born babies to perform better than the July/August-born babies. We merge the January and February babies into "Group 1" and the July and August babies into "Group 2". Under this conjecture, academic test scores, grades, and income should be consistently higher for Group 1 than Group 2. We may not see this for ACT and SAT scores because we found earlier that seasonality does not seem to affect standardized testing performance.

For each of the periods and academic subjects in the ECLS-K dataset, the mean score of Group 1 is indeed always higher than that of Group 2. We then calculate the grand mean for each subject test and period, and compute the difference between the Group 1/Group 2 mean and the grand mean. These differences are graphed in Figure 10. It can be seen that Group 1 differences are always above Group 2 differences, meaning that, on average, Group 1 children did consistently better than Group 2 children. Moreover, Group 1 differences are mostly positive, while Group 2 differences are all negative, indicating that Group 1 children did better than average, while Group 2 children did worse than average. We can also see the difference wearing off. An observation that might be interesting is that the magnitude of the difference seems to increase and reach a maximum in Periods 3 and 4, i.e., first grade. We repeat the previous caution that there were a lot of missing observations in the third period of the ECLS-K dataset.

Figure 10: Group 1 and Group 2 Differences for ECLS-K Academic Tests



To test this statistically, we do a one-sided t-test. [7] The null hypothesis is that the mean scores of the two groups are equal, and the alternative hypothesis is that the mean score of Group 1 is higher than the mean score of Group 2. As Figure 11 suggests, the null hypotheses, for the most part, are rejected, based on a significance level of 5%. We concluded earlier using ANOVA that mean scores are not equal over the twelve birth months. Now, we can further say that children who are older in their class perform better than their younger peers on average. These results line up with the findings in [1].

Figure 11: One-Sided T-Test P-Values Comparing Group 1 and Group 2 ECLS-K Test Scores from Various Academic Subjects

	Mathematics	Reading	General Knowledge	Science
Period 1	< 2.2e-16	1.303e-09	< 2.2e-16	N/A
Period 2	< 2.2e-16	1.249e-08	< 2.2e-16	N/A
Period 3	2.422e-09	6.716e-05	2.985e-07	N/A
Period 4	6.738e-12	5.736e-07	1.386e-09	N/A
Period 5	2.172e-05	0.001073	N/A	0.0002627
Period 6	0.02892	0.03078	N/A	0.009411
Period 7	0.09416	0.03229	N/A	0.05658

Performing such analyses with the academic-related variables from NLSY97 data yield somewhat different results (Figures 12 and 13). While the means of Group 1 are higher than those of Group 2 for eighth grade grades, high school grades, and ACT scores, the differences do not register as statistically significant for high school grades or ACT scores in one-sided t-tests. That is, we fail to reject the null hypothesis that high school grades and ACT scores for Group 1 and Group 2 have equal means. For SAT scores, the Group 2 mean is actually higher than the Group 1 mean. This strengthens our claim that birth month likely has no effect on success on standardized tests, since the results of ACT and SAT scores go in opposite directions.

Figure 12: Group 1 and Group 2 Means for Grades and Standardized Testing

	Group 1 Mean	Group 2 Mean
8th Grade Grades	2.82044	2.76252
High School Grades	2.76329	2.73620
ACT Score	19.985	19.88806
SAT Score	1048.223	1049.364

Figure 13: One-Sided T-Test P-Values Comparing Group 1 and Group 2 Grades and Standardized Testing

8th Grade Grades	0.02379
High School Grades	0.1787
ACT Score	0.4216
SAT Score	0.5301

The longitudinal income variables are much harder to interpret. Figure 14 illustrates that Group 1 differences are always higher than Group 2 differences. However, Group 1 differences are typically much higher than zero, while Group 2 differences range between somewhat below zero to slightly above zero. This would suggest that the grand means for income from 1997 to 2010 are being pulled down by births in other months. Since we block off the months September through December for our analysis, it is possible that a subset of these months is the culprit. For example, in states where December is the cutoff, it might be the case that November babies earn the least amount of income. Without information on the state of residence during primary school, we have no means to analyze this further.

Figure 14: Group 1 and Group 2 Differences for Income

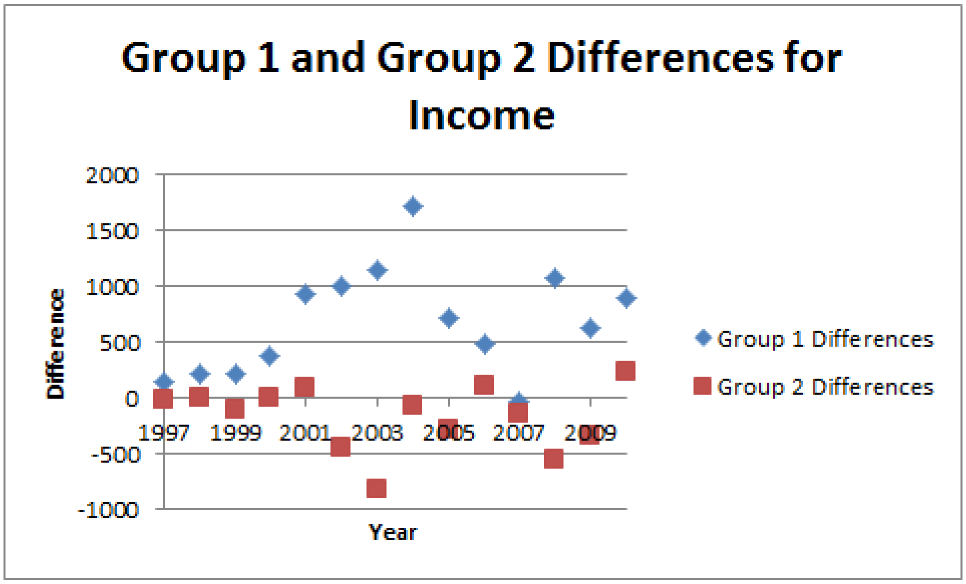


Figure 15, which has all of the p-values from the one-sided t-tests for income for each year, does not paint a clear picture. While it is quite clear from the diagram that Group 1 did better than Group 2 on average, the differences between them do not seem to be statistically conclusive.

Figure 15: One-Sided T-Test P-Values Comparing Group 1 and Group 2 Incomes

1997	0.03799
1998	0.06529
1999	0.1148
2000	0.1226
2001	0.01526
2002	0.0005852
2003	2.812e-05
2004	0.003913
2005	0.0636
2006	0.2903
2007	0.456
2008	0.03464
2009	0.1634
2010	0.2838

Caveats

As discussed earlier, this would have been a better analysis had we been able to find a single dataset that followed a group of people from kindergarten to their early working years. Such a dataset does not seem to be out there, and understandably so. One of the biggest issues with longitudinal surveys is non-response. [5] Though there may be many willing participants at the beginning of a study, the sample size likely dwindles as years go by when people decide that they no longer want to participate or when they are no longer reachable. Receiving a firm commitment from a large and representative enough group to be part of a longitudinal study for 20 years is a difficult task. Such a longitudinal survey would have been ideal though, since we could only use two surveys with different samples and methodologies in our study. To what extent we can combine our findings from these separate datasets is unclear.

The kindergarten cutoff dates that we have access to were for only the years 1975, 1990, and 2005. We have no idea about the cutoff dates in other years. It is possible, though unlikely, that the cutoff date in a certain state during the time our NLSY97 cohort attended kindergarten was very different from those in 1975 and 1990. We encountered a similar issue with the ECLS-K cohort as well, though we look at the 1990 to 2005 period instead. Furthermore, the unavailability of information on the geographical location of the children when they began kindergarten prompted us to use the approximate Group 1/Group 2 approach. It would have been ideal to have the cutoff dates that our respondents were subject to when they began kindergarten.

Another assumption in our study is that students entered the education system at the earliest point they could, while still adhering to the cutoffs of their states of residence. For example, we do not take into account that parents could have potentially held their children back by a year or that they could have enrolled their children a year early. Additionally, we cannot account for children who later skipped or repeated a grade. These scenarios are not too common though, and would have added another layer of complexity to our analyses.

<u>Conclusion</u>

By performing these analyses, we want to see if there are any academic, economic, or social implications for being born in a particular month. We find that there certainly are dissimilarities between people born in different months. But are these differences innate or the result of something that could possibly be controlled? We investigate one such possible factor, which is conscious timing. If births right before or right after kindergarten entry cutoff dates register particularly low or high results, it would make sense for parents to have their children born in certain months to give them an advantage later in life. While our analysis of this is not ideal, as discussed in the “Caveats” section, there is some statistical backing to lend support to the claim that children born right before the cutoff date suffer, especially in the early years of education. Given that the kindergarten cutoff theory does indeed seem to hold, we would expect parents to choose their children’s birth months to be between September and December. However, this does not seem to match up with current trends in birth seasonality.

From Figures 1 and 2, it seems that more babies in our samples were born in the summer, suggesting that their parents had not timed births to be after kindergarten cutoff dates. While births before or after cutoff dates do seem to have an effect on children’s educational success (and maybe economic success as well), it seems that parents in these two studies had not timed their children’s births solely to take advantage of this. Observed seasonality in these studies was likely due to some other stronger driving forces. Further studies would be needed to establish what these forces were.

From a policy standpoint, suggestions such as age normalization of test results, flexible school entry depending on stage of development instead of age, and special attention and intervention because of magnified effects for at-risk children, have been discussed. [1, 8, 9] Nobody would argue against fairness and equal opportunity in education. Much research and thought would need to be put into this seemingly natural and biological phenomenon to achieve equity.

Appendix

1. ECLS-K Variables Used

   DOBMM: CHILD COMPOSITE DOB MONTH

   C*R4MSCL: C* RC4 MATH IRT SCALE SCORE, where * denotes the period

   C*R4RSCL: C* RC4 READING IRT SCALE SCORE, where * denotes the period

   C*RGSCAL: C* REC GENERAL KNOWLEDGE IRT SCALE SCORE, where * denotes the period

   C*R2SSCL: C* RC2 SCIENCE IRT SCALE SCORE, where * denotes the period

   P*CONEMO: P* CHQ350 CONCERNS ABOUT EMOTIONAL BEH, where * denotes the period

2. <u>NLSY97 Variables Used</u>

KEY!BDATE_M: KEY!BDATE, RS BIRTHDATE MONTH/YEAR (SYMBOL)

YSCH-6800: GRADES R RECEIVED IN 8TH GRADE

YSCH-7300: GRADES R RECEIVED IN HIGH SCHOOL

TRANS_ACT_COMP: COMPOSITE ACT SCORE

TRANS_SAT_VERBAL: SAT VERBAL SCORE

TRANS_SAT_MATH: SAT MATH SCORE

YINC-1700: TOTAL INCOME FROM WAGES AND SALARY IN PAST

YEARKEY!BDATE_M: KEY!BDATE, RS BIRTHDATE MONTH/YEAR (SYMBOL)

YSCH-6800: GRADES R RECEIVED IN 8TH GRADE

YSCH-7300: GRADES R RECEIVED IN HIGH SCHOOL

TRANS_ACT_COMP: COMPOSITE ACT SCORE

TRANS_SAT_VERBAL: SAT VERBAL SCORE

TRANS_SAT_MATH: SAT MATH SCORE

YINC-1700: TOTAL INCOME FROM WAGES AND SALARY IN PAST YEAR

YFRD-210: HOW CLOSE R FEELS TO BEST FRIEND

YFRD-230: HOW OFTEN DOES R COMMUNICATE WITH BEST FRIEND

Works Cited

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