Follow-up of Two RCTs of CUNY's ASAP Model – Educational and Labor Market Outcomes

Pre-Analysis Plan

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Project Background

CUNY ASAP is a three-year program offering comprehensive student support, financial aid, and structured pathways. The program has served over 100,000 students since 2007 and been replicated across seven states. Evaluations show it significantly increases three-year graduation rates, with an 18-percentage point rise at the City University of New York (CUNY) and 16-percentage points in Ohio. This study will assess the program's long-term impacts on education, employment, and earnings over 10+ years, marking the first analysis of its labor market outcomes in CUNY, an important complement to the recent examination of 6-year earnings impact in Ohio.[1] Moreover, by combining data from both CUNY ASAP and Ohio ASAP evaluations, the present study aims to provide precise estimates of ASAP's effects, explore variations across colleges and subgroups, and update research on the program's economic benefits.

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Intervention Description[2]

CUNY ASAP is a three-year program offering comprehensive support to address barriers to student success. Key components include personalized advisement from dedicated advisers with small caseloads, mandatory bi-monthly meetings, career planning support, and required weekly tutoring for students in remedial courses. Financial supports include tuition waivers, free textbooks, and monthly MetroCards. The program also offers structured pathways with block scheduled courses to minimize on-campus time, an ASAP seminar covering essential skills, early course registration, and a full-time attendance requirement. In its Ohio replication, adjustments were made to fit the local context, such as using existing student success courses and career services, providing gas/grocery gift cards instead of MetroCards, and adopting a triage advising model. Both programs use a specialized Management Information System (MIS) for tracking and improving student outcomes.

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[1] Please note that there is separate funding, from the Laura and John Arnold Foundation, supporting a study of the effect of ASAP in Ohio on academic and labor market outcomes through 10-years. The present study is unique in that it will first examine employment and earnings from the RCT of ASAP in CUNY and then will synthesize findings across the CUNY and Ohio studies. Please see https://osf.io/r3p9h for the analysis plan for the Ohio long-term follow-up.

[2] This section describes the model as it operated during MDRC's original efficacy study, starting in 2010. CUNY has since made some modifications in the program, but the core components remain largely the same. In future publications we may include descriptions of how the program has changed since the study.

Theory of Change

ASAP's primary goal is to increase the completion of college associate degrees. Specifically, the comprehensive intervention is expected to change students' community college experience through increased academic support and career guidance, the promotion of full-time enrollment (including enrollment in winter and summer sessions, where applicable), reduced financial barriers, stronger peer connections, and increased satisfaction. These changes, in turn, are expected to improve students' academic outcomes, culminating in increased associate's degree attainment.

By increasing rates of degree attainment, ASAP has the potential to effect labor market outcomes. The association between community college degrees and increased employment and earnings has been well-documented (Belfield & Bailey, 2017; National Center for Education Statistics, 2023; U.S. Bureau of Labor Statistics, 2023), and studies that rely on natural experiments or admissions cutoff scores to estimate the causal effects of a college education offer further evidence of earnings gains (Oreopoulos & Petronijevic, 2013). The returns to higher education vary across different postsecondary factors, such as institution type (e.g., 2-year or 4-year college) and educational program (e.g., vocational, field of study, etc.) (Lovenheim & Smith, 2023). In the short-term, ASAP's success in increasing persistence and transfer, could result in a labor market opportunity cost. While effects on earnings are not the direct goal of CUNY's ASAP, it is plausible that the program could indirectly effect earnings through enrollment effects, degree completion effects, and possibly through other program services, such as interactions with career and employment specialists.

Evaluation Impact Research Questions

Confirmatory Research Questions

RQ1a: What is the effect of ASAP on degree completion?

RQ1b: What is the effect of ASAP on labor market outcomes?

The central aim of this project is to estimate the average effect of the offer to participate in ASAP on students' degree completion and labor market outcomes. The comparison condition is students admitted to the same college who are not offered ASAP's services but do have access to all other services at their college (e.g., traditional advising, tutoring, and financial supports). These questions will be examined for the CUNY sample (deliverable 3, see Table 1 below) and the pooled CUNY and Ohio sample (deliverable 4, see Table 1 below). For ease of exposition, we group these questions together as RQ1. We prioritize earnings towards the end of the follow-up period for each deliverable.

Exploratory Research Questions

RQ2: **To what extent do ASAP's effects vary across colleges?**

Answering this question across the 6 total colleges in CUNY and Ohio provides a useful starting point for considering the generalizability of study findings. If effects are consistent across all colleges, this demonstrates that ASAP works in a variety of contexts across a variety of implementing organizations, speaking to generalizability.

If there's evidence that effects vary, we may *explore* the extent that college-level factors (including college context) predict the magnitude of effects (e.g., do colleges with larger impacts on completion of specific degree types tend to be colleges with larger earnings impacts?). With so few colleges, such analyses will be speculative and be primarily for hypothesis generation.

RQ3: What is the effect of ASAP for subpopulations of students?

Relying on the pooled sample, we will estimate ASAP's effect on degree completion and labor market outcomes for key subgroups highlighted in the original evaluations: developmental education requirements, gender, age, race/ethnicity, and employment status at study entry.

RQ4: Through 10 years, how do the costs of ASAP compare with some of its benefits?

Capitalizing on the estimated effects on earnings based on observed labor market data, we will update an earlier cost-benefit analysis that relied on forecasted earnings in the absence of observed earnings.

RQ5: What is the effect of degree completion on earnings (i.e., returns-to-degree)?
These *exploratory* analyses will illuminate the pathways through which degree completion affects labor market outcomes and contribute to the contextualization of the main effects.

Project Papers

The project will generate multiple major papers covering multiple topics. These papers are noteworthy since they answer different questions and rely on different research samples.

Table 1. *Products schedule and names.*

Schedule	Paper Name
2024	1. **Pre-analysis plan**
2025	2. **Returns to CUNY degrees (← not included in this analysis plan)**
2025 – 2026	3. **CUNY ASAP's effects on academic & labor market outcomes** (~14-years)
2027 – 2028	4. **Synthesis of CUNY & Ohio ASAP effects on academic & labor outcomes** (10 years)

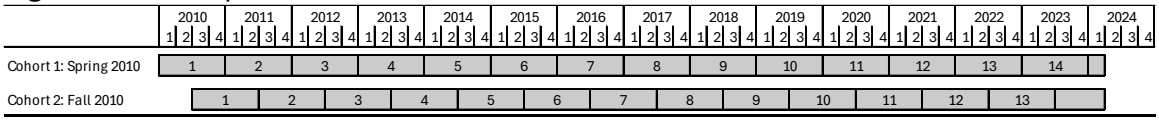
Note: Paper 4 will come in multiple formats – a working paper, a short brief, and a journal article.

The present document is the **pre-analysis plan** (paper #1).

The **returns-to-CUNY-degrees** paper (paper #2, focused on research question 5) is intended to provide important context for the estimated effects of CUNY ASAP on labor market outcomes. The paper will not focus on ASAP specifically, rather it will explore the returns to degrees that students earn at CUNY. These analyses will rely on a broad population including nearly all students enrolled at CUNY institutions. This research is not included in this analysis plan, but has its own separate complementary analysis plan.

The report on **CUNY ASAP's effects on academic and labor market outcomes** (paper #3) will cover 14 years of follow-up and will rely on 885[3] out of 903 randomized students in the original CUNY ASAP evaluation sample (see Appendix Figure 3 for details). Throughout this analysis plan, we refer to 14 years of follow-up. The actual length of follow-up will be through Q1 2024. The evaluation includes two study cohorts: a spring 2010 cohort that was randomly assigned prior to the spring 2010 semester and a fall 2010 cohort that was randomly assigned prior to the fall 2010 semester. Full sample results will go through 13 and ¾ years, starting in Q1 2010 for cohort 1 and Q3 2010 for cohort 2.

Figure1. *Follow-up Visual for Deliverable 3.*



Note: Follow-up will be reported for the length of time where data is available for the full sample only.

The **synthesis of CUNY and Ohio ASAP effects on academic and labor market outcomes** (paper #4) will cover 10 years of follow-up and will rely on 896[4] out of 903 students from the original CUNY ASAP evaluation sample and around 1,501 (for academic outcomes) or

[3] For the academic outcomes, we plan to examine 896 students, for the labor market outcomes, we plan to examine 885 students. The difference has to do with data limitations with respect to the New York State UI data that will be used to examine labor market outcomes.

[4] The difference of 11 students comparing deliverable 3 vs. 4 is due to data limitations. Labor market data for deliverables 3 and 4 will come from a different data source with different restrictions.

1,482 (for labor market outcomes) out of 1,522 students from the original Ohio replication sample for a pooled sample of 2,397 (academic outcomes) or 2,378 (labor market outcomes) students (see Appendix Figures 3 and 4). The Ohio "replication" study began later than the CUNY study, which is the reason for the shorter follow-up period for the synthesis.

Evaluation Design

Eligible Population of Individuals and Sites

Individuals (Students): Students were eligible for ASAP and the study if they met several criteria:

- **Low income**: their family income was below 200 percent of the federal poverty level or they were eligible for a Pell Grant;
- **New or relatively new to college**: they were new to college or had earned fewer than 12 credits in CUNY or fewer than 24 credits in Ohio;
- **Willing to attend full-time.** Prior to random assignment (and joining the program), students were informed that to be part of ASAP they had to enroll full-time.
- **In an ASAP-eligible major.** Excluded majors included nursing, allied health, and some engineering programs, usually because of program requirements that make it difficult for complete within three years (the goal of ASAP).[5]

The CUNY and Ohio studies differed **with respect to developmental education** requirements. For CUNY, the evaluation only included students who had one or two developmental education requirements (excluding "college-ready" students). In Ohio eligibility was extended to students with or without developmental education requirements at study entry. Both programs excluded students with extensive (more than two) developmental education requirements, given that they were unlikely to earn a degree within three years.

Sites (Colleges): The three colleges that participated in the original CUNY evaluation are:

- Borough of Manhattan Community College (BMCC),
- Kingsborough Community College (KCC), and
- LaGuardia Community college (LCC).

They were selected based on their willingness to participate in a random assignment evaluation, capacity to reach the desired sample size goals, and interest of program administrators to serve additional students. These three colleges are the largest of

[5] For CUNY ASAP, the excluded majors at the time of the study were: at BMCC, Allied Health Sciences, Pre-Clinical Nursing, Forensic Science, and Engineering Science; at KCC, Nursing; and at LGCC, Allied Health Sciences and Engineering Science (Scrivener et al., 2015). For the Ohio programs, the excluded majors at the time of the study were: at Cincinnati, Nursing, Aviation, Civil Engineering Technologies, Respiratory Care, Diagnostic Medical Sonography; at Lorain, computer science Bachelor's'. At Tri-C, the eligibility criteria was being an AA, AS, AAB, or AAS pre-degree major.

CUNY's community colleges, and most of their students attend full-time.

The three colleges (including 4 campuses) that participated in the original Ohio evaluation include

- Cincinnati State Technical and Community College,
- Cuyahoga Community College (in Cleveland), and
- Lorain County Community College (outside of Cleveland).

Similar to CUNY, the Ohio colleges were selected based on size of the student population, support for the program from leadership, and willingness to participate in a RCT.

Sampling Strategy

CUNY ASAP Students: In the CUNY evaluation, a total of 903 students were initially randomly assigned (452 program group and 451 control group).

One program group student withdrew from the study. Four control group students withdrew from the study, one informed consent form was unrecovered, and one control group student was determined ineligible. These seven students are excluded from ALL analyses.

For the synthesis (paper 4), the remaining 896 students will be in the evaluation analytic sample across the three CUNY colleges—451 in the program group and 445 in the control group for the synthesis.[6]

For the report on CUNY ASAP's effects on academic and labor market outcomes (paper 3), we expect we will need to exclude an additional 11 students based on our understanding of the coverage of the CCRC-NYDOL data match (8 control group and 3 program group). These students will be excluded from the labor market outcomes owing to the nature of the data sharing agreement between CCRC and the New York State Department of Labor, yielding a total of 885 students—448 in the program group and 438 in the control group. The exact number of excluded students will be known later.

Ohio Replication Students: A total of 1,522 students were initially randomly assigned (819 program group and 703 control group).

Nine program group students withdrew from the study, consent forms for two program group students were unrecovered, and two program group students were deemed ineligible. Two control group students withdrew from the study and informed consent forms for six control group students were unrecovered. These 21 students are excluded from ALL analyses.

[6]A discussion of attrition is provided in the section describing the data analysis plan.

For Ohio, a total of 1,501 students are in the evaluation analytic sample, with 806 in the program group and 695 in the control group. This is the case for academic outcomes.

For labor market outcomes, an additional 11 program and 8 control group students will be excluded from analyses since they did not provide their social security number. So, for labor market outcomes a total of 1,482 students will be in the analytic sample—795 in the program group and 687 in the control group.

Timing of joining the study: In the CUNY ASAP study, students were enrolled into the study between just prior to the spring and fall 2010 semesters. In Ohio, students were enrolled into the study just before the start of the spring 2015, fall 2015, and spring 2016 semesters.

In CUNY and Ohio, not all eligible students participated in the evaluation or the program. Students in both locations were recruited to participate in the intervention and evaluation and should not be assumed to be representative of the entire eligible population.

Target of Inference

CUNY ASAP and Ohio ASAP: The target of inference for deliverables 3 (CUNY ASAP) and 4 (Synthesis) is the effect for the average person in the evaluation (i.e., not the effect for the average college, which would count each college equally).

For deliverable 3 (CUNY ASAP), this is the 896 or 885 students in the analytic sample (outcome dependent) – or similar students at those colleges in the evaluation.

For deliverable 4 (Synthesis), this is the 2,397 (896+1,501) or 2,387 (896+1,482) students in the CUNY and Ohio studies – or similar students at those colleges in the studies.

Here, results will most clearly apply to the colleges in the study – no attempt at statistical generalization to colleges beyond those in the study will be made. However, examination of variation in effects may support logical arguments regarding the likely generalizability of findings.

Identification Strategy (Study Design)

CUNY ASAP and Ohio ASAP: The CUNY and Ohio ASAP evaluations both used a multisite (blocked) random assignment design, which was deemed to meet the What Works Clearinghouse (WWC) evidence standards *without reservations*.[7] Each student was randomly assigned using a computer algorithm either to the program group, whose members had the opportunity to participate in ASAP, or to the control group, whose members could not participate in ASAP but could receive the college's standard services. Random assignment was conducted within "blocks", which were college X cohort combinations.

[7] CUNY: What Works Clearinghouse (2023a). Ohio: What Works Clearinghouse (2023b).

Data Sources (Collection Methods and Instruments)

The main data sources to be used in the proposed analyses are described next. Table 2 presents which data sources will be used in each deliverable.

Table 2. *Data Sources Used for Each Deliverable*.

Source	3. CUNY ASAP	4. Synthesis
Baseline Survey	✓	✓
NSC	✓ (14 years)	✓ (10 years)
CUNY IRDB	✓ (14 years)	✓ (10 years)
Ohio HEI		✓ (10 years)
NY State UI	✓ (13.75 years)	(TBD)
Ohio UI		✓ (10 years)
CENSUS LEHD		✓ (10 years)

Notes: The Ohio UI data *may* be used to measure employment and earnings for the Ohio ASAP sample in Synthesis for the last few years of follow-up (e.g., years 7-10). This will depend on the availability of LEHD data for later years. LEHD data releases do not follow an annual schedule so it is difficult to anticipate what data will be available at the time of the research. NY State UI data may be used in the Synthesis to assess alignment of findings when using NY State UI data and CENSUS LEHD.

Baseline survey: Administered immediately prior to random assignment in the CUNY ASAP and Ohio ASAP evaluations, baseline questionnaire data will be used to describe the evaluation sample, as covariates in the impact analyses, and to identify student subgroups.

National Student Clearinghouse (NSC): The NSC collects and distributes enrollment, degree, and certificate data from more than 3,500 colleges that combined enroll more than 98 percent of the nation's college students. NSC data will be collected for all sample members to determine degree and certificate attainment (but not degree major, which is not available) at any college in the U.S. This data will be available for 10-14 years after each student joined the study – approximately 14 years for CUNY ASAP and 10 years for Ohio ASAP.

CUNY Institutional Research Database (IRDB): The CUNY IRDB includes data from the three community colleges in the study as well as all other colleges in the CUNY system. The IRDB includes student-level demographic, placement test, transcript, and degree/certificate data. Placement test data in reading, writing, and math were used by CUNY to determine if students would be referred to developmental education. For this

research, placement test data are used to describe the evaluation sample and to identify subgroups. Degree data will be used to provide a detailed look at students' academic outcomes, including types of degrees earned for approximately 14 years after each student joined the study.

Ohio Higher Education Information (HEI). The HEI database contains individual-level records on the academic achievement and degree attainment for all students at Ohio public colleges. For this research, these data will be used to measure graduation rates (in conjunction with NSC data) and to explore the types of degrees (i.e., major) students have earned for 10 years after each student joined the study.

New York State and Ohio Unemployment Insurance (UI): The UI data include quarterly employment and earnings information, as reported by employers to the state UI system. The wages in these data represent any wages earned in employment covered by that state's UI laws. These records therefore cover most employment in a given state; however, they do not capture certain types of jobs, including self-employment, federal government employment, military jobs, informal jobs, and out-of-state jobs. Study participants employed outside of New York and Ohio will not be included in this data; however, publicly-available data suggests that this may not be a significant limitation. At the New York study colleges, 83 to 85 percent of community college graduates are employed in New York 10 years after graduation; at the Ohio study colleges, it is 76 to 86 percent (U.S. Census Bureau Center for Economic Studies). UI data from both states will be available for 10 years after each student joined the study. The Census Bureau data described below will help us capture wages in neighboring states to fill this gap.

U.S. Census Bureau Longitudinal Employer-Household Dynamics (LEHD): The LEHD dataset covers over 95% of employment in the United States. It is a compilation of UI earnings data and other employment-related administrative records from most states in the US (*Post-Secondary Employment Outcomes Explorer*). For this research, we will prioritize getting access to New York, Ohio, and neighboring states where study participants are most likely to be employed.[8]

Sample Size and Minimum Detectable True Effect (MDTE)

CUNY ASAP and Synthesis: For the pooled sample (n=2,397), the MDTE for a dichotomous outcome, such as "received a degree," is 0.048, or 4.8 percentage points. In other words, if the true effect of ASAP on degree receipt is at least 4.8 percentage points, then there is an 80 percent chance of estimating a positive and statistically significant effect at the 10

[8] These states are: NY, NJ, CT, OH, KY, PA, WV, IN, and MI. At the time of writing these states are in the 2021 LEHD snapshot with data sufficient to cover 10 years of follow-up for the CUNY study and six years for the Ohio study. If additional data becomes available, we will use it as well. See U.S. Census Bureau (2022) for details.[9] Assumes a 1:1 random assignment ratio and an r^2 of 0.10.

percent level. The MDTE for the CUNY sample (n=896) is 0.079, also within the range of plausible effects.[9]

The MDTE for annual earnings are $1,400-$2,900 for the pooled sample and $2,400-$4,700 for the CUNY sample.[10] If average annual earnings in the later years of follow up are assumed to be about $26,000, then these MDTEs represent increases of 6-11 percent and 9-18 percent, respectively.[11] Increases of this size are policy-relevant and practically meaningful. There are reasons to expect that ASAP's effects on earnings may be in this range.

Of most direct relevance, recent findings from the Ohio ASAP study show estimated average earnings gains of $1,948 in Year 6 with evidence of larger effects in year 8 (not yet public). This suggests annual earnings effects of $1,400 to $2,400 are plausible, although less plausible for our higher estimate of the MDTE ($4,700).

It is, however, important to acknowledge that *if effects on annual earnings come through degree receipt alone*, then the economic return to a degree would need to be very large for this study to be adequately powered to detect average earnings effects of $1,400-$2,900 (pooled) or $2,400-$4,700 (CUNY). With ASAP's pooled effect on degree completion being around 13 percentage points, the returns to a degree would need to be $10,770 annually (calculated as $1,400 / 0.13). Non-experimental research using data from several states suggests that associate degree receipt, compared with obtaining some college credits but no degree, can lead to increases in earnings of 18 to 26 percent (Belfield & Bailey, 2017), or around $5,700 annually.

That said, in Ohio the estimated effect on six-year degree receipt was 15 percentage points and the estimated earnings effects, in year six, were $1,948. If the overall average earnings effects came from degree completion alone, this implies an estimated return to degree of $12,986 (calculated as $1,948/0.15), representing an increase of over 50%. This may suggest that, in Ohio, ASAP influenced earnings through mechanisms other than degree completion alone.

Overall, the evidence suggests that the study is decently powered, but probably not adequately powered (especially for the CUNY only deliverable 3) to detect effects of the size we might expect to see if impacts come through degree completion alone. As is often the case, a strict thumbs-up thumbs-down interpretation of estimated effects on earnings based on crossing p-value thresholds for statistical significance alone, is ill-advised. There

[9] Assumes a 1:1 random assignment ratio and an r^2 of 0.10.

[10] The MDTE is influenced by several factors, one of which is the standard deviation of the outcome. The ranges we provide assume a low of $15,000 and a high of $30,000, which is an estimate for the long-term average earnings. We assume r^2=0.10 and a 1:1 random assignment ratio.

[11] This estimate is based on Belfield and Bailey (2017). In addition, data from the Ohio ASAP study indicate average earnings in Year 6 of about $24,000.

are few RCTs of community college interventions that have even estimated long-term earnings effects for students, so there is still a lot to learn. No matter what the findings, we will present point estimates, standard errors, and p-values, so that our best estimate of effects is presented along with indications of uncertainty. We may even present confidence intervals at different levels (e.g., 75% and 90%). It will also be important to consider the trends of the impact estimates on earnings.

With respect to subgroup analyses (**RQ3**), the Table 3 (below) presents MDTE from subgroups that represent varying proportions of the full sample, to provide estimates for different groups. Black students, for example, make up about a third of the sample. MDTEs representing 30 percent of the full sample are most relevant for these groups. The MDTEs for subgroups smaller than 50 percent of the pooled sample are large. In addition, a key examination of subgroup effects involves investigating the difference in impacts between the groups (e.g., Female vs. Male), which requires much larger samples to achieve the same statistical power than the test for the significance of a given subgroup. As noted earlier, all subgroup analyses are exploratory.

Table 3. Minimum Detectable True Effects (MDTE)

Sample	Sample size	Outcome	
		Degree receipt	Annual earnings
Pooled	2,397	0.048	$1,930
CUNY	896	0.079	$3,157
Ohio	1,501	0.061	$2,439
Subgroups			
20% of pooled sample	479	0.121	$4,669
30% of pooled sample	719	0.088	$3,524
50% of pooled sample	1,199	0.068	$2,729

Notes: As described earlier, some of the sample sizes are not exact to various limitations on accessing data. These differences are small and have little influence on the presented MDTEs. The MDTE for binary and continuous outcomes are computed with equation (1) from Bloom (1995):

$$\text{MDTE(binary)} = 2.49 * \sqrt{\frac{\pi(1-\pi)(1-r^2)}{T(1-T)n}} \text{ or } \text{MDTE(continuous)} = 2.80 * \sqrt{\frac{\sigma^2(1-r^2)}{T(1-T)n}}$$

Where:

$2.49 =$ The appropriate multiplier for 80 percent power and a 10 percent significance level with a two-tailed hypothesis test.[12]

$\pi =$ The proportion of the study population that would have a value of 1 for a binary outcome (degree receipt) in the absence of the program (assumed = .50)

$r^2 =$ The explanatory power of the impact regression (assumed = .10)

$T =$ The proportion randomly assigned to the treatment group (T = .50)

$n =$ The total size of the study sample

[12] This "multiplier" is a good approximation when the number of degrees of freedom is greater than 30. Use of this multiplier is similar to the use of 1.96 * standard deviation for creating a 95 percent confidence interval.

$\sigma =$ The standard deviation of a continuous outcome, or annual earnings (assumed=$20,000[13])

Outcome Variables

Confirmatory outcomes. This project's central deliverables include an analysis of long-term (approximately 14-year) effects for CUNY ASAP (Paper 3) and a synthesis of long-term (10-year) effects for CUNY and Ohio combined (Paper 4).

The follow-up periods are different because the CUNY study occurred several years prior to the Ohio study and we aim to pool the data in the synthesis.

Also of note, 10 years after random assignment in the CUNY study is calendar years 2019 and 2020 (depending on if the student was part of the spring 2010 or fall 2010 cohort). Year 10 for the Ohio study spans 2024 through early 2026 (depending on the semester the student joined the study). Thus, the onset of the COVID-19 pandemic has implications for estimating the 10-year effects on earnings for the CUNY sample.

Table 4 summarizes the confirmatory outcomes and their timing, by deliverable with explanation below.

Table 4. *Table of Confirmatory Outcomes, by deliverable.*

Source	3. CUNY ASAP	4. Synthesis
Degree Receipt[14] (any college)	✓ - As of 14 years after random assignment	✓ - As of 10 Years after random assignment
Average Annual Earnings	✓ - Years 11.75 - 13.75 after random assignment	✓ - Years 7.5 - 9.5 after random assignment

Degree receipt will be a binary indicator of whether a student earned a degree by the end of the 14th year of follow-up for Paper 3 (CUNY only) and by the end of the 10th year of follow-up for Paper 4 (synthesis).[15]

- **Data sources**: Degree receipt will be derived from CUNY IRDB and Ohio HEI data, as well as the NSC. When there are discrepancies between CUNY IRDB and NSC or Ohio HEI and NSC, CUNY IRDB and Ohio HEI data will take precedent over NSC data.
- **Outcome timing**: For each deliverable the confirmatory measure of degree receipt will be whether a student earned a degree at any time during the relevant follow-up

[13] In our proposal we assumed σ = $11,000 based on a past workforce development project. We revisited this here and consider σ = $15,000 to $30,000 owing to internal analyses from the Ohio programs (earnings years 6-8) as well as past values from Weiss et al. (2015). Table uses σ = $20,000.

[14] Certificate receipt is not included in this measure. As shown in the 3-year point, less than 2 percent of each research group had earned a certificate.

[15] Year 14 or 10 will be determined relative to when a student joined the study.

period. By the 10-year mark, we expect effects on degree completion will have largely stabilized (for stability of CUNY ASAP's degree effects at year eight, see: Azurdia & Galkin, 2020), with rates of new degrees being similar between program and control groups. Thus, 10-year effects (and beyond) may closely represent ASAP's effects on getting people to earn a degree who otherwise would not have done so.

This outcome will not capture ASAP's effects on getting students to graduate more quickly. It is documented that this is one positive effect of CUNY ASAP (Weiss, Ratledge, Sommo, & Gupta, 2019). Our exploratory outcomes will further document this by examining impacts on degree receipt throughout the entire follow-up period.

Average Annual earnings will be measured as the yearly average of quarterly earnings from UI records.

- **Data sources**: Paper 3 will rely on NY State UI data due to the relative ease with which the research team can access those data immediately. Paper 4 aims to rely on LEHD data for both the CUNY and Ohio samples, owing to its broader coverage. Depending on LEHD data availability, the last few years of Ohio earnings data may rely on Ohio UI data. Release dates for LEHD data are unknown, so this decision will be based upon data availability at the time of acquisition. As noted earlier, the UI records, to be obtained from the LEHD data, cover UI-reported employment and earnings in Ohio, New York, and neighboring states.
- **Outcome timing**: In Paper 3 (CUNY only), earnings will be considered confirmatory during the last 2 years of follow-up (11.75 - 13.75 years after random assignment). We will also pay careful attention to years 8 and 9 of follow-up, which were the last two pre-pandemic years of follow-up, as well as overall trends in impacts on this outcome. In Paper 4 (Synthesis), earnings will be considered confirmatory in years 7.5 - 9.5. Approximately 10 years of follow-up will be available for the Ohio sample at the time of working on this deliverable, thus this length of follow-up allows us to pool data across CUNY and Ohio. For CUNY, one cohort was in the pandemic during the year 9.5 – 10 after random assignment, thus focusing on years 7.5 – 9.5 covers the last two full years before the pandemic for all study participants in the CUNY sample. This timing for Ohio is well after the onset of the pandemic.

For both deliverables, we look earnings across two years (instead of annually or quarterly) due to variation in earnings from quarter to quarter and year to year – we expect averaging across two years will stabilize earnings and any effects. We look at average *annual* earnings due to its more intuitive interpretation (compared with total earnings over two years).

Our focus is on earnings for the longest follow-up possible for the full sample (with the pandemic exception) for several reasons. First, at later time points fewer sample members are still engaged in school and the more sample members are focused on the labor market. Second, at later time points the potential returns-to-degree may be more likely to show up. Sine the program effected short-term enrollment rates, it's possible that the control group

worked at higher rates or higher intensity in the short-term. This could benefit there earnings, although in the long-term the expectation is that the value of the degree will be greater than the value of a small amount of additional experience. Finally, most sample members are early in their career and any labor market benefits of earning a degree could occur throughout their career. Thus, the longest-term earnings effects may be the most relevant when considering any effects on earnings beyond the study timeframe.

Note: We will present effects estimates on degree receipt and annual earnings during each year throughout the entire follow-up period. The earlier time points are important, but will not treated as the confirmatory indicators of success for research questions 1a and 1b.

Exploratory outcomes. Numerous exploratory outcomes will be assessed to contextualize the effects on degree receipt and earnings. These include:

- associate's degree completion at any college,
- bachelor's degree completion at any college,
- certificate completion,
- degree completion by degree major (field of study),
- number of semesters enrolled.
- ever employed (defined as having any earnings reported to the UI system, during a given quarter and during the year),
- earnings (measured during each quarter and year of follow-up, marginally and cumulatively)
- UI applications (measured annually and cumulatively)

Associate's and bachelor's degree completion will be measured using CUNY IRDB and Ohio HEI college records and the NSC. Data on field of study will be obtained from CUNY IRDB and Ohio HEI records (NSC does not include field of study). Degrees earned will be grouped into broad categories, such as Arts, Business, and STEM, and effects will be estimated on these outcomes. All employment and earnings exploratory outcomes will be obtained from UI wages records from New York, Ohio, and neighboring states (LEHD).

Subgroup Definitions

Effects across colleges. To address **RQ2**, effects will be estimated for each of the six colleges in the pooled sample.

The estimates for the pooled sample provide an overall average estimate of ASAP's effectiveness. Estimating effects by college will provide further evidence of the replicability of the model in different settings and the generalizability of the findings beyond these colleges and students. A caveat to this analysis is the smaller sample sizes at each individual college, limiting the statistical power of tests of effects at individual colleges and testing for variation in effects across colleges. The analysis will estimate effects for each

individual college and test whether the variation in impacts across colleges is more than what would be expected by chance.

An earlier analysis through six years found some variation in effects on degree receipt, although that variation was not statistically significant. That analysis also examined the association between impacts on degree receipt and service contrast (e.g., the number of additional advising visits induced by the program) at each campus. This non-experimental analysis documented a positive association between service contrast and impacts on degree receipt, even though colleges with smaller treatment contrasts still achieved sizable effects on degree receipt.

In this work we will examine whether college-level effects on degree receipt and college-level effects on earnings appear to be correlated, including whether the types of degrees (meaning Associates and Bachelors, as well as field of study) impacted are correlated with earnings effects.

It is worth noting that with only six colleges in two states, it will be difficult to gain a deep understanding of why impacts might vary across colleges or states. The New York City and Ohio labor markets are different, the interventions were implemented differently across colleges, the student populations vary across colleges, etc. Even teasing out which factors are correlated with impacts will provide suggestive evidence, at best. The potential influence of these factors will be described in more detail in deliverable 2 – the returns-to-degrees report.

Effects for subgroups. The nation's community colleges serve a disproportionate number of low-income and underrepresented students. This fact is reflected in the characteristics of the study samples: a third are the first in their families to attend college, the majority have developmental education needs, and many are "nontraditional" students who face challenges to completion. ASAP was designed to address inequity in education by providing these students with the supports needed to complete their degrees. The evaluations in both states were designed to assess whether it improved outcomes for all students and whether its effects were spread broadly across different types of students. The earlier evaluations documented similar, positive effects for a range of students, defined by:

- **developmental education requirements (none, one, two or more),**
- **gender,**
- **age (19 or younger, 20-23, and 24 or older),**
- **race/ethnicity (Hispanic, White, Black), and**
- **employment status at study entry**.

An important question is whether this pattern holds for the longer term and whether the similar effects on degree receipt lead to similar effects on labor market outcomes.

To address **RQ3**, effects for subgroups will be estimated using equation 1 (below) over the subsample of interest. Key subgroups are listed above. Differences in estimated impacts between groups, for example, between women and men, will not be tested for statistical significance. As described in the Power Analyses section, the study is not well-positioned to detect differences in effects across subgroups. All analyses of subgroups effects are exploratory. Positive effects for subpopulations will not be emphasized (e.g., in an abstract) unless they are found in conjunction with positive overall effects.

Impact Model Specifications

Grand Mean Effect

Given that the CUNY and Ohio studies were well-executed RCTs, the basic estimation strategy is to compare regression-adjusted average outcomes for the program and control groups. We will estimate the following regression model:

$$Y_i = \sum_{j=1}^{J} \alpha_j Block_{j,i} + \beta * T_i + \boldsymbol{\phi} * \boldsymbol{X}_i + e_i \qquad (1)$$

where Y_i is the outcome of student i; $Block_{j,i}$ are a series of J random assignment block indicators with $Block_{j,i}$ = 1 if student i is in block j and zero otherwise; T_i is a treatment indicator set to 1 if student i was randomly assigned to treatment and zero otherwise; and $\boldsymbol{X}_i$ is a vector of baseline characteristics. The key parameter of interest is β, which captures the effect of the offer of ASAP on the outcome of interest (Y).

Baseline characteristics ($\boldsymbol{X}$) will include:

- Gender
- Race/ethnicity
- Age (19 years or younger, 20-23 years, 24 years or older)
- Has any children
- Weekly hours worked
- Dependence on parents for 50% or more of financial support
- High school diploma
- First-generation college student
- Number of development education requirements (None, one, or two or more)

The baseline characteristics primarily come from a baseline survey. Developmental education requirements are derived from college administrative records (placement tests). When baseline characteristics are missing, we will use a binary "missing" indicator. So a student will be categorized as, for example, *has dependents*, *does not have dependents*, or *has dependents is missing*.

These baseline covariates were selected in an attempt to align the covariates used in the Ohio analysis plan and past CUNY ASAP papers.[16]

All analyses will use heteroskedastic robust standard errors to account for the possibility that outcome variances may differ across random assignment blocks and experimental groups.

Earnings analyses will include the addition of pre-random assignment earnings as a covariate, if available.

Given the random assignment of T, including the covariates ($\boldsymbol{X}$) is not required to have an unbiased estimator of effects. The purpose of the inclusion of these covariates is for their potential to improve the precision of the estimator (Bloom, Richburg-Hayes, & Black, 2007), which will occur if these variables are correlated with the outcome of interest, regardless of the reason for that correlation. We do not intend to interpret the estimated coefficients of these covariates.

The estimate of the program effect in this model is an intent-to-treat (ITT) estimate, or the effect of the offer to participate in ASAP. Over 90 percent of all program group members experienced at least one semester of ASAP, so there is little difference between the ITT estimate and an estimate of the program's effect for those who receive it (i.e., treatment-on-the-treated).[17]

To address RQ1, effects on degree receipt and earnings will be estimated for the CUNY sample (Paper 3) and the pooled sample (Paper 4). Effects will be presented in the original units of the outcomes in question, rather than as standardized effect sizes since all outcomes are in units with meaning in their original units. Effects on degree completion, for example, will show the percentage point effect in degree receipt, while effects on earnings will show the dollar increase in earnings. All dollar amounts will be inflation adjusted.

Heterogeneous Effects (E.g., Subgroups)

To address **RQ2** and **RQ3**, effects for subgroups will be estimated using equation (1) estimated over the subsample of interest. Key subgroups are: college, gender, age, race/ethnicity, developmental education requirements, and employment status at study entry. Differences in estimated impacts for women and those for men, for example, will not be tested for statistical significance. As described in the Power Analyses section, the study is not well-positioned to detect differences in effects across subgroups. All analyses of subgroups effects are exploratory.

[16] The CUNY ASAP paper used: gender, race, age, has any children, single parent, working, depends on parents for more than half of expenses, first in family to attend college, and earned a high school diploma

[17] In CUNY ASAP, 95 percent of program group students participated in ASAP during the first semester (Scrivener, Weiss, & Sommo, 2012). In Ohio ASAP, over 90 percent of students in the program group experienced at least one semester of the program (Miller, Headlam, Manno, & Cullinan, 2020).

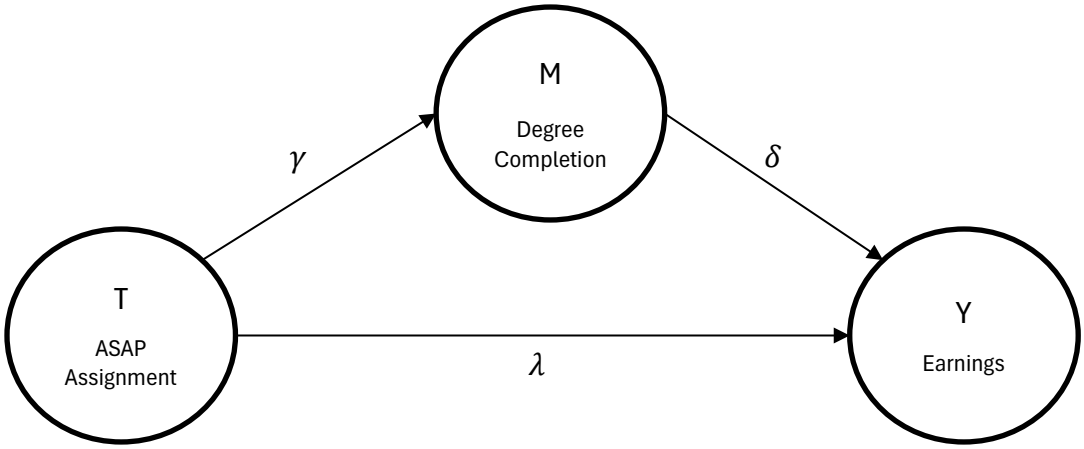
For college – if we find evidence that effects vary across colleges we will examine whether there's a correlation between short-term degree receipt (e.g., through 6 years) and long-term earnings (through 10 years).

Additional Analyses

It is possible that any effect ASAP has on earnings may operate largely through degree receipt.[18] Mediation analysis in this context helps to address an important question in the field: What is the return to a college degree? This project provides a unique opportunity to examine this question (**RQ5)**.

Figure 2 (below) provides a visual depiction of a hypothesized mediator relationship between ASAP, degree receipt, and earnings.

Figure 2. Mediation Model



ASAP's Effect on Mediator = γ
Mediator's Effect on Outcome = δ
Indirect Effect = $\gamma\delta$
Direct Effect = λ
Total Effect = $\lambda + \gamma\delta$

Note: T denotes assignment to treatment (ASAP), which for some students determines their value of our hypothesized Mediator, M, an indicator of whether the student completes a degree or not. The average causal effect of ASAP on degree completion is denoted by γ. The mediator value for each student in turn affects their outcome (Y), earnings. The average value of the mediator's effect on the outcome is denoted by δ. Thus, δ is the effect of degree completion (M) on earnings (Y), or the "returns-to-degree." This is the key parameter of interest for RQ 5.

[18] We include in our conceptualization of "degree receipt" the credits earned that enable degree receipt.

The *indirect effect* of ASAP on earnings produced through degree completion is a product of the average effect of ASAP on the degree completion (γ) times the average effect of degree completion on earnings (δ), or $\gamma\delta$.

The *direct effect* of ASAP on earnings, denoted by λ, is the average effect of ASAP assignment on earnings produced through *all mediators other than degree completion*.

The *total effect* of ASAP assignment on earnings is therefore $\lambda + \gamma\delta$.

Source: Adapted from Bloom, Unterman, Zhu, and Reardon (2020, pp. 12-14).[19]

With that context, we may examine the returns to an ASAP-induced degree within the experiment as follows:

Instrumental Variable Analysis: In Paper 3 and/or 4 we may estimate the returns to a degree using instrumental variables methods with a two-staged least squares (2SLS) estimator. This approach is roughly equivalent to taking the estimated effect of ASAP on earnings in years 13-14 (Y) and dividing it by the estimated effect of ASAP on degree completion (M, in year 6 when effects on degrees have mostly stabilized). In practice, the 2SLS estimator involves first estimating the effect of treatment assignment on degree completion:

$$M_i = \sum_{j=1}^{J} \alpha_j' Block_{j,i} + \gamma * T_i + \boldsymbol{\phi}' * \boldsymbol{X}_i + \varepsilon_i' \quad (3)$$

where the coefficient γ is the "first-stage effect" of the instrument (i.e., ASAP's effect on degree completion). The other variables are defined as in equation (1). In the second stage, predicted degree completion for each observation is plugged into the following model:

$$Y_i = \sum_{j=1}^{J} \alpha_j'' Block_{j,i} + \delta * \widehat{M}_i + \boldsymbol{\phi}'' * \boldsymbol{X}_i + \varepsilon_i'' \quad (4)$$

From this model, $\hat{\delta}$ is the estimated returns to an ASAP-induced degree.

Notably, the ideal situation for causal mediation analysis is random assignment to the mediator (degree completion). However, this is not feasible. The major strength of the IV approach is that it takes advantage of the indirect randomization of individuals to different mediator values. This classic IV relies on two key assumptions: *monotonicity* and the *exclusion restriction*. Monotonicity implies that ASAP did not decrease anyone's likelihood of earning a degree—a plausible assumption for this intervention. The exclusion restriction implies that $\lambda = 0$ in Figure 1, that is, random assignment to ASAP only effects earnings through degree completion. It is *possible* that ASAP effects earnings through, for example, career and employment services[20], in addition to through degree completion. Thus, the

[19] Bloom, H. S., Unterman, R., Zhu, P., & Reardon, S. F. (2020). Lessons from New York City's Small Schools of Choice about High School Features that Promote Graduation for Disadvantaged Students. *Journal of Policy Analysis and Management, 39*(3), 740-771. doi:https://doi.org/10.1002/pam.22192

[20] At the time of the study, ASAP offered program-hosted career and employment services. This was a feature of the program, albeit one that had a more immediate job placement focus at this time.

exclusion restriction *might* be violated and the estimator may be upward biased. Also of note, due to a weak instrument and small sample, these estimates will be imprecise.

We are not aware of a way to deal with the precision challenge. To address the potential bias in our estimator we may consider using a multisite instrumental variables approach described next.

Multi-site Instrumental Variables: In paper 4 (synthesis), we *may* estimate the average returns to an ASAP-induced degree using a multi-site instrumental variables approach described by Reardon and Raudenbush (2013). This method involves estimating the average effect of ASAP on earnings at site j, $\hat{\beta}_j$, and the average effect of ASAP on degree completion at site j, $\hat{\gamma}_j$, using a model like equation (1), but with site-by-treatment interaction terms. To estimate the average returns to a degree, $\hat{\delta}$, we regress $\hat{\gamma}_j$ on $\hat{\beta}_j$ through a V-known random effects meta-analysis, as implemented and described in detail in Bloom et al. (2020). The resulting coefficient on $\hat{\gamma}_j$ represents an estimate of the effect on earnings for every one percentage point increase in degree completion.

A major strength of this approach is that it relaxes the classic IV exclusion restriction—the second stage regression's intercept represents the direct effect of the program on earnings (λ). Nonetheless, for unbiased estimation of δ we still must assume there are no important omitted *correlated* mediator contrasts. Classic IV assumes no omitted mediators at all, be they correlated or uncorrelated with the mediator of interest, so this approach is a relaxation of that assumption. This approach also has the potential to allow for the inclusion of multiple mediators, such as AA completion and BA completion, although with only six colleges, degrees of freedom are quite limited.

While the multi-site IV approach minimizes assumptions, it has even less statistical power that the classic IV approach so the conclusions drawn from this line of inquiry will be suggestive at best.

Weights

No weights will be used in the analyses.[21]

Attrition and Missing Outcome Data

The academic outcomes measures (i.e., degree completion) will be derived from CUNY student degree data, which include all CUNY institutions, and Ohio Department of Higher Education (ODHE) degree data, which includes all Ohio public colleges. These records will be merged with data from the National Student Clearinghouse, which collects and

[21] The estimator in Equation 1 is "precision weighted". As described in Miratrix, Weiss, and Henderson (2021), this estimator is potentially biased with respect to the estimand (the effect for the average individual in the study) under certain circumstances. However, in practice they find minimal differences in effect estimates compared to unbiased estimator counterparts, including those that use weights such that the weighted random assignment ratio is consistent across blocks.

distributes enrollment, degree, and certificate data from more than 3,600 colleges that enroll more than 98 percent of the nation's college students.

These administrative records will be obtained for all members of the relevant analytic samples (see Figures 2 and 3 for CONSORT diagrams). All sample members will be included in the impact analyses. Students who are not found in any database will be treated as having not earned a degree during the relevant time period. Therefore, attrition and/or differential attrition should not bias impact findings with respect to completion at the institutions covered by these databases. In other words, attrition is not an issue in the normal sense for this study because we can locate students at almost any college.

Employment and earnings outcomes will be captured using wage records reported to the Unemployment Insurance system. UI data cover nearly all employment in a state, with the exception of self-employment, federal government, informal work, and out-of-state jobs. Thus, they will not capture employment for individuals who work outside of the state in question. As noted earlier, the large majority of community college graduates in New York and Ohio work in their respective states 10 years later, suggesting that UI data for each individual state will capture most employment. New York and Ohio UI data will be available through 10 years after students entered each study.

LEHD data will help to capture additional employment in neighboring states. For the CUNY sample (which joined the study in 2010), LEHD data is available for the full 10-year follow-up period. For the Ohio sample (which joined the study in 2015-2016), LEHD data is available through 6 years, with the possibility that additional years may become available during the grant. Thus, in Ohio we will examine the sensitivity of estimated effects on labor market outcomes to the inclusion of neighboring states in years 1-6. In years 7-10, we can only guarantee the examination of effects on labor market outcomes derived from Ohio UI records.

For students who have no UI wages records in a given quarter, it will be assumed that they did not work in a UI-covered job in that quarter and their earnings are zero. Thus, attrition is not an issue for the analysis of earnings and employment.

Outliers and Unusual Data

CUNY ASAP and Synthesis: The project has two confirmatory outcomes: degree completion and earnings. There are no outliers for degree completion. For earnings, we will run sensitivity tests by dropping the top 1 percent of observations to test how sensitive our findings are to their removal.

Accounting for Multiple Inference (Multiple Hypothesis Testing)

CUNY ASAP and Synthesis: The primary approach to addressing multiple hypothesis testing is that we have limited the number of outcome domains to two: college completion and labor market. Within domain, we have limited the number of *confirmatory* outcomes to one: earned a degree at any college and average annual earnings, respectively.

Cost and Benefits

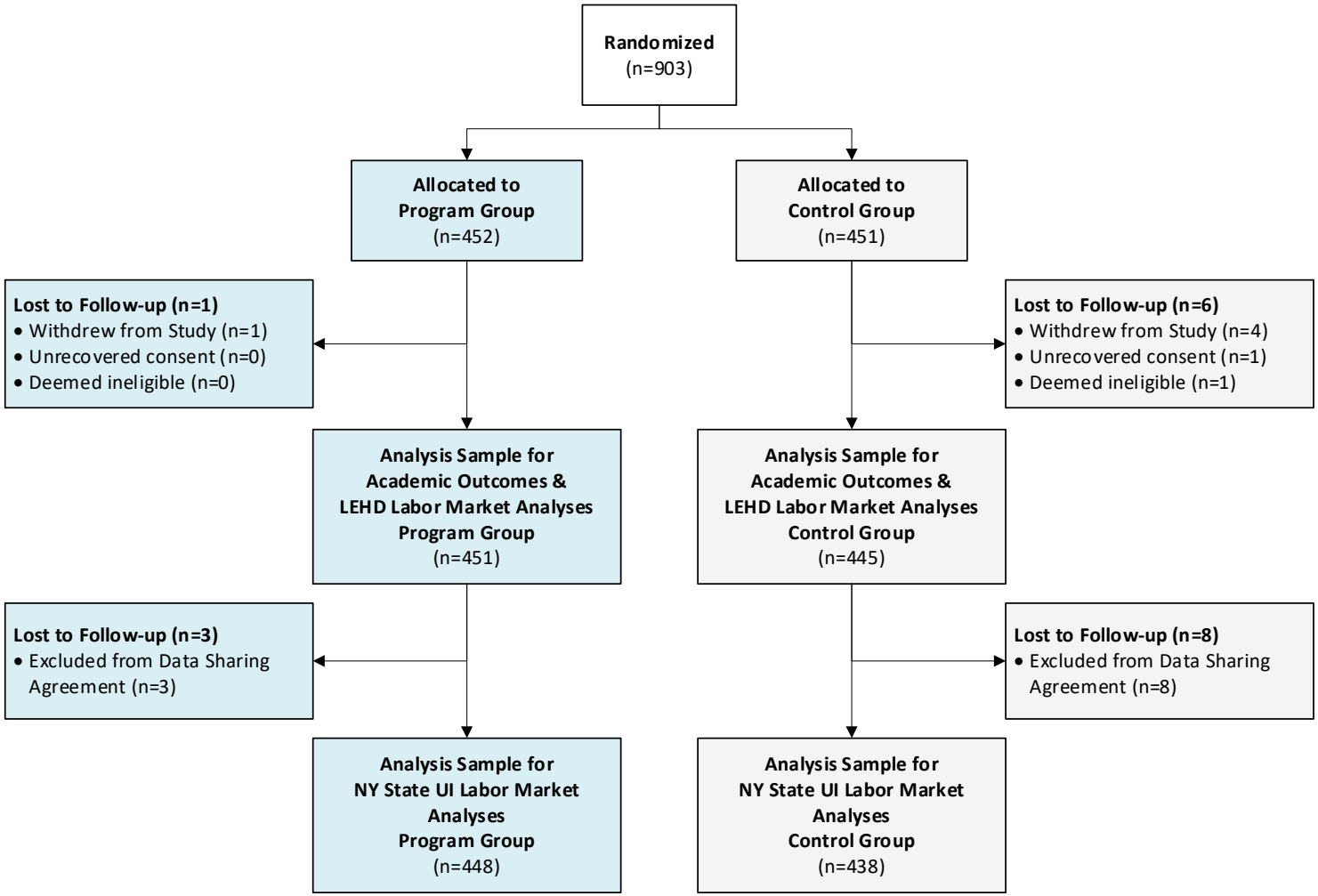
CUNY ASAP and Synthesis: Prior analyses examined the incremental cost of ASAP at CUNY and in Ohio as part of the original evaluations. The incremental cost (i.e., new resource requirements compared to implementation of business-as-usual) was estimated to be approximately $4,700 per student per year in CUNY and $1,800 per student per year in Ohio.

RQ5: Through 10 years, how do the costs of ASAP compare with some of its benefits?

This study will update the analyses of Levin and Garcia (2017) by estimating benefits using observed earnings impacts through 10 years. Individual earnings data will be used to estimate the additional revenues gained from federal, state, and local taxes. Although we will not estimate the other components of the fiscal benefits, federal, state, and local tax receipts accounted for most benefits in the Levin and Garcia study. These data will provide an estimate of the benefits relative to the costs of ASAP through 10 years.

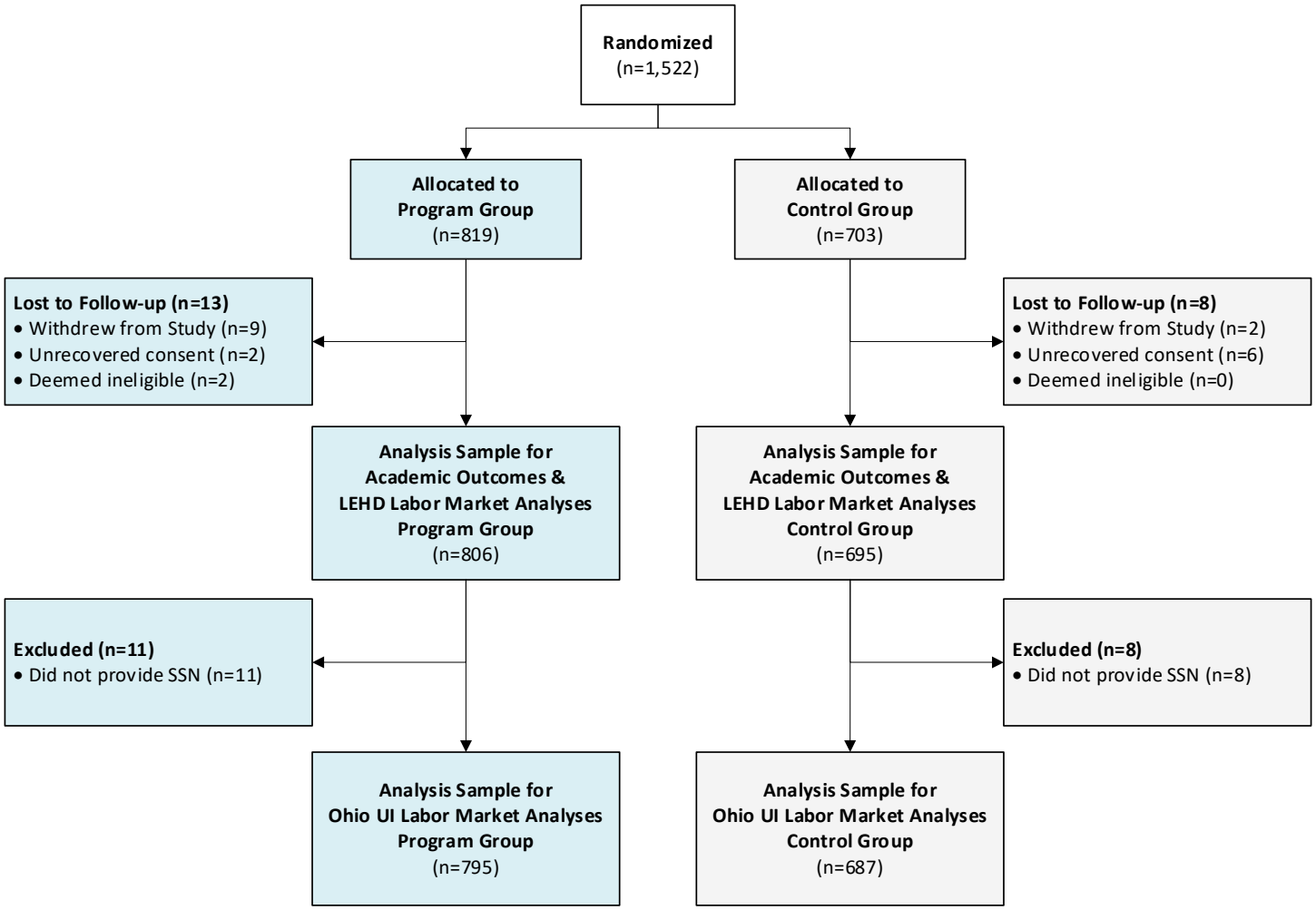
Estimates of tax revenues at the federal and state level will be obtained using published data on effective tax rates for individuals with incomes in the range of the ASAP study participants.

Figure 3. CUNY ASAP Anticipated CONSORT Flow Diagram (Pre-analysis Plan)



Note: Paper three will rely on the "Analysis sample for Academic Outcomes" and the "Analysis sample for NY State UI Labor Market Analyses" samples. Paper 4 will rely on the "Analysis sample for Academic Outcomes & LEHD Labor Market Analyses" sample only.

Figure 4. ASAP Ohio Anticipated CONSORT Flow Diagram (Pre-analysis Plan)



Note: Paper 4 will rely on the "Analysis sample for Academic Outcomes & LEHD Labor Market Analyses" sample whenever LEHD is available. If it is not available, than the "Analysis Sample for Ohio UI Labor Market Analyses" will be relied upon.

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