

*Imagine Early*  
Improves Course  
Performance and  
Reduces Course  
Failure, with Larger  
Impacts for Students  
from Lower-Income  
Households

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# SUMMARY

This study supplements a prior analysis for the same study of the impact of *Imagine Early* on test scores (see Elliott, Sorensen, Zheng, & O'Brien, 2023).<sup>1</sup> We build on this prior work by examining the relationship between enrollment and participation in *Imagine Early* and course performance in the middle grades. Specifically, we focus on students in Grades 4-6 in the 2016-17 school year and subsequently in Grades 5-7 in the 2017-18 school year and examine course performance for Grades 6-8 in the 2018-19 school year. We address the following three research questions:

1. What is the impact of enrollment and participation in *Imagine Early* on average course performance?
2. What is the impact of enrollment and participation in *Imagine Early* on course failure?
3. To what extent do the impacts of participation in *Imagine Early* vary for students from lower-income households (i.e., receiving free/reduced-priced lunch)?

We conducted a quasi-experimental analysis comparing students who enrolled in *Imagine Early* at any time during the 2016-17 or 2017-18 school year with their counterparts who did not enroll in the program during this time. We employed an inverse-propensity weighting design to adjust for baseline differences in characteristics between students who did enroll in *Imagine Early* (treatment) and students who did not enroll in the program (comparison) using available pretreatment administrative data from 2015-16. That is, students in the comparison group were weighted at baseline to more closely resemble students in the treatment group. This IPW approach successfully removed baseline differences exceeding 0.25 standardized mean differences, meeting What Works Clearinghouse Evidence Standards v4.1 (2021)<sup>2</sup> for baseline equivalence between a treatment and comparison group. Our findings show that enrollment and participation in *Imagine Early* results in improved average course grades and reduced course failure. We observed significant average impacts for all students, with larger effects for student receiving free/reduced lunch. In short, these findings suggest that *Imagine Early* may be an effective program for improving student performance in school and an effective gap-closing intervention for students from lower-income households. Effects are stronger for students who were enrolled as scholars for longer periods of time and for students who earned more award dollars by participating in more incentivized engagement activities across the 2016-17 and 2017-18 school years.

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<sup>1</sup> Imagine Early was most recently called the Early Award Scholarship Program and before that Promise Scholars.

<sup>2</sup> Retrieve from <https://ies.ed.gov/ncee/wwc/Docs/referenceresources/WWC-Standards-Handbook-v4-1-508.pdf>



## Sample

The analytic sample included N=1,174 students enrolled in Grades 4-6 (N=402 in Grade 4, N=394 in Grade 5, N=378 in Grade 6) during the 2016-17 school year.<sup>3</sup> The sample included students from N=6 schools in Wabash County, Indiana (N=389 in Manchester Intermediate School, N=117 in OJ Neighbours, N=25 in Saint Bernard, N=239 in Sharp Creek, N=184 in Southwood Elementary, and N=220 in Wabash Middle School). Although students in Grades 7 and 8 in 2016-17 were eligible to enroll in Imagine Early and participate in incentivized engagement activities, our analyses focus on those in Grades 4-6 for two reasons: (1) all students in Grades 6-8 in 2018-19 were enrolled in courses where schools issue meaningful grades based on performance, but had not yet entered high school, and (2) all students in Grades 3-5 in 2014-15 were enrolled in tested grade levels and would have had the opportunity to take the state ISTEP assessment in 2015-16—providing an important baseline measure of student achievement in the year prior to enrolling/participating in Imagine Early. The sample included N=536 females (46%), N=589 males (50%), and N=49 students with an unknown gender (4%, information missing from dataset). The sample was predominantly white (N=1,040, 89%) but included N=39 (3%) Hispanic students, N=8 (<1%) Black students, N=8 (<1%) Asian students, N=5 (<1%) Native American/American Indian students (<1%), N=34 (3%) Multi-racial students, and N=40 (3%) students who were missing race/ethnicity information. A total of N=153 (13%) students were receiving special education services (N=75 students [6%] were missing information on special education status), N=23 (2%) were English language learners (N=74 [6%] were missing information on language status), and N=619 (53%) were receiving free/reduced lunch (N=29 were missing information on lunch status). The average age of the student analytic sample as of September 1, 2016 (the start of the first treatment year) was M=10.77 years (SD=0.93, Min=8.89, Max=13.97).

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<sup>3</sup> The analytic sample excluded N=25 students who enrolled in Imagine Early during the 2018-19 school year because this study examined attendance and state test scores during that same year as outcomes of enrollment and participation in the program.

# IMAGINE EARLY PROGRAM

To raise awareness and promote participation, the program developed marketing materials such as brochures, posters, and school-related products (i.e., rulers, pencils, sports bags, and water bottles). The program also used a variety of other approaches for enrollment including opportunities at both in-person and online school registration, parent-teacher conferences, athletic and community events. Regardless of enrollment method utilized, all parents were required to complete the Participation Agreement and have a linked CollegeChoice account before enrollment was complete.

Of the N=1,174 students in the analytic sample, N=771 (66%) enrolled in Imagine Early during 2016-17 or 2017-18 school years (see Table 1 for enrollments by quarter), N=401 (34%) did not enroll during this time.

**TABLE 1**

***Analytic Sample Enrollment by Year and Quarter***

School Year	2016-2017	2017-2018
<b>Quarter 1</b>	468	84
<b>Quarter 2</b>	46	11
<b>Quarter 3</b>	101	18
<b>Quarter 4</b>	42	3
<b>Total</b>	657	116

Once enrolled, students in Imagine Early can participate in engagement activities and earn scholarship award dollars. In general, these activities are focused on three areas: (1) learning (which includes goal setting, completion of assignments and formative assessment related goals), (2) saving (which includes receiving incentives for family savings of at least \$20 per semester), and (3) college preparation (though these activities were most prevalent in 8th grade (excluded from the current study—see Sample above). Tables 2 and 3 outline the scholarship award dollars available for different opportunities for students in Grades 4-6 in 2016-17 (Table 2) and 5-7 in 2017-18 (Table 3).

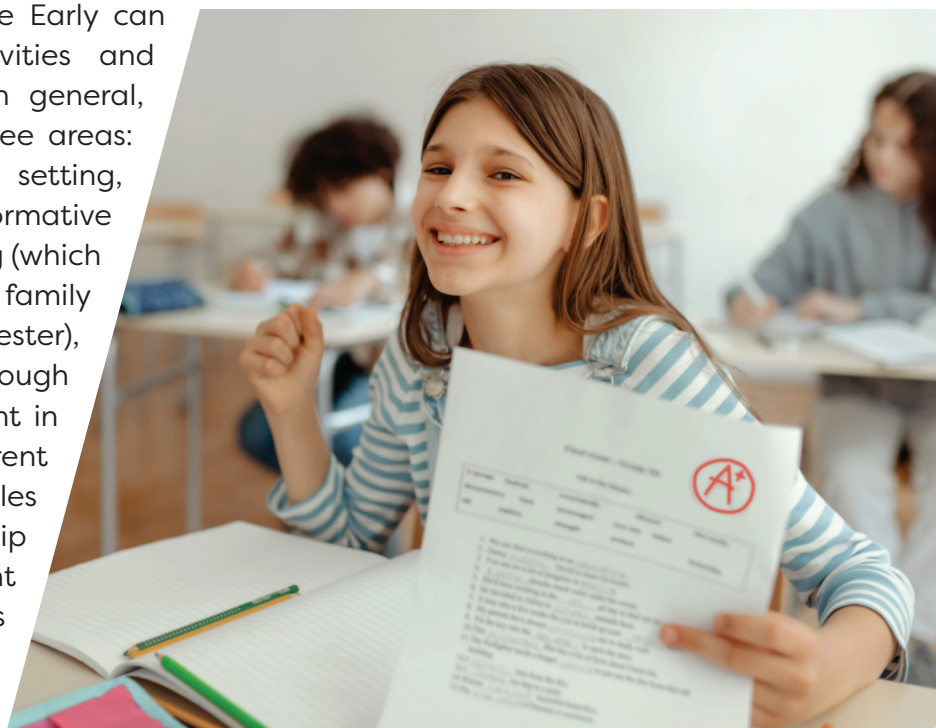


TABLE 2

**Program Scholar Award and Savings Activities in 2016-17, Grades 4-6**

	Q1	Q2	Q3	Q4	Totals
<b>4th Grade</b>					
Goal Setting	\$10				
Reading assignments <i>and</i> reach NWEA goal in Q4	\$10	\$10	\$10	\$10	
Math assignments <i>and</i> reach NWEA goal in Q4		\$10	\$10	\$10	
Language Arts essays		\$10	\$10		
Savings Match (if \$10 is deposited into 529 account each quarter)	\$10	\$10	\$10	\$20	
					<b>\$150</b>
<b>5th Grade</b>					
Savings Match (if \$10 is deposited into 529 account each quarter)	\$10	\$10	\$10	\$20	
					<b>\$50</b>
<b>6th Grade</b>					
Goal Setting	\$10				
Reading, Math, and Language Arts assignments <i>and</i> reach 2 out of 3 NWEA goals in Q4	\$10	\$10	\$10	\$10	
College Go Activity #1	\$25				
College Go Activity #2			\$25		
Savings Match (if \$10 is deposited into 529 account each quarter)	\$10	\$10	\$10	\$20	
					<b>\$150</b>

TABLE 3

**Program Scholar Award and Savings Activities in 2017-18, Grades 5-7**

	Q1	Q2	Q3	Q4	Totals
<b>5th Grade</b>					
Essay/Presentation			\$10		
College Go Activity #1		\$25			
College Go Activity #2				\$25	
Savings Match (if \$20 is deposited into 529 account each semester)		\$20		\$30	
					<b>\$110</b>
<b>6th Grade</b>					
NWEA Goal Setting	\$10				
Reading, Math, and Language Arts assignments <i>and</i> reach 2 out of 3 NWEA goals in Q4	\$10	\$10	\$10	\$35	
College Go Activity #1	\$25				
College Go Activity #2				\$25	
Savings Match (if \$20 is deposited into 529 account each semester)		\$20		\$30	
					<b>\$175</b>
<b>7th Grade</b>					
Essay/Presentation			\$10		
College Go Activity #1		\$25			
College Go Activity #2				\$25	
Savings Match (if \$20 is deposited into 529 account each semester)		\$20		\$30	
					<b>\$110</b>



## Program Enrollment and Participation Measures

We assessed enrollment in *Imagine Early* in two ways:

- ***Imagine Early* enrollment.** A binary indicator for whether a student enrolled in *Imagine Early* during one of 8 quarters across the 2016-17 and 2017-18 school years.
- **Total quarters enrolled in *Imagine Early*.** A count of the number of quarters (8 total) that a student was enrolled in *Imagine Early*.

We assessed participation in *Imagine Early* as follows:

- **Total Scholarship Award Dollars Earned.** The total award dollars earned across the 2016-17 and 2017-18 school years for engagement activities completed.

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# STUDY DESIGN

This study employed an inverse propensity weighting approach to conduct a quasi-experimental analysis of outcomes resulting from enrollment and participation in *Imagine Early*. Specifically, this study compares the outcomes of students enrolled in *Imagine Early* with their counterparts who did not enroll in the program. A challenge to internal validity (confidence in causal attribution) is that students who self-select to enroll in the program may differ systematically from students who do not enroll. As detailed above, for this study, 2 out of 3 students enrolled during the 2016-17 and 2017-18 school years. Inverse propensity weighting allows us to adjust for these differences at baseline (to the extent possible) in two steps. First, we run a selection model (a logistic regression) using all pre-treatment characteristics available to us in the dataset to predict each student's propensity to enroll (1) or not enroll (0) in *Imagine Early*. Second, we apply weights to the student sample that make the comparison group of students more closely resemble the characteristics of the treatment group—those students who enrolled in *Imagine Early*. The selection model was estimated as follows:

$$\eta_i = \beta_0 + \beta_1^*(\text{PriorMath})_i + \beta_2^*(\text{PriorELA})_i + \beta_3^*(\text{PriorAttendance})_i + \beta_4^*(\text{Student Characteristics})_i + \beta_5^*(\text{Grade})_i + \beta_6^*(\text{MissingIndicator})_i + \beta_7^*(\text{School})_i + e_i \quad (1)$$

where

- $\eta_i = \log(\varphi_i / 1 - \varphi_i)$  (that is, the log of the odds of enrolling in *Imagine Early*) and  $\varphi_i$  is the probability enrolling in *Imagine Early* for student  $i$ .
- $\beta_0$  is the average student's log odds for enrolling in *Imagine Early*.
- $\text{PriorMath}_i$  is the 2015-16 ISTEP prior mathematics achievement score for student  $i$ .
- $\text{PriorELA}_i$  is the 2015-16 ISTEP prior ELA achievement score for student  $i$ .
- $\text{PriorAttendance}_i$  is a vector of 2015-16 attendance measures (total absences, total unexcused absences) for student  $i$ .
- $\text{StudentCharacteristics}_i$  is a vector of dummy indicators for the demographic characteristics (e.g., ethnicity, gender, special education status, English learner status, free/reduced lunch status, age as of September 1, 2016) for student  $i$ .
- $\text{Grade}_i$  is a vector of dummy indicators representing the grade level in fall 2016 for student  $i$ .
- $\text{MissingIndicator}_i$  is vector of dummy indicators for missing data for student  $i$ .
- $\text{School}$  is a vector of dummy indicators representing the fixed effects of each school for student  $i$ .
- $e_i$  is the error associated with the log odds of enrolling in *Imagine Early* for student  $i$ .

We used dummy covariate adjustment to address missing data. Specifically, missing data on baseline measures were imputed with the sample average for each variable. The selection model controlled for the imputed missing data points by including *MissingIndicator<sub>i</sub>*.

To estimate the average treatment-on-the-treated (ATT) effect, all students who enrolled in *Imagine Early* were assigned a weight=1. Those students who did not enroll were assigned a weight that is the inverse of their propensity score generated from the selection model ( $1/(1-\text{propensity score})$ ).

Practically, this procedure reduces the contribution of comparison students who differ from treatment students and increases the contribution of comparison students who more closely resemble the characteristics of treatment students.

We assess the success of this procedure by examining baseline differences between treatment and comparison students with and without the weights to determine if baseline differences without weights are eliminated or attenuated to acceptable thresholds recommended by What Works Clearinghouse Evidence Standards v4.1 (2021).



### Baseline Equivalence of Inverse-Propensity Weighted Samples

In Table 4, we highlight standardized mean differences between treatment and comparison students with and without weights for the full analytic sample, as well as separately for subsamples of students receiving and not receiving free/reduced lunch. The inverse propensity weighting procedure successfully attenuated baseline differences for the analytic sample with non-missing outcome data including the overall sample and subsamples (FRL, Non-FRL). The inverse propensity weighting procedure reduced all baseline standardized mean differences (SMD) to less than 0.14 or lower for the overall sample and 0.18 or lower for the FRL and non-FRL subsamples. Per What Works Clearinghouse Evidence Standards v4.1, baseline SMDs between 0.05 and 0.25 can be addressed with residual covariate adjustment in the impact analytic model; for maximum precision, we include all pretreatment variables in our impact model (see **Impact Analysis Approach**).



TABLE 4

***Unweighted and Weighted Baseline Standardized Mean Differences (Treatment-Comparison) for the Full Analytic Sample with Course Performance Outcome Data in 2018-19, a Free/Reduced Lunch Subsample, and a Non-Free/Reduced Lunch Subsample***

Baseline Variable	Full Sample: Unweighted SMD	Full Sample: Weighted SMD	FRL Sample: Unweighted SMD	FRL Sample: Weighted SMD	Non-FRL Sample: Unweighted SMD	Non-FRL Sample: Weighted SMD
2015-16 Total Absences	-0.22	-0.04	-0.17	-0.05	-0.09	0.07
2015-16 Unexcused Absences	-0.11	-0.03	-0.09	-0.03	-0.03	0.00
2015-16 ISTEP ELA	0.43	0.14	0.36	0.18	0.36	0.09
2015-16 ISTEP Math	0.45	0.07	0.33	-0.05	0.46	0.19
Age	-0.07	-0.03	-0.10	-0.03	-0.03	-0.01
Male Indicator	-0.12	-0.07	-0.14	-0.10	-0.17	-0.03
Black Indicator	-0.07	-0.05	-0.01	0.00	-0.19	-0.12
Hispanic Indicator	-0.33	-0.11	-0.34	-0.13	-0.27	-0.18
Multirace Indicator	0.06	0.05	0.07	0.09	0.11	-0.02
Asian Indicator	0.06	0.07	0.10	0.10	0.01	0.04
Native American/ American Indian Indicator	-0.11	-0.01	-0.20	-0.09	0.06	0.07
White Indicator	0.21	0.03	0.24	0.05	0.06	0.08
Special Education Indicator	-0.16	-0.03	-0.14	-0.05	-0.03	0.05
English Learner Indicator	-0.32	-0.10	-0.40	-0.16	-0.06	-0.04
Free/Reduced Lunch Indicator	-0.36	-0.14	–	–	–	–

**Note.** <sup>a</sup>SMD = Standardized Mean Difference (calculated by dividing the model-adjusted coefficient for *Imagine Early* enrollment, controlling for fixed effects of grade and school, by the pooled standard deviation of the sample or subsample). <sup>b</sup>The baseline measure of total absences was trimmed to exclude outliers (students with more than 100 absences). Noteworthy, N=100 students had 180 absences (entire year) which likely represents a data recording error. Outliers were designated as missing.

## Outcome Measures

To assess the impact of *Imagine Early* on average course performance (Research Question 1) and course failure (Research Question 2), we examine the following outcome measures:

- Average course performance for the school year, calculated by converting all course letter grades to a numeric grade point average (GPA) on a 0-4 scale (F=0, D=1, C=2, B=3, A=4) and calculating the mean for each student.
- Proportion of course grades earned that were F's, calculated by dividing the total count of F's for each student by the total grades earned (including non-traditional letter grades—e.g., pass fail).

## Impact Analysis Approach

To assess impacts on average course performance and course failure (Research Questions 1 and 2) we estimated the following impact model (applying the weights detailed under the **Study Design**):

$$Y_i = \beta_0 + \beta_1*(PriorMath)_i + \beta_2*(PriorELA)_i + \beta_3*(PriorAttendance)_i + \beta_4*(Student Characteristics)_i + \beta_5*(Grade)_i + \beta_6*(MissingIndicator)_i + \beta_7*(School)_i + \beta_8*(PromiseScholar)_i + e_i \quad (2)$$

where

- $Y_i$  is the 2018-19 course performance outcome measure for student  $i$ .
- $\beta_0$  is the average student's outcome.
- $PriorMath_i$  is the 2015-16 ISTEP prior mathematics achievement score for student  $i$ .
- $PriorELA_i$  is the 2015-16 ISTEP prior ELA achievement score for student  $i$ .
- $PriorAttendance_i$  is a vector of 2015-16 attendance measures (total absences, total unexcused absences) for student  $i$ .
- $StudentCharacteristics_i$  is a vector of dummy indicators for the demographic characteristics (e.g., ethnicity, gender, special education status, English learner status, free/reduced lunch status, age as of September 1, 2016) for student  $i$ .
- $Grade_i$  is a vector of dummy indicators representing fixed effects for the grade level in fall 2016 for student  $i$ .
- $MissingIndicator_i$  is vector of dummy indicators for missing data for student  $i$ .
- $School$  is a vector of dummy indicators representing the fixed effects of each school for student  $i$ .
- $PromiseScholar_i$  is one of three measures of enrollment or participation in *Imagine Early* during the 2016-17 and 2017-18 school years for student  $i$  as detailed above—(1) a binary measure of enrollment, (2) a continuous measure of the total number of quarters enrolled, or (3) a continuous measure of the total scholarship award dollars earned.
- $e_i$  is the residual error term for student  $i$ .

To assess whether impacts of participation in *Imagine Early* vary for students from lower-income households (Research Question 3), we added an interaction term between the *PromiseScholar* enrollment or participation variable and student free/reduced lunch status. Finally, we also examined impacts within each subsample (students receiving or not receiving free/reduced lunch) to decompose observed interactions.

We employed listwise deletion for students with missing outcome data, resulting in an analytic sample of N=918 students (78.19% of the full sample).

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# RESULTS

Table 5 summarizes findings from the impacts models executed assessing the relationship between enrollment in *Imagine Early* (enrolled in 2016-17 or 2018-19, total number of quarters enrolled in 2016-17 and 2017-18) or participation in *Imagine Early* engagement activities (total scholarship award dollars earned) and each of the two course performance outcomes of interest—2018-19 GPA, and proportion of letter grades earned that were F's (representing course failure).

**Average course performance.** This study found statistically significant impacts of enrollment and participation on student course performance. Overall course performance averaged 2.57 for the control group. Scholars on average had a 2018-19 GPA 0.22 points higher than non-scholars ( $d=0.24$ ). Effects were significantly larger for students receiving free/reduced lunch—scholars had a GPA 0.29 points higher than non-scholars ( $d=0.30$ ). This effect was smaller but also significant for more economically advantaged students not receiving free/reduced lunch—scholars had a GPA 0.11 points higher than non-scholars ( $d=0.15$ ). In terms of standardized effect sizes, the effect of being a scholar on GPA was twice as large for students receiving free/reduced lunch. We find the same pattern of results when examining enrollment as a count of the total quarters that a student was scholar prior to the 2018-19 school year (instead of a binary indicator for being a scholar vs. non-scholar) and when examining the effect of total award dollars earned. That is, each additional quarter a student had been a scholar resulted in 0.03 increase in GPA on average, and effects were marginally significantly larger for students receiving free/reduced lunch (0.04 increase in GPA per additional quarter as a scholar) relative to their more economically advantaged counterparts (0.02 increase in GPA per additional quarter as a scholar). Similarly, each additional \$100 earned in total award dollars was associated with a 0.20 increase in GPA, with significantly larger effects for students receiving free/reduced lunch (0.30 increase in GPA for each additional \$100 earned) relative to their more economically advantaged counterparts (0.10 increase in GPA for each additional \$100 earned).

**Course failure.** This study also found statistically significant impacts of enrollment and participation on reducing course failure. Overall course failure averaged 12% for the control group. Scholars on average failed 2.8% fewer courses than non-scholars ( $d=0.19$ ). Effects were marginally significantly larger for students receiving free/reduced lunch—scholars failed 3.8% fewer courses than non-scholars ( $d=0.21$ ). This effect was smaller but also significant for more economically advantaged students not receiving free/reduced lunch—scholars failed 1.4% fewer courses than non-scholars ( $d=0.19$ ). We find the same pattern of results when examining enrollment as a count of the total quarters that a

student was a scholar prior to the 2018-19 school year (instead of a binary indicator for being a scholar vs. non-scholar) and when examining the effect of total award dollars earned. That is, each additional quarter a student had been a scholar resulted in 0.04% reduction in the proportion of courses failed, and effects were marginally significantly larger for students receiving free/reduced lunch (0.05% reduction in proportion of courses failed per additional quarter as a scholar) relative to their more economically advantaged counterparts (0.02% reduction in proportion of courses failed per additional quarter as a scholar). Similarly, each additional \$100 earned in total award dollars was associated with a 2% reduction in course failure, with significantly larger effects for students receiving free/reduced lunch (3% reduction in course failure for each additional \$100 earned) relative to their more economically advantaged counterparts (1% reduction in course failure for each additional \$100 earned).

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## CONCLUSION

These findings suggest that *Imagine Early* improves average course performance and reduces course failure, and that it may be an effective gap-closing program—with larger effects for students from lower-income households. Effects were significantly stronger for students who had been enrolled as a scholar for longer periods of time, and for students who earned more award dollars by participating in more engagement activities across the 2016-17 and 2017-18 school years.

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## REFERENCE

Elliott, W., Sorensen, N., Zheng, H., and O'Brien, M. (2023). Early Award Scholarship Program results in improved attendance and state math test scores for students from lower-income households. *Economies 11*: 82.

TABLE 5

**Effects of Enrollment and Participation in Imagine Early on 2018-19 Average Course Performance and Course Failure (Grades 6-8)**

	Full Sample				FRL Subsample		Non-FRL Subsample	
	Impact		Interaction w/FRL Status		Impact		Impact	
	Coef.	p-value	Coef.	p-value	Coef.	p-value	Coef.	p-value
<b>Outcome: Average Course Performance Enrollment</b>								
<i>Enrolled in Imagine Early</i>	0.215	<0.001	0.203	0.049	0.291	<0.001	0.108	0.085
<i>Total Quarters Enrolled in Imagine Early</i>	0.029	<0.001	0.027	0.057	0.038	0.001	0.016	0.063
<b>Participation</b>								
<i>Total Award Dollars Earned</i>	0.002	<0.001	0.002	0.002	0.003	<0.001	0.001	0.006
<b>Outcome: Proportion of Course Grades Failed Enrollment</b>								
<i>Enrolled in Imagine Early</i>	-0.028	0.002	-0.031	0.081	-0.038	0.015	-0.014	0.044
<i>Total Quarters Enrolled in Imagine Early</i>	-0.004	0.005	-0.004	0.083	-0.005	0.033	-0.002	0.045
<b>Participation</b>								
<i>Total Award Dollars Earned</i>	-0.0002	<0.001	-0.0003	0.004	-0.0003	0.005	-0.0001	0.006