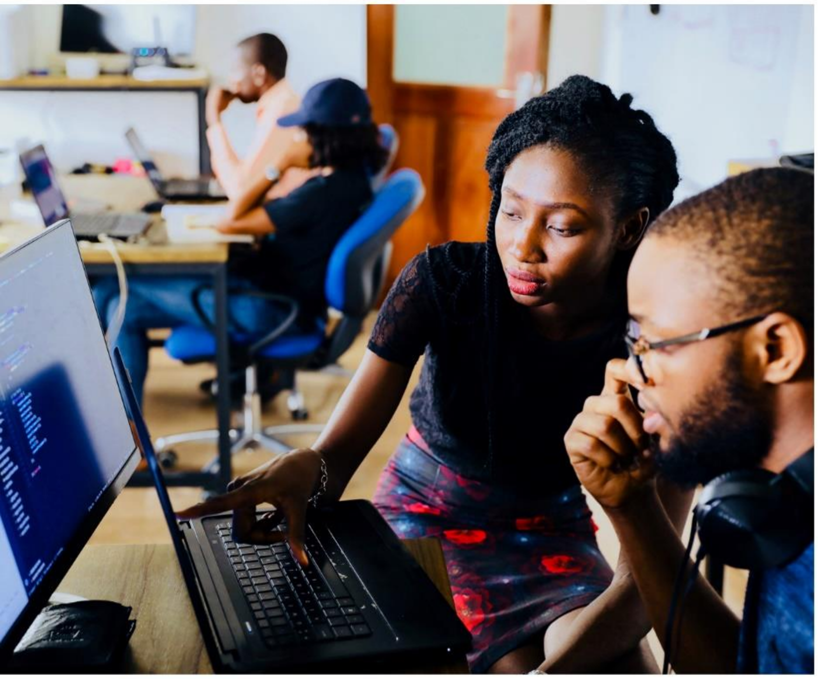

# Pathways to Success:

## Improving the Transparency of Student Outcomes in the Virginia Community College System

Prepared by Brian Heseung Kim
for the Virginia Community College System
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University of Virginia, May 2019

Disclaimer

The author conducted this study as part of a program of professional education at the Frank Batten School of Leadership and Public Policy, University of Virginia. This paper is submitted in partial fulfillment of the course requirements for the Master of Public Policy degree. The judgments and conclusions are solely those of the author, and are not necessarily endorsed by the Batten School, by the University of Virginia, or by any other entity, including the Virginia Community College System.

Acknowledgements

The author thanks Catherine Finnegan and her collaborators at VCCS for their openness, enthusiasm, wisdom, and support in this analysis. The author also expresses his deep appreciation and gratitude to…

… the many mentors and teachers who have helped him grow, learn, and develop,
… the many friends and family members who have supported him along the way,
… the many peers who have pushed his thinking and his understanding,
… and the many members of the UVa and Charlottesville communities who have created a place he can call home.

Honor Statement

On my honor as a student, I have neither given nor received unauthorized aid on this assignment.

Brian H. Kim

Virginia's Community Colleges

University of Virginia | Frank Batten School of Leadership and Public Policy

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## I. Executive Summary

The Virginia Community College System (VCCS) plays an important role in the educational and economic experiences of many Virginians: over 1.3 million unique residents of the state have entered one of its 23 institutions over the past two decades. Each year, another 25,000 students enroll in a VCCS institution for the first time, seeking their very first post-secondary degree.

While not all students enroll in VCCS in the explicit pursuit of higher wages, research shows that post-graduation earnings are an influential factor in *whether* and *what* students choose to study in the community college context. This is in some ways wise, especially when our best estimates of the wage return to a community college degree show that the choice of a college major can mean the difference between an associate's degree that increases earnings by $5,400 per year, and an associate's degree that does not increase earnings at all.

Despite this large variation in post-graduation earnings by major, there does not exist any comprehensive *and* disaggregated source of outcomes information for students to reference while deciding what to study at VCCS. And, critically, students have been found to be systematically misinformed about how much graduates of various majors earn; when asked to estimate the earnings of graduates in a particular field of study, community college graduates were off by as much as 47% in either direction. In other words, students are making a critical life decision based off of incomplete and inaccurate information.

In this analysis, I present four potential policy alternatives that VCCS could implement to address this misinformation and lack of outcomes transparency within its network. In doing so, VCCS has the opportunity to vastly improve the welfare of students versus keeping with the status quo. These alternatives are varied in terms of their investment levels (low and high) and implementation methods (digital and in-person):

1. *Online Data* - Integrate Extant Program-Level Outcomes Data into VCCS Web Presence
2. *Outcomes Explorer* - Develop an Online "Outcomes Explorer" Platform for Students
3. *Advising Data* - Integrate Extant Program-Level Outcomes Data into Advising Efforts
4. *Advising Expansion* - Expand College and Career Advising for Newly Enrolled Students

I examine each alternative on the degree to which it influences students to switch into higher-earnings majors, the magnitude of net benefit that students experience as a result of changing majors, the extent to which these benefits are equitably distributed across student subgroups, and the difficulty and costs associated with implementation.

Ultimately, I recommend that VCCS implement (4) *Advising Expansion* as soon as practicable. It reaches and supports the most students in making more informed major selection decisions, produces the most overall benefit to students by encouraging them to pursue higher-earnings majors, and distributes those benefits most equitably to students of all backgrounds. It is by far the most expensive alternative presented, but I find that these costs are offset by benefits to students at a cost-benefit ratio of 1:8. Attaining these strong benefits will require careful implementation and thoughtful planning, and I provide a series of implementation considerations to conclude this report.

## II. Problem Statement

One of the most important decisions for a community college student is their choice of a major. The best causal evidence we have available shows that, depending on the major, an associate's degree can increase the yearly earnings of graduates by as much as 103% and *as little* as 0%. And while there are many reasons why a student would select one major over another besides just earnings, we know that earnings do indeed matter to students. Evidence from experimental settings reveals that a 1% increase in the reported earnings of a major's graduates results in a 1.4% greater likelihood that community college students select that major. In other words, many students pick their major at least *partially* because they think it will help them earn more money after graduation.

Unfortunately, research also shows that students severely misjudge the earnings associated with different majors. When students at a community college in California were asked to rank four categories of their college's majors in order of student earnings after graduation (Business, Arts, Social Sciences, and STEM), fewer than *half* of students could correctly identify even the first and last place correctly. Only 15% could correctly rank all four. Further, when asked to estimate actual dollar amounts, students were off by an average of 47% *in either direction*. These facts together reveal that community college students are basing one of the most important decisions of their life on strikingly inaccurate perceptions.

And students are not necessarily to blame for these inaccurate perceptions, either. The College Scorecard, an initiative by the U. S. Department of Education, is one of the most prominent sources of outcomes information for students across the country. Yet despite an overwhelming body of evidence at all levels of post-secondary education that major matters, the College Scorecard only displays earnings information aggregated at the whole-college level. The State Council of Higher Education for Virginia (SCHEV) publishes similar information disaggregated by program for each college in Virginia, but in a format and platform completely inaccessible to the public. Simply put, there are no public-facing resources available to inform VCCS students' major selection decisions.

Each year, the Virginia Community College System enrolls about 100,000 full-time students, and a combined total of 240,000 students take at least one credit through their system. Since 2000, the network has served over 1.3 million unique Virginia residents. **Unless intervention is taken, students of the Virginia Community College System will continue to lack detailed information about the labor market outcomes of graduates, resulting in potentially severe inefficiencies with regards to student employment outcomes, student persistence, and student debt burden.**

## III. Key Terms, Definitions, and Acronyms

| | | |
|---|---|---|
| VCCS | - | Virginia Community College System |
| VDOE | - | Virginia Department of Education |
| SCHEV | - | State Council of Higher Education for Virginia |
| UI | - | Unemployment Insurance |
| FAFSA | - | Free Application for Federal Student Aid |
| BLS | - | Bureau of Labor Statistics |
| "The Commonwealth" | - | The designation for the state of Virginia |
| "The General Assembly" | - | The designation for the legislative body of Virginia |
| "Member Institution" | - | The designation for an individual community college institution within VCCS |

## IV. Background

a. The Benefits of a Community College Degree

At the core of this policy problem is the fact that students benefit from a community college degree - but they also benefit *differentially* by major. To illustrate: if all community college degrees uniformly provide zero measurable economic benefit to students, it would be prudent to discourage students from attending community college at all. Conversely, if all community college degrees uniformly provide significant benefit to students regardless of major, it would not matter that students make misinformed major decisions, because their outcomes will ultimately be unaffected by that misinformed decision. In this section, I review the evidence showing that neither of these scenarios are the case.

The *average* wage returns to an associate's degree are generally positive, and this result holds across time periods and state contexts. In Virginia, researchers using a rigorous study design found that an associate's degree from VCCS increases average student earnings by $900-1,350 per quarter, or $3,600-5,400 per year (Xu & Trimble, 2016). They also find that graduates are 7 percentage points more likely to be employed in the period after graduation. Assuming no wasted credits, that degree would cost approximately $9,240 in tuition and fees (not inclusive of other fees and missed wages due to enrollment); the average student could recoup this initial cost in as little as two years of employment after graduation, with a lifetime of increased earnings beyond that.

These positive average returns to an associate's degree are corroborated by similar studies in multiple other states. An analysis from Ohio's technical and community college system found that female students receiving an associate's degree saw a 27% increase in earnings on average, while males saw a 24% increase (Bettinger & Soliz, 2016). Another study set in Kentucky found much higher returns: 56% for women and 24% for men (Jepsen, Troske, & Coomes, 2014). In a broad review of several additional studies of this kind, Belfield & Bailey (2017) reiterated this trend of uniformly large returns to an associate's degree, the only exceptions being for men in Arkansas and Washington - returns for these groups were still positive, but relatively small compared to other states. Though there is variation in these estimates, the overall consensus is clear: a community college degree pays.[1]

But while the *average* return to an associate's degree is generally quite positive, students of Health, Nursing, and Engineering see consistently larger returns, and students of General Studies, Liberal Arts, and Education see consistently lower or null returns (Belfield & Bailey, 2017). For example, in Ohio, an associate's in Liberal Arts showed a precise null return, but a degree in health services saw an exceptional 50% return (Bettinger & Soliz, 2016). This spread was even more striking in Michigan: Liberal Arts again had a precise null return, while Nursing provided a 103% return for females and 86% return for men (Bahr et al., 2015). No major across these studies showed *negative* returns, but this is little solace given how long it often takes students to complete these degrees, alongside the financial burden and lost earnings that pursuing these degrees entails. In other words, the returns to community college degrees across the country are highly dependent on the course of study a student selects.

That said, all the aforementioned returns estimates are contingent on individuals completing their degrees. Belfield & Bailey (2017) remark on the potential that there may still be returns to taking individual credits even if a student does not complete a degree, but the estimates of these

[1] Note that these studies deployed nearly identical methodologies with equally robust sources of data, meaning it is unlikely that the variation is due to flaws in methodology, underpowered datasets, etc.

returns are so small as to be negligible: students earn an additional $10-20 per quarter for each credit they earn (Zeidenberg, Scott, & Belfield, 2015). Given that the cost of a single credit-hour at VCCS is $154 (not inclusive of other fees and potential lost wages due to enrollment) community college is unlikely to be a worthwhile investment for individuals unless they receive a degree.

This significantly complicates the sort of cost-benefit math that an individual may conduct as they decide whether or not to enroll in a degree program with VCCS, especially because graduation rates at VCCS, and community colleges more generally, are strikingly low. For associate's degree students who enrolled at a VCCS institution starting in 2011, only about 25% of them graduated within three years ("Fall Headcount Enrollment Reports," 2018).[2] If prospective students were to factor in the very real possibility that they may not complete their degree, the cost-benefit analysis of attending VCCS suddenly becomes less clear-cut.

b. The Transparency of Community College Student Labor Market Outcomes

The above studies illustrate how beneficial a community college degree *can* be, but these detailed insights are not in any format accessible to the public. This is in spite of the fact that federal and state policymakers have championed efforts over the past few years to more transparently communicate to potential students and their families the costs and potential benefits associated with individual colleges. For instance, the U. S. Department of Education's "College Scorecard" provides college-level information on price net of financial aid and median earnings ten years after graduation, while the "Gainful Employment" regulations put pressure on for-profit institutions and non-degree programs to demonstrate positive earnings outcomes for students or risk losing eligibility for Title IV funding. In this section, I review the primary sources of outcomes information currently available to students.

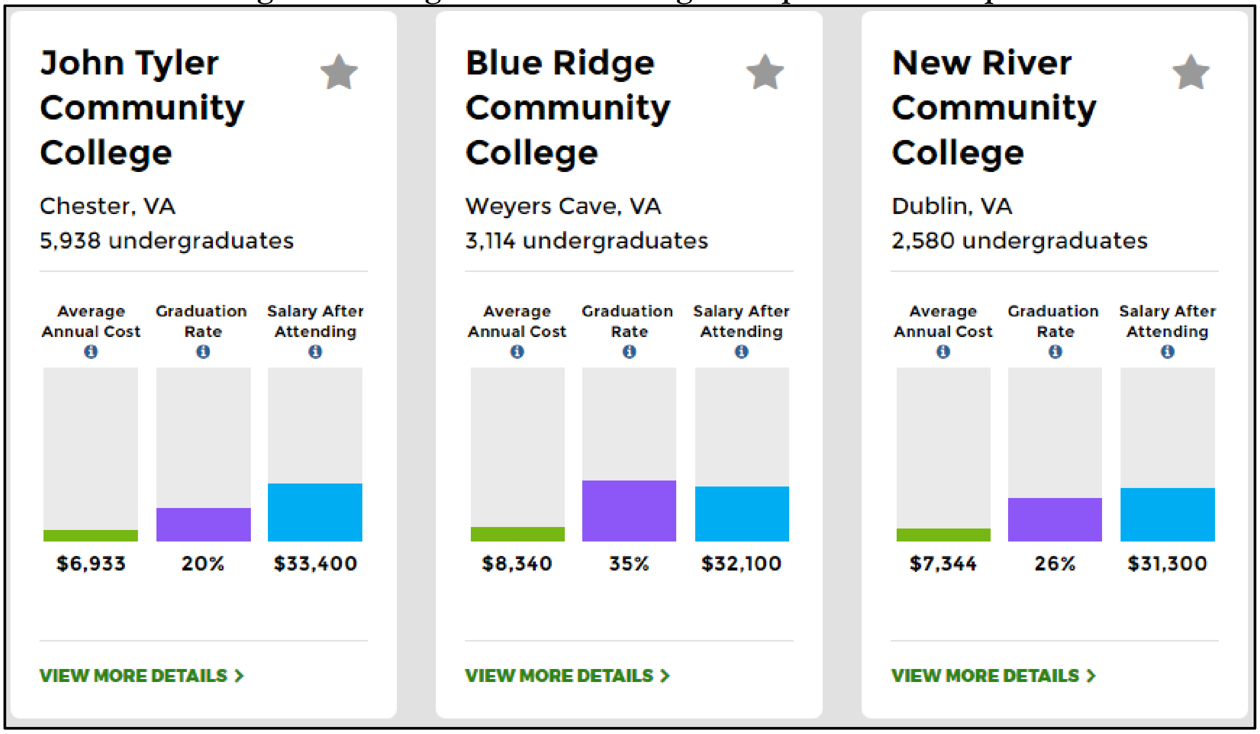
The Obama Administration passed the "Gainful Employment" regulations in 2015, which tied any for-profit or non-degree program's eligibility for federal student aid dollars to a ratio of student debt payments and earnings (Cellini, Looney, Deming, & Matsudaira, 2017). If their students' annual earnings after graduation were not commensurate with the amount of debt they needed to take on to obtain that degree, they would be forbidden from admitting students who required federal financial aid to attend ("Gainful Employment," 2017). The goal of this regulation was primarily to protect students from predatory for-profit institutions; many for-profit schools are hugely dependent on federal student aid dollars, and so this created enormous financial incentive for for-profits to demonstrate their value-add to students and ensure positive outcomes (Cellini & Turner, 2016; Itzkowitz, 2017). Importantly, all programs subject to these Gainful Employment regulations were also required to publish these outcomes, providing fairly detailed program-level outcomes information for at least a subset of colleges. However, this was motivated less in the interest of informing student decisions, and more in the interest of accountability.

Also formulated under the Obama administration in 2015, the "College Scorecard" is an online platform operated by the Department of Education designed to make costs, graduation, and earnings data for schools as transparent to students and their families as possible (Whitehurst & Chingos, 2015). Students can search the nation for colleges that match their interests and desired geographic location, after which they are presented with a series of visually clear and salient statistics about each school, seen in Figure 1. The platform explicitly facilitates the comparison of colleges,

[2] I refer to three years in this figure as it corresponds to 150% of anticipated time for a two-year associate's degree, a standard benchmark for graduation rates.

and it also allows students to drill down into more specific statistics for each one, to include: retention rate after the first year of enrollment, the average total debt after graduation, aggregated student demographics of the school, and average cost broken down by family income brackets.

**Figure 1. College Scorecard College Comparisons Example**




Source: The College Scorecard, U.S. Department of Education, 2018

This initiative is a boon to any student looking to become more informed about their college choice process, and the Department of Education makes all the underlying data for the College Scorecard public. However, in the interest of presenting clear and approachable information for students, it aggregates all data to the *college level* (Whitehurst & Chingos, 2015). Given that there is significant variation in both graduation and labor market outcomes by major, it is unclear whether this information actually supports students in making informed major decisions, or exacerbates misinformation by providing students with data that is not necessarily applicable to their course of study. This brings into question the utility of the statistics presented, but it remains one of the most robust sources of outcomes data designed *specifically* for students and families.

To that point, the State Council of Higher Education for Virginia provides data similar to the College Scorecard for each college in the state - even disaggregated by grouped programs of study - but targeted for *policymakers and researchers*. For each college-by-program combination available in Virginia, they display rolling 5-year averages for graduates in terms of graduation rates, earnings, employment rates, and even percent of graduates earning a proxy for livable wage (State Council of Higher Education for Virginia, 2018). But looking at how they display the results in Figure 2, note the enormous contrast in viewability, interpretability, and clarity versus the College Scorecard in Figure 1. Further, the College Scorecard is actively advertised to students and their families as a tool for use in college decision-making; by contrast, it is unclear if SCHEV does anything comparable to provide this information to students in Virginia. Despite the robustness of their data, it remains inaccessible and likely underutilized by VCCS students as a result.

**Figure 2. SCHEV Program-Level Outcomes Report Example**

# WG02: Wages of Graduates, List Programs By Institution

Wages of graduates, List Programs By Institution

Select a reporting year: 2012-13

Select an Institution: J Sargeant Reynolds Community College

Update!

</> Embed · Share · Tweet · Recommend 0

Tags: degrees awarded, HB639, wage outcomes

## J Sargeant Reynolds Community College
## Graduates from 2008-09 to 2012-13
## Wage Outcomes

Wage Outcome of Graduates 18 months Post-Completion, Graduates from 2008-09 to 2012-13

| Program | Degree | Graduates (n) | FT Wages (%) | Enrolled at Higher Level (%) | Part-Time Wages (%) | No Information (%) | Median Wages |
|---|---|---|---|---|---|---|---|
| All Reportable Programs at this Level (XTOTAL) | Award of less than 1 academic year | 1,961 | 33% | 51% | 16% | % | $ 27,657 |
| Allied Health Diagnostic, Intervention, and Treatment Professions, Other (510999) | Award of less than 1 academic year | 91 | 47% | 36% | 16% | % | $ 22,684 |
| Computer and Information Sciences, General (110101) | Award of less than 1 academic year | 68 | 34% | 43% | 24% | % | $ 43,581 |

Source: The State Council of Higher Education for Virginia, 2018

c. The Impact of Outcomes Data on Student Enrollment Behavior

It is clear that the major of a community college graduate matters, and it is further clear that the outcomes data currently available to students do not help them parse this fact. That said, does that matter? In other words, would providing students with this detailed information even make a difference in their major selection decisions? Traditional models used to describe the college choice process agree that students incorporate many points of information in their decision-making, often mediated through their parents, peers, teachers, and counselors (Cabrera & Nasa, 2000). Factors like financial aid, location, perceived rigor, and available programs of study all play a significant role in student decisions. However, these traditional models often exclude information on graduation and employment outcomes, likely as a result of these data becoming widely and systematically accessible to the public only recently with the advent of the College Scorecard (Whitehurst & Chingos, 2015).

In this section, I review what we currently know about the impact of outcomes data on student decision-making.

Researchers and policy analysts have made several recent attempts to examine whether these graduation and labor market data influence student decision-making in the college choice process through small-scale lab experiments. For *graduation* outcomes, Schneider & Kelly (2011) ran a simple experiment (n=1000) to determine if providing parents with college graduation rates would influence their hypothetical preference for one college over another. They found that 46% of the parents who were not provided any graduation data expressed a preference for colleges with higher graduation rates (i.e. based on factors besides graduation rate, such as location and demographics), but 61% of those who were provided with graduation data did. This 15 percentage point difference indicates that graduation information can strongly impact parental college preference, which is likely to then also impact student preference. It still remains to be seen whether this effect would persist in the noisy reality of the actual college choice process, but these lab results are a useful starting point.

In terms of the effect of *labor market* outcomes on student decision-making, there are several worthwhile studies pointing to meaningful impacts. Wiswall & Zafar (2015) conducted a similar lab experiment; they asked 4-year university students to estimate their probability of majoring in a variety of fields, and then measured whether that probability changed when students were provided with the earnings data of graduates from their university, in each field. The authors ultimately found that students responded positively to perceived increases in the earnings of various majors: a 1% increase in perceived earnings resulted in a 4-6% increase in a student's stated probability of enrolling in a given major. This difference is potentially quite meaningful - the authors went on to estimate the expected welfare increases if students *actually* changed majors at that rate and *actually* earned the average stated earnings for their new major, finding that the average earnings of students would increase by roughly 5-6% holding all else equal. Importantly, that welfare analysis relied on a heavy set of assumptions, and so we should interpret that finding with caution. Further, this was a lab experiment, and so the authors were not able to measure whether *actual* major decisions would be affected by the information.

The prior study looked specifically at results in a 4-year college setting, but Baker et al. (2017) replicates this same study in the community college context. They first find via survey that college students were not able to accurately estimate labor market outcomes for students at their own institutions: they mis-estimated the earnings of each major by an average of 47%, mis-estimated the probability of employment by 40%, and could not accurately rank four broad categories of majors[3] in order of earnings. This points to the potentially distorted decisions that students are currently making in the absence of rigorous outcomes information. They go on to conduct the same style of survey experiment as Wiswall & Zafar, asking students for their probability of majoring in each field of study and measuring responses to new information on earnings (n=376). Their results were smaller than those in the 4-year context, but still substantial depending on earnings gaps between majors: a 1% increase in perceived salary for a major resulted in a 1.4-1.8% increase in probability of choosing that major. This study's results are more likely to be relevant for VCCS's context than Wiswall & Zafar, though it is still unclear whether these lab results would translate to actual student decision-making.

To address this question of whether prospective students would actually respond to labor market data while making their college choice and major decisions, Blagg et al. (2017) conducted an

[3] Only 13% of students were able to correctly rank the categories of (1) Business, (2) Arts and Language Arts, (3) Humanities and Social Sciences, and (4) Science, Math, and Engineering, in order of their average earnings.

innovative small-scale experiment in Virginia. In a small pilot of 25 schools, half of the students were given access to a website with standard college information (location, demographics, etc.), while the other half of students were given access to a website with otherwise unavailable labor market outcomes like earnings, in the same style as the experiment by Schneider & Kelly (2011). Their results highlight the importance of recognizing the actual decision-making context that students experience: they found absolutely *no effect* on the college or major choices of students.

The authors point out that this is may not necessarily be evidence *against* the impact of providing students with information, but rather that any provided information likely needs to be far more *salient* to have an effect approaching what we saw in the experimental survey studies. They deployed this information to students in a new, separate website, rather than a tool students were already using or comfortable with such as Naviance or College Scorecard; students may have prioritized other sources of information and guidance in their thinking, which would potentially wash out any effect of information from the experiment website. And in addition to reducing effectiveness, it may also be the case that creating a new website would greatly increase costs of implementation - Blagg et al. unfortunately do not comment on the costs of their intervention. Regardless, these findings make it clear that the provision of information to influence student decisions may be far more complicated than the work of Wiswall & Zafar or Baker et al. may lead us to believe.

We can look to the informational nudge literature for one final point of reference about how providing students with data can impact behavior and outcomes. Hoxby & Turner (2014) ran an experiment to provide high-achieving, low-income students with semi-personalized information on the college application process and net costs for their estimated family income levels; importantly, this information was *already publicly available*. Their results were striking: treated students were more likely to apply to and be admitted to more colleges. Further, the colleges they applied to and were admitted to were of higher quality by all metrics - graduation rates, average SAT scores, spending per student, and so on. The authors and other researchers theorize that this is because underserved and low-income students are much less likely to be aware of information on the costs and benefits of higher education (Page & Scott-Clayton, 2016; Scott-Clayton, 2013). Thus, overcoming that difference with informational interventions, as is possible at VCCS, could demonstrably improve student outcomes - especially in those programs more likely to produce positive earnings returns for students. Especially for community colleges that serve disproportionately low-income, minority, and non-traditional students - students whose enrollment decisions are demonstrably more sensitive to incomplete information - such interventions could also be meaningful steps towards equity.

### d. The Virginia Community College System

This body of literature reveals the importance of college major on student outcomes, the lack of information that students have available on this subject, and the potential impact that providing such information could have. Before discussing the ways in which VCCS may possibly intervene in this policy problem, it is crucial to understand the context of VCCS first.

VCCS is comprised of 23 independently-run public community college institutions ("Virginia's Community Colleges," 2018). Each institution is funded separately by the General Assembly, and each maintains its own administrative hierarchy. VCCS itself is a state-run umbrella organization that serves as the overarching administrative body for its constituent member institutions. While the member institutions maintain full autonomy in terms of programs and courses offered, budgetary decisions, staffing decisions, and so on, VCCS facilitates crucial collaboration between the colleges that advances their shared mission and shared responsibility to the Commonwealth. The official mission statement of VCCS is as follows: "We give everyone the opportunity to learn and develop the right skills so lives and communities are strengthened" ("About VCCS," 2018).

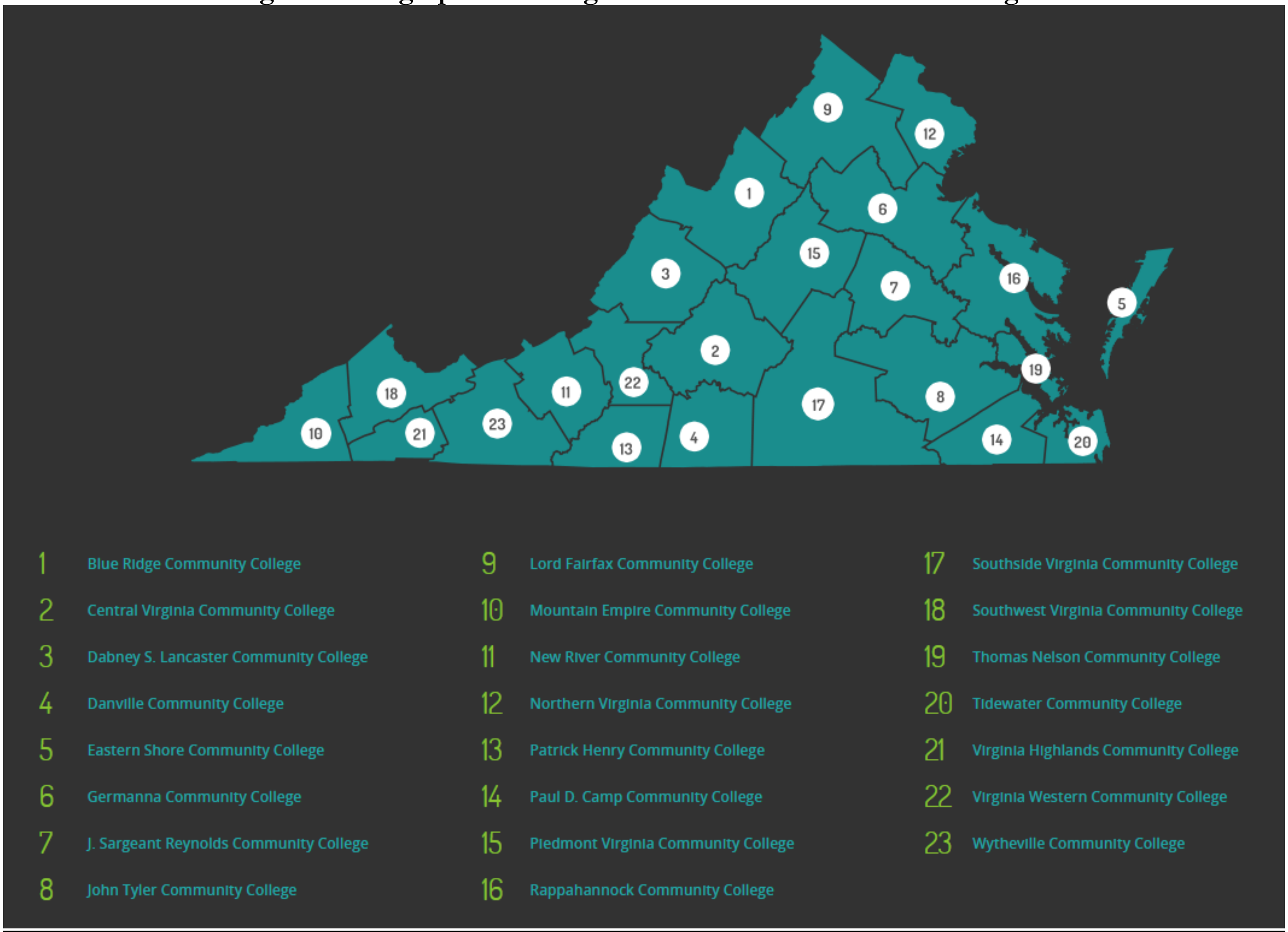
VCCS takes on a number of specific responsibilities in pursuit of this mission. For example, it serves as the primary representative for its member institutions in legal and governmental affairs. Further, VCCS orchestrates a number of network-wide initiatives to enhance their operations. It organized the use of a common course and program numbering system to facilitate student transfers across the network and into other public institutions within Virginia (e.g. The University of Virginia, Virginia Polytechnic Institute and State University, etc.). This is directly tied into its management of the Guaranteed Admission Agreement program, which offers qualifying graduates of any VCCS institution guaranteed admission into any of the Commonwealth's public four-year institutions. Through network-wide analyses, it encourages investment among member institutions in high-performing and high-needs programs and courses of study. While VCCS does not dictate policy to be enacted at the institution-level, its recommendations and advisements are taken into serious consideration across the network.

Through its member institutions, VCCS enrolls about 100,000 full-time students annually, and an additional 140,000 part-time students take at least one credit in a given year ("Virginia's Community Colleges," 2018). Its 23 member institutions are evenly distributed across the geography of the Commonwealth; thanks to the expansion of satellite campuses in the network, any resident of the Commonwealth of Virginia also lives within 30 miles of a VCCS campus. Figure 3 displays the general service region of each member institution, though individuals are not restricted to attending only their local college.

This geographic diversity makes it difficult to characterize VCCS's student body. Like many state community college networks, VCCS serves a large share of "non-traditional" students: 43% of VCCS students are non-white, 43% are first-generation college, 50% are older than 25 years-old, and 26% receive Federal Pell Grants.[4] This also reflects the broader national trend of two-year public institutions serving higher proportions of these students than public or private four-year institutions (Ma & Baum, 2016). However, network-wide demographic averages are not necessarily representative of individual institutions due to their unique contexts and populations. For example, Tidewater is located in Norfolk, VA, which is also home to the world's largest naval base ("Naval Station Norfolk," n.d.). Tidewater, as a result, serves a hugely disproportionate share of students with military backgrounds relative to other schools - 17% of its students have a military background, versus only 5% of students at other network colleges. Similarly, Northern Virginia serves students in the larger Washington, D.C. metropolitan area. Students at Northern are more racially diverse than the overall network average, and are substantially more likely to be from foreign countries as well: 19% of Northern Virginia students hold a foreign travel visa, versus only 3% of students at other VCCS colleges.

[4] All demographic figures here are author's calculations using student-level demographic, enrollment, and financial aid data for students taking any classes in the 2016-2017 academic year. Restricted student-level data provided by VCCS.

**Figure 3. Geographic Coverage of VCCS Institutions Across Virginia**




Source: Virginia Community College System, 2018

This variation in demographics across VCCS institutions will play a large role in how we think about policy alternatives in later sections, and the administrative role of VCCS vis-à-vis its member institutions will shape how we think about the implementation of said alternatives as well.

## V. Evaluative Criteria

VCCS has the opportunity to address this lack of transparency in student outcomes across its network. In doing so, it would ensure that students are making their major selection decisions using the best and most representative information available. Given insights from Baker et al. (2017), Hoxby & Turner (2014), and Wiswall & Zafar (2015), this new information is likely to change what major students finally enroll in; given insights from the community college wage returns literature, this changing major selection behavior may result in dramatically different earnings outcomes as well.

At this stage, it is unclear whether providing this information to students would actually improve student outcomes, and the aforementioned studies demonstrate the importance of *how* that information is delivered. In **Section VI**, I articulate a series of policy alternatives that VCCS could implement to provide its students with better outcomes information by program. In the present section, I articulate how I will compare and assess those alternatives in as objective a framework as possible.

In order to assess the appropriateness of each potential policy alternative, I examine them using the following set of criteria:

a. **Influence**
b. **Net Benefit to Students**
c. **Equity**
d. **Feasibility**

For this analysis, criteria are assessed on a time horizon of 10 years from the time of implementation as applicable. I summarize the definitions and processes I use to quantify these criteria below, and more in-depth explanations of my methodology are available in the **Appendices a-d**. I integrate the results of all four of these criteria into a single, numeric score for each alternative to arrive at my final recommendation, explained in **Subsection e** below.

### a. Influence

However VCCS chooses to disseminate outcomes information to students, it is important to consider *who* is likely to actually receive and understand the information, and how likely students are to adjust their major selection behavior as a result of that information. I formalize this process by assessing three related metrics for each alternative:

**Degree of Reach** - How many students is this alternative likely to provide the information to? I am interested in whether a policy alternative reaches only a handful of students, versus every student enrolling at VCCS. I calculate this as the percentage of first-time, first-degree VCCS students exposed to the information because of the policy alternative, assessing each alternative based on its medium for information dissemination.

**Degree of Salience** - For those students who receive the information, how salient and digestible is that information? Oftentimes information can be presented to students in a way that they will ignore or cannot understand, especially when it is provided in the context of a complex and information-rich circumstance like the college enrollment process. I calculate this as the percentage of the reached audience likely to actually *notice* and *understand* the provided information, drawing upon insights from the marketing and behavioral nudge literatures.

**Degree of Actionability** - For those students who receive, notice *and* understand the information, how likely are they to actually change their enrollment behavior as a result? Major selection is driven by a wide variety of factors, to include personal preference, perceptions of program prestige and difficulty, and so on (Baker et al., 2017). Even if VCCS were able to provide this information to *every* student in a way that they could understand, relatively few students would feel able or willing to change their major. I calculate this as the percentage of the reached audience that noticed and understood the information that are *also* likely to change their major selection. I draw extensively from the behavioral nudge literature to inform these estimates.

By multiplying all of these calculated figures together with the total number of first-time, first-degree VCCS students enrolling each year, I can arrive at an estimate for the total number of students *per cohort* likely to select a higher-earnings major due to the implementation of the policy alternative. I then utilize this number, and its constituent components, to calculate the Net Benefit to Students and the Equity score.

A full explanation of my Influence methodology can be found in **Appendix a**.

b. Net Benefit to Students

After calculating the Influence criterion above, I will have a rough estimate of how many students per year will actually change to a higher-earnings major as a result of the outcomes information for each alternative. With this in mind, it is possible to calculate whether and how much students will actually benefit in dollar terms from each alternative. For this criterion, I conduct a cost-benefit analysis from the perspective of a single student who switches their major,[5] incorporating their likely change in earnings, their likely change in tuition/loan costs, and their likely change in missed wages due to enrollment. All values are assessed separately by alternative, using a ten-year time horizon and a future discounting rate of 5%.

I model this cost-benefit analysis separately by student subgroups of race and gender (e.g. I calculate the net benefits of switching major separately for white males, white females, non-white males, and non-white females).[6] In the VCCS student-level data, I find that there are meaningful differences in both earnings and graduation rates across these subgroups, which would then translate into meaningful differences in the overall costs and benefits of changing majors as well. To provide an accurate estimate of costs and benefits to students, I must then incorporate these differences into my calculations.

However, I assume that students at VCCS are influenced *at random* to change their major - in other words, that no one subgroup of students (along the lines of race, gender, or college) is any more or less likely to change their major than another.[7] Using this assumption, I can then calculate the *total* expected net benefit to students over a ten-year time horizon for each alternative. I multiply the expected net benefit to a random student with the number of students expected to change their

[5] I quantify the costs to VCCS of each alternative in the Feasibility criterion to increase the clarity of this analysis and account for the logistical burden of navigating the state budgeting process.

[6] There are additional student subgrouping I attempted to incorporate in this analysis, such as low-income status, military service history, and age. However, every additional subgroup I include in the analysis reduces the precision and stability of my estimates exponentially due to smaller sample sizes. I explain my empirical selection process for the categories of race and gender in more detail in **Appendix b**.

[7] I attempt to account for this differential influence across subgroups in my Equity metric instead. Incorporating it more finely into the cost-benefit analysis would require many more assumptions, increased complexity, and reliance on a number of plug-ins from the college access literature. All of these factors would reduce confidence in my final estimates, and so I opt for a more parsimonious model instead by relying on this assumption of randomness.

major each year (i.e. the Influence criterion), accounting for differential per-student benefit for each subsequent year of students.[8]

A full explanation of my Net Benefit to Students methodology can be found in **Appendix b**.

c. Equity

The Net Benefit to Students criterion assesses the extent to which VCCS students *generally* benefit from an alternative, and by how much; however, this has the potential to mask an inequitable distribution of these benefits across student demographics. Especially because VCCS serves a more disadvantaged or otherwise underserved student demographic compared to 4-year institutions, any efforts to provide students with more complete outcomes information should also be assessed based on this potential for inequitable benefit.

To that end, I create a weighting function to adjust the total net benefit to students. For each policy alternative, I assess the extent to which there may be differential accessibility and benefit based on my assessments in the Influence and Net Benefit to Students criteria. Policy alternatives that are likely to be equally beneficial among all student subgroups will have their net benefit amount multiplied by a weight of 1 (no adjustment). Policy alternatives that are likely to be less accessible, actionable, or beneficial to underserved demographics will be penalized based on the extent of that theoretical disparity, down to a minimum multiplier of 0.5 (effectively cutting calculated total net benefit in half). Policy alternatives that are likely to be especially accessible, actionable, or beneficial to underserved demographics will be rewarded based on the extent of that theoretical equitability, up to a maximum multiplier of 1.5 (effectively increasing calculated total net benefit by 50%). I set this range of 0.5 to 1.5 so as not to completely disregard the net benefits of an alternative for the average student (as a range that approaches 0 on the low-end would), while still making equity a valued priority in this analysis.

A full explanation of my Equity methodology can be found in **Appendix c**.

d. Feasibility

Finally, I assess each policy alternative based on its feasibility of implementation. Feasibility concerns can include political pushback, difficulty finding skilled applicants for new positions, and so on. As VCCS is funded by the state, it is especially important to carefully consider the costs of any alternative *to VCCS* as a component of its feasibility, due to the logistically complex and political nature of most state budgeting processes. Monetary costs might include hiring new staff (data analysts, graphic designers, web designers, etc.), printing and materials, and training for existing staff - but convincing the General Assembly to cover those monetary costs will also incur additional non-monetary costs (e.g. political capital, stakeholder goodwill, etc.). However, due to analytic limitations, I do not incorporate the potential change in costs to VCCS institutions as a result of differential per-student program costs.[9]

[8] A student influenced to change their major in the first year of implementation will have ten years of earnings changed and considered within this ten-year time horizon. However, a student influenced to change their major in the *second* year of implementation will have only *nine* years of earnings changed and considered in the time horizon. Further, their earnings changes happen one year further in the future relative to the first cohort, requiring additional future discounting of their net benefit.

[9] It may be the case that a student enrolling in Business costs VCCS a differential amount compared to a student enrolling in Biology. However, it is not currently feasible to estimate the extent of this differential per-student cost for

To formalize this process, I first estimate the costs to VCCS of implementing each alternative. Following that, I create a feasibility score that quantifies the likelihood that VCCS can actually propose and pass a budget in the General Assembly to cover the estimated costs of implementation. If an alternative has a strong ratio of costs to VCCS versus total net benefit to students, I argue that it is easier to pass any corresponding increases to the VCCS budget, and its feasibility score trends towards 1 (no adjustment). Conversely, if an alternative has a poor cost-to-benefit ratio, I argue that it is significantly more difficult to pass the corresponding budget, and its feasibility score increases above 1 as a result (a higher penalty). I then multiply this feasibility score with an alternative's estimated costs to VCCS, as a way to represent the non-monetary costs of attempting to pass an infeasible budget (in terms of political capital, time and energy, stakeholder goodwill, etc.). In other words, alternatives that do not have a strong value proposition will be treated as costing more than their raw dollar cost would suggest for my final evaluation.

A full explanation of my feasibility methodology can be found in **Appendix d**.

### e. Final Evaluation

By combining the (a) Influence, (b) Net Benefit to Students, and (c) Equity criteria, I will have an **adjusted total net benefit to students** for each alternative. As the final product of the (d) Feasibility criterion, I will have an **adjusted total cost to VCCS** for each alternative. By subtracting the latter from the former, I can arrive at a **total adjusted net benefit** to both students and VCCS.[10] While there may be additional contextual considerations that VCCS must weigh as it decides whether to implement any policy alternative, my final recommendation will go to the alternative that produces the greatest total adjusted net benefit.

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each college, for each program; the public budgetary information is insufficient to generate a meaningful estimate here. For this reason, I currently assume that each seat in each program costs VCCS the same amount relative to per-credit tuition, which implies that any changes to student major enrollment behavior has no impact on cost to VCCS. As I note in my cost-benefit methodology, I also do not attempt to model whether overall enrollment at VCCS increases or decreases, further simplifying the costs to VCCS in this regard.

[10] I do not consider broader state-wide implications of an alternative for this analysis; for example, it may be the case that improving student outcomes via an alternative increases the tax base in the state and produces other, positive externalities. However, this level of macroeconomic modeling is outside the scope of this analysis, and beyond my ability to meaningfully quantify outcomes.

## VI. Policy Alternatives

In order to address the lack of transparency in student outcomes for VCCS students, I explore a series of four potential policy alternatives, in addition to holding the status quo. I create a slate of alternatives that represent a spectrum of investment levels (low and high) and implementation methods (digital and in-person). The higher-touch alternatives I present here (*Outcomes Explorer* and *Advising Expansion*) require significantly more investment on behalf of VCCS, but with greater likelihood of producing large, positive outcomes for students. This is a tension I explore using the aforementioned evaluative criteria in **Section VII**.

a. *Status Quo* - Let Present Trends Continue

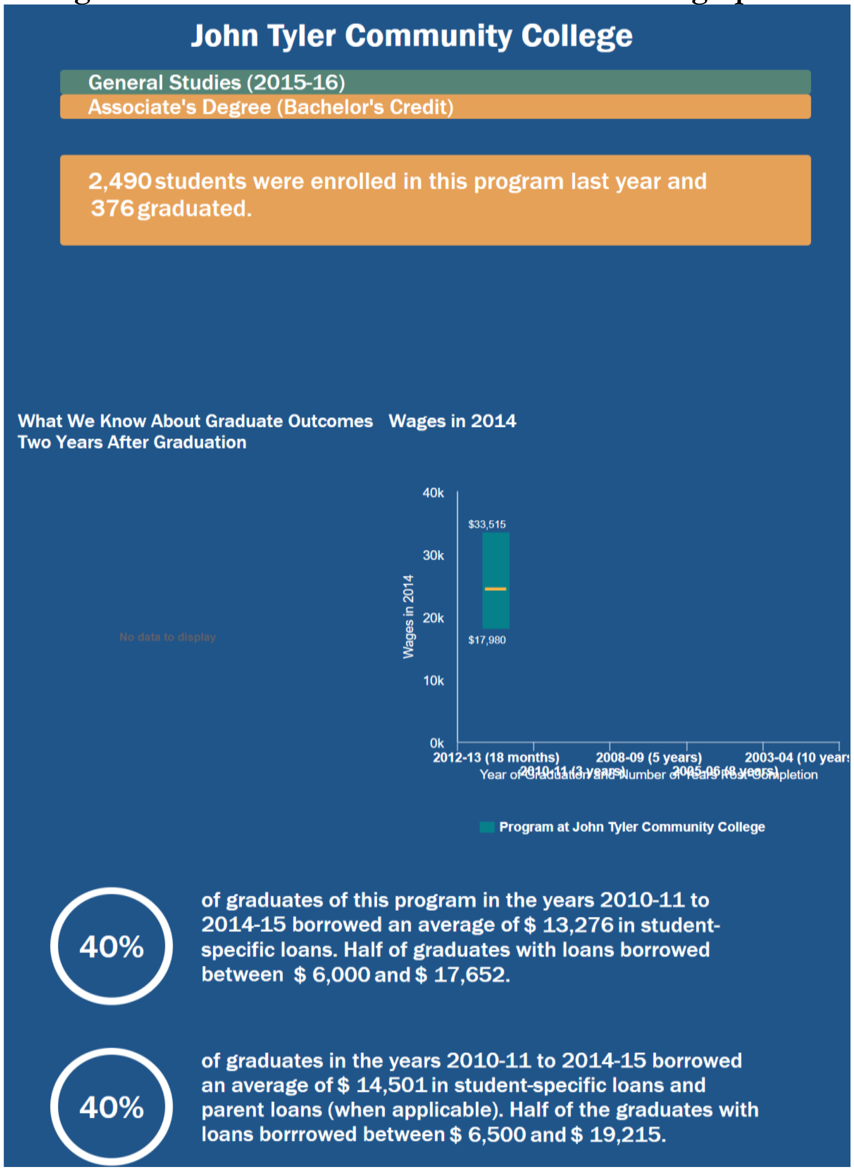
VCCS will take no direct action to increase the transparency of student outcomes. Any institution-specific initiatives already in place (such as efforts from individual college admissions offices) or federally mandated policies (such as expansions to the Gainful Employment regulations) would continue as-is. However, I am not currently aware of any such initiative that would meaningfully impact outcomes transparency and student outcomes. For this reason, this alternative can be thought of as having zero impact relative to the other alternatives, and will serve as the baseline comparison rather than an alternative of its own. For example, if an alternative is said to have an adjusted total net benefit to students and VCCS of $1,000,000, that is relative to the baseline of holding the status quo.

b. *Online Data* - Integrate Extant Program-Level Outcomes Data into VCCS Web Presence

VCCS will recommend that its member institutions incorporate the detailed program-level student outcomes data from SCHEV into each individual college webpage, in an accessible graphical style similar to the College Scorecard. In practical terms, this could be the replication of data visualizations like those seen in Figure 1 from the College Scorecard, but specific to each program offered at each college within VCCS. Because this is program-specific information, this data would likely be housed on the program-specific pages of each college website, alongside program descriptions, course requirements, and so on.

SCHEV is already moving towards more public-facing infographics for this kind of information, as seen in Figure 4, but this alternative would make such information more immediately accessible to students via their home institution webpages, whether they are familiar with SCHEV or not.

**Figure 4. SCHEV Labor Market Outcomes Infographics**




Source: State Council of Higher Education for Virginia, 2019

<u>c. *Outcomes Explorer* - Develop an Online "Outcomes Explorer" Platform for Students</u>

VCCS will create its own, proprietary "outcomes explorer" platform. In broad brushstrokes, this online platform will allow students to examine the extant outcomes data for VCCS students at the program-level, like *Online Data*, but in a personalizable format. Similar to online platforms that allow people to get a rough estimate of their income tax liability by inputting a sparse set of personal information, the platform will allow students to input a sparse set of academic and demographic information (covariates like age, high school GPA, race and ethnicity, gender, expected program of study, expected college attended, and so on). The platform will then calculate a set of outcome metrics (probability of graduating within 150% of anticipated time, average earnings of graduates two years after graduation, employment rates two years after graduation, etc.) using a subset of historical student data that aligns with the inputted values. This will give students a personalized set of outcomes data that, while not necessarily predicting what their actual outcomes will be upon enrollment, are more relevant to students and more representative of students like them.

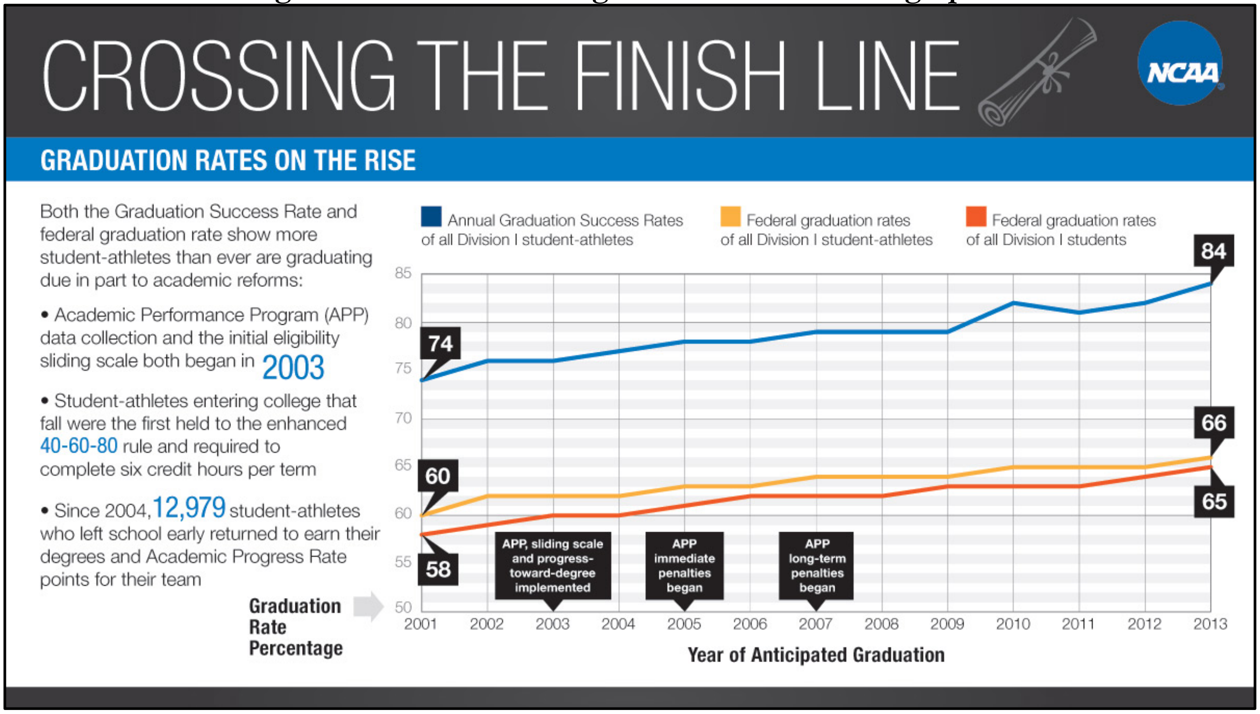
This platform would be hosted on the main VCCS webpage, and VCCS would offer advisement to its member institutions to prominently host the platform on their individual websites as well. Because this platform would span programs, it would be hosted on each individual website more centrally than the information provided via *Online Data*.

d. *Advising Data* - Integrate Extant Program-Level Outcomes Data into Advising Efforts

VCCS will recommend the publication of detailed program-level student outcomes data from SCHEV into all physical college advising materials used by individual member institutions. The intention here is to append student outcomes information to already existing materials as a light-weight intervention. To minimize costs, VCCS will not recommend costly staff trainings, though VCCS will develop a simple explanation of the data for advisors to reference. VCCS will also provide a data analyst to field questions from advisors about the outcomes data.

Because the outcomes data is not intended to be obtrusive or strongly integrated into new advising practices, advisors would use these updated materials in largely the same way as any pre-existing materials up to this point. In other words, it would most likely be incumbent upon the student to ask their advisors about the information from the materials, rather than the other way around. Each member institution will be expected to create a unified set of visual "infographics" similar to the kind produced by the NCAA in Figure 5, but each member institution will ultimately have discretion with regards to how they are integrated into individual advising systems and pre-existing materials.

**Figure 5. NCAA "Crossing the Finish Line" Infographic**




Source: National Collegiate Athletic Association, 2014

e. *Advising Expansion* - Expand College and Career Advising for Newly Enrolled Students

VCCS will lobby the General Assembly for additional funding to bolster the advising services already in place at VCCS. Specifically, this funding will be used to increase the number of academic advising staff available at each college, facilitating more face-to-face and one-on-one interaction with newly enrolled students. The ultimate goal of this alternative is to provide intensive advising meetings with as many students as possible each year.

In these sessions, academic advisors will be equipped with a comprehensive set of relevant outcomes data for a wide variety of students (requiring data analysis similar to what would be produced for the *Outcomes Explorer*). In meeting with students, the academic advisors will be able to solicit student information and provide personalized, one-on-one feedback on their likely outcomes, their intended courses of study at VCCS, their likely career trajectories afterwards, and so on. These advisors would need to be trained in the implementation of these detailed outcomes data, and would likely require significant changes to the advising systems currently in place at each institution.

## VII. Policy Comparisons and Analysis

Before I compare the alternatives along the evaluative criteria, it is useful to outline the primary theory of action underpinning this analysis.

Let's assume for simplicity that VCCS implements an alternative at the end of a given academic year, such that incoming students have access to any newly available outcomes information for the entirety of the summer preceding their entry. Given the limitations of my data and the assumptions that I make, we are focusing on students new to VCCS who are: (a) enrolling in college for the first time, (b) pursuing an associate's degree, (c) are not concurrently dual-enrolled at a high school. For the 2016-2017 academic year, 25,389 of these students entered VCCS for their first semester of study.

These students all have pre-existing preferences and opinions towards the majors available at their local VCCS institution; these preferences might be driven by the news, family members, friends, their own personal tastes, personal experiences, and so on. However, these preferences are at least partially driven by how much students think graduates of each major earn. As the work of Baker et al. (2017) shows, many of these students will inaccurately estimate the earnings of each major available to them, and so many of these students will ultimately select their major - at least in part - based on these inaccurate estimates.

After implementing an alternative, some fraction of these students will be exposed to the new outcomes information. A smaller fraction of these students will notice the information and understand it, updating their preferences for each major available to them accordingly. Finally, an even smaller fraction of these students will actually change their declared major as a result of this new information - perhaps because they value the higher-than-anticipated post-graduation earnings of another major, or perhaps because they are troubled by the lower-than-anticipated post-graduation earnings of their previously intended major.

Either way, as these students arrive at VCCS in the fall (or spring, for some students), the overall distribution of students across majors at each college is now slightly different than it would have been without giving students access to this outcomes information. Because college major is strongly correlated with student outcomes at VCCS - in terms of persistence, graduation, and labor market outcomes - we would expect that this change in the distribution of students across majors will also result in some change in the overall welfare of students. We would also expect this change in welfare - be it positive or negative - to occur for any students enrolling in subsequent cohorts as well, so long as the same outcomes information is made available.[11]

With this framework in mind, comparing each alternative along the evaluative criteria is in service of the broader question about how these alternatives change the welfare of students and VCCS as a whole. Below, I provide a high-level summary of how each alternative scores for each criteria, but detailed methodological explanations are again available in **Appendices a-d**.

[11] It may also be the case that *currently enrolled* students at VCCS choose to change their major as a result of this new outcomes information. However, I am not able to model the potential change in welfare for students who have already accumulated some level of credits for one major prior to switching. In the VCCS data, there is a generally negative correlation between switching major after accumulating credits and ten-year earnings, but the sample size of post-enrollment switchers for each college-by-program combination is too small to incorporate into my full analysis.

a. Comparing Influence

Table 1 below shows how each alternative scores for each subcomponent of the Influence metric, in addition to how many students will actually be influenced to change their major.

**Table 1. Influence Scores by Alternative**

| Alternative | Number of Students | Overall Reach Score | Overall Salience Score | Overall Actionability Score | Students Influenced Per Year |
|---|---|---|---|---|---|
| *Online Data* | 25,389 | 0.94 | 0.43 | 0.038 | 385 |
| *Outcomes Explorer* | 25,389 | 0.99 | 0.71 | 0.038 | 671 |
| *Advising Data* | 25,389 | 0.93 | 0.43 | 0.056 | 570 |
| *Advising Expansion* | 25,389 | 0.98 | 0.71 | 0.075 | 1334 |

Source: Author's calculations.

In general, I find that all alternatives score fairly well on Reach. This is because students regularly access their college websites for crucial resources like program requirements, course registration interfaces, and coursework assignments. Further, many colleges require new students to meet with advisors, and even if colleges do not explicitly require it, nearly all make it readily available and highly suggested for students. The *Outcomes Explorer* alternative scores slightly better than *Online Data* because the information would be hosted more centrally, rather than in the less-trafficked program-specific webpages. Similarly, the *Advising Expansion* alternative scores slightly better than *Advising Data* because colleges would be able to hire more advisors, making mandatory advising sessions more feasible for more colleges, and reducing scheduling frictions and other barriers to students accessing advising.

The *Outcomes Explorer* and *Advising Expansion* alternatives score uniformly higher on Salience for slightly different reasons. First, both score highly because of their more personalized nature. However, students are likely to notice the information provided by the *Outcomes Explorer* because it is interactive, which the marketing literature shows improves recall of information by viewers (Calder, Malthouse, & Schaedel, 2009; Sundar & Kim, 2005). However, students are less likely to actually *understand* the information, which is where the *Advising Expansion* shines; students would not only get personalized information, but they would have immediate access to a resource that could help them better understand it.

This is also why the *Advising Data* and *Advising Expansion* alternatives score better on Actionability; students would essentially be able to change their major on-the-spot if they so choose, or at least get more information from advisors about what the major change process entails. *Advising Expansion* scores even more highly because the personalized nature of the data and the ability of the advisor to further contextualize it for the student would reduce many barriers to students actually acting on the information.

Ultimately, the *Advising Expansion* alternative influences almost **twice as many students** to change major as the next closest alternative, *Outcomes Explorer*. *Online Data* trails in a far last place.

b. Comparing Net Benefit to Students

Table 2 displays the final calculation steps involved in estimating the total net benefit to students for each alternative. First, we see that the net benefit to students of changing to a higher-earnings major is uniformly very positive. This is after factoring in missed earnings due to enrollment, higher tuition costs, higher debt taken on, and even potentially lower graduation rates. This is driven mostly by how large some of the earnings differentials are across majors at the same college; in some cases, students could earn *three times as much* over ten years in one major versus another.

Because students are provided with aggregated graduate outcomes information in *Online Data* and *Advising Data*, they have a slightly lower net benefit to students than the *Outcomes Explorer* and *Advising Expansion* alternatives, which provide disaggregated, subgroup-specific graduate outcomes information. The intuition here is that the disaggregated data allow students to select majors that have more positive outcomes for *their particular subgroup,* rather than just positive outcomes generally. However, this difference is actually relatively small in magnitude at about $2,000 per student influenced, per cohort.

**Table 2. Net Benefit to Students by Alternative**

| Alternative | Students Influenced Per Year | Net Benefit of Influencing One Random Student Per Cohort | Total Net Benefit to Students Over 10 Years |
|---|---|---|---|
| *Online Data* | 385 | $123,626.50 | $47,620,643.96 |
| *Outcomes Explorer* | 671 | $125,419.40 | $84,203,225.71 |
| *Advising Data* | 570 | $123,626.50 | $70,427,036.77 |
| *Advising Expansion* | 1334 | $125,419.40 | $167,261,222.99 |

Source: Author's calculations.

The far larger driver of differences between alternatives in terms of net benefit to students is actually the Influence metric. While *Outcomes Explorer* and *Advising Expansion* have the same net benefit per student, per cohort, *Advising Expansion* influences twice as many students to change major, and thus produces roughly **twice as much total net benefit to students** over ten years. Again, *Online Data* trails by quite a bit as a function of its low Influence.

c. Comparing Equity

Table 3 displays the final calculations involved in creating the Equity score for each alternative. Column 1 sums up the total number of characteristics of each alternative that would likely support underserved students, while Column 2 sums up the total number of characteristics of each alternative that would likely pose barriers to underserved students. *Online Data, Outcomes Explorer*, and *Advising Data* likely posed barriers to students because the data would be conveyed to students in a way that they could easily misinterpret without proper context and support, perhaps even discouraging them from pursuing their studies. *Advising Expansion* was the only alternative that would allow students to contextualize the data with the support of an expert, preventing misinterpretation and ensuring that students could more completely access and understand the information regardless of their background.

**Table 3. Equity Scores by Alternative**

| Alternative | Supports for Underserved Students | Barriers to Underserved Students | Equity Modifier |
|---|---|---|---|
| *Online Data* | 0 | 3 | **0.7** |
| *Outcomes Explorer* | 3 | 4 | **0.9** |
| *Advising Data* | 1 | 3 | **0.8** |
| *Advising Expansion* | 5 | 1 | **1.4** |

Source: Author's calculations.

*Outcomes Explorer* and *Advising Expansion* were more likely to be supportive of students, again because of their more personalized nature. This personalized information results in a higher net benefit to students of underserved demographics than in the *Online Data* and *Advising Data* alternatives, as calculated in the Net Benefit to Students criterion. Further, the detailed data analysis could also facilitate additional equity-oriented interventions on behalf of VCCS in the future. Lastly, *Advising Expansion* gets an additional point of support because it is the only alternative that will likely have additional positive externalities in the college experiences of underserved students, perhaps improving their persistence and graduation rates (Bettinger & Baker, 2014; Crisp, Baker, Griffin, Lunsford, & Pifer, 2017).

For these reasons, *Advising Expansion* has a far higher Equity modifier than all other alternatives, while the pros and cons of *Outcomes Explorer* nearly balance each other out.

d. Comparing Feasibility

While *Advising Expansion* has had much more positive performance on the criteria up to this point, the Feasibility criterion reveals that this does not come without tradeoffs. Table 4 displays the total cost to VCCS over ten years for each alternative, in addition to the Feasibility modifier, and the final adjusted cost to VCCS.

**Table 4. Feasibility Scores by Alternative**

| Alternative | Cost to VCCS Over 10 Years | Feasibility Modifier | Adjusted Cost to VCCS Over 10 Years |
|---|---|---|---|
| *Online Data* | $251,167.72 | 1.01 | $252,492.46 |
| *Outcomes Explorer* | $976,801.45 | 1.01 | $988,132.86 |
| *Advising Data* | $97,947.76 | 1.00 | $97,947.76 |
| *Advising Expansion* | $24,923,174.75 | 1.15 | $28,636,914.42 |

Source: Author's calculations.

We see here that *Advising Expansion* is orders of magnitude more costly than the other alternatives: it is **250 times more expensive** than the *Advising Data* alternative, **100 times more expensive** than the *Online Data* alternative, and **25 times more expensive** than the *Outcomes Explorer* alternative. This significantly higher cost would also make it much more difficult and time-consuming for VCCS to convince the General Assembly to approve a budget increase; VCCS may need to expend substantial political capital in the process. The high Feasibility modifier of the *Advising Expansion* reflects this, further increasing its adjusted cost relative to each other alternative.

## VIII. Recommendation

Despite the substantially higher adjusted cost of ***Advising Expansion***, I recommend that VCCS enact it as soon as practicable. The benefits that it offers to students - both in the context of influencing students to change their major, and in the context of providing valuable ongoing support to students throughout their college enrollment - more than counterbalances its high costs and potential issues of feasibility.

Table 5 compiles all of the evaluative criteria together into a single outcome matrix, and I calculate each alternative's final score in the last column (adjusted net benefit to students, minus adjusted cost to VCCS). Other alternatives have exceptionally high *ratios* of adjusted net benefit to students versus adjusted costs to VCCS; for example, *Advising Data* has a benefit-cost ratio of 575:1 ($56,243,545.43 : $97,947.76). In other words, for every adjusted dollar that VCCS spends on implementing *Advising Data*, students experience an adjusted net benefit of $575. Though it is less efficient *by comparison*, *Advising Expansion* is still efficient in *absolute terms* with a benefit-cost ratio of 8:1. Further, it produces the single largest overall net benefit to students and VCCS combined. To illustrate, it produces more than **2.5 times more net benefit** to students and VCCS than the next closest alternative, *Outcomes Explorer*.

**Table 5. Alternative-Criteria Matrix and Final Scores**

| | Influence | Net Benefit to Students | | Equity | | Feasibility | | | Final Score |
|---|---|---|---|---|---|---|---|---|---|
| Alternative | Students Influenced Per Year | Net Benefit of Influencing One Random Student Per Cohort | Total Net Benefit to Students Over 10 Years | Equity Modifier | Adjusted Net Benefit to Students Over 10 Years | Cost to VCCS Over 10 Years | Feasibility Modifier | Adjusted Cost to VCCS Over 10 Years | Total Adjusted Net Benefit to Students and VCCS |
| *Online Data* | 385 | $123,626.50 | $47,620,643.96 | 0.7 | $33,334,450.77 | $251,167.72 | 1.01 | $252,492.46 | **$33,081,958.31** |
| *Outcomes Explorer* | 671 | $125,419.40 | $84,203,225.71 | 0.9 | $75,782,903.14 | $976,801.45 | 1.01 | $988,132.86 | **$74,794,770.28** |
| *Advising Data* | 570 | $123,626.50 | $70,427,036.77 | 0.8 | $56,341,629.41 | $97,947.76 | 1.00 | $97,947.76 | **$56,243,545.43** |
| *Advising Expansion* | 1334 | $125,419.40 | $167,261,222.99 | 1.4 | $234,165,712.19 | $24,923,174.75 | 1.15 | $28,636,914.42 | **$205,528,797.77** |

Source: Author's calculations.

Beyond looking at the final score, it performs exceptionally well across each criterion except for Feasibility. It influences twice as many students per cohort to ultimately change their major versus any other alternative. Even if the goal were only to *provide* students with information, irrespective of changing student outcomes, *Advising Expansion* is still tied for first in terms of Reach and Salience. Further, it disseminates the more personalized outcomes information, improving the Net Benefit to Students overall *and* providing slightly higher net benefit to each subgroup of students considered. And just as importantly, it is the most likely of all the alternatives to equitably benefit underserved demographics; my analysis actually suggests that the other alternatives may further exacerbate gaps between majority and minority student outcomes.

## IX. Implementation

The large projected benefits of the *Advising Expansion* are contingent on successful implementation of the expansion across colleges; VCCS will need to take many steps to ensure that the additional advising resources are allocated efficiently and in alignment with the stated goals of the alternative. Below, I articulate some of the primary considerations VCCS should prepare for to ensure a high fidelity of implementation.

First, VCCS should conduct a comprehensive and thorough inventory of the advising systems across its network. In this assessment, they should pay particular attention to the capabilities of each advising system to *meet individually with students* and offer comprehensive, personalized guidance to students on their college and career aspirations. My survey of advising systems (explained in more detail in **Appendix a**) reveals that many colleges do not require new students to meet with an advisor, and even colleges that do require advising may focus more on logistics (e.g. walking students through class registration systems) than selecting an appropriate course of study. For this reason, the inventory that VCCS conducts should involve meetings and interviews with the advising staff of each college whenever possible to assess their specific needs and goals. By conducting this inventory and meeting directly with advising staff, VCCS will be able to more precisely allocate additional advising resources and expand access to high quality advising for the greatest number of students. VCCS will also be more capable of responding to the unique context of each institution in the expansion rollout, increasing the buy-in of key staff and administrators.

Importantly, the benefits of this alternative are driven not just by providing students access to individualized advising, but by providing students access to individualized advising with highly personalized and data-driven *outcomes information*. For this reason, the robustness of the data analysis VCCS conducts to produce this outcomes information is critical; for example, publishing inaccurate earnings estimates could influence students to switch into majors where they actually earn less than they would otherwise - ultimately creating a net *detriment* to students. Once the outcomes data are calculated, VCCS will also need to construct a comprehensive orientation to navigating the data for all advising staff. We see that significantly fewer students would benefit in the *Advising Data* alternative, and this is primarily driven by the fact that students are far more likely to understand and act on the data when they have an expert available to help them *interpret* the data. Thus, successful implementation of this alternative relies on advisors who are fluent in what the data means, the limitations of the data, and how the data might apply to individual student circumstances.

Lastly, VCCS should strive to create a detailed data collection system that tracks the implementation and utilization of advising expansion resources. Individual colleges should note how any additional resources are being spent, alongside justification for why those resources are the most prudent use of funds. Further, staff should do their best to track how outcomes information is utilized in actual meetings with students, as well as the volume and demographics of students being served. This is an expensive policy alternative, and it behooves VCCS to ensure that the money being spent is actually benefiting students - *all* students - in a measurable way.

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## XI. Appendices

a. Influence Analysis Methodology

Because my ultimate goal with the Influence analysis is to arrive at an estimate for the number of students whose enrollment behavior is likely to change as a result of implementing an alternative, I first calculate the overall possible sample for this estimate: the total number of first-time, first-degree, associate's degree-seeking students enrolling in VCCS from year to year. This number is **25,389** students per enrollment cohort. I restrict my consideration to these students because the outcomes and enrollment behavior of "stopped-out," multi-degree, and certificate-seeking students are markedly different, but there are too few of these students in my sample to meaningfully adjust my analysis to account for these differences. Further, the outcomes information being provided is most likely to be salient to students before they have actually invested in a chosen major, either in terms of credits, dollars, or time.

Out of these 25,389 students, I then calculate how many of these students are likely to encounter the information provided by each of the alternatives to assess **degree of reach**.

- **Website Reach**: I do not have access to current website utilization information at each college. Instead, I assess the ease of use and utility of each individual college's website as a whole, as well as their program-specific webpages, through an array of characteristics intuitively associated with increased student website use. I do this to proxy for how likely a newly-enrolling student is to encounter the new outcomes information in their regular use of their college's website. The characteristics I assess, as well as their presence on each individual college's website, can be viewed in Table A1 below.
    - These likelihoods are generally high, as all students at all colleges are *required* to interact with their institution websites for initial applications, course registration, course materials, class announcements, etc. Further, all the websites are fairly robust and useable with only few exceptions. Assuming individual institutions made even a minor attempt to publicize new outcomes information, almost all students would likely see it.
    - These likelihoods are ultimately subjective judgments on my part given the characteristics examined. I use a simple average of the characteristics examined to generate the final likelihood, as there is not sufficient theoretical foundation to draw upon for any more complicated a model here.
    - For the *Outcomes Explorer* alternative, where the outcomes information will likely be stored centrally on a college's webpage, I generate this likelihood as a function only of the overall website's utility.
    - For the *Online Data* alternative, where the outcomes information will likely be stored in program-specific webpages on each college's website, I generate this likelihood as a function of the website's overall utility, as well as the utility of program-specific webpages. The reach of the *Online Data* alternative is generally smaller than the reach of the *Outcomes Explorer* alternative, partially reflecting the fact that accessing program-specific webpages requires additional navigation on every single member institution's website, and thus would be featured less centrally.

**Table A1. Website Characteristics and Website Reach by VCCS College**

| | Relevant to *Online Data* and *Outcomes Explorer* | | | | | Relevant to *Online Data* Only | | | |
|---|---|---|---|---|---|---|---|---|---|
| College Name | Would students be **required** to regularly interact with the website for application, enrollment, etc.? | Is the website **easy to navigate**, use, and read? | Does the website feature content students would **choose to access frequently**? (e.g. news, activities, etc.) | Does the website contain **up-to-date** information? | Can several non-essential **tasks be completed** by students via the website? | Are **program-specific pages** easily **accessible** and **useful**? | Do **program-specific pages** contain information students are likely to **reference frequently**? | Percent of students reached by *Online Data* | Percent of students reached by *Outcomes Explorer* |
| Blue Ridge | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1.00 | 1.00 |
| Central Virginia | 1 | 1 | 0 | 1 | 0 | 1 | 0 | 0.57 | 0.60 |
| Dabney S. Lancaster | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 0.86 | 1.00 |
| Danville | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1.00 | 1.00 |
| Eastern Shore | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 0.71 | 1.00 |
| Germanna | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1.00 | 1.00 |
| J. Sargeant Reynolds | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1.00 | 1.00 |
| John Tyler | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1.00 | 1.00 |
| Lord Fairfax | 1 | 1 | 1 | 1 | 1 | 0 | 1 | 0.86 | 1.00 |
| Mountain Empire | 1 | 1 | 1 | 1 | 1 | 0 | 1 | 0.86 | 1.00 |
| New River | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1.00 | 1.00 |
| Northern Virginia | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1.00 | 1.00 |
| Patrick Henry | 1 | 1 | 0 | 1 | 0 | 0 | 0 | 0.43 | 0.60 |
| Paul D. Camp | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 0.86 | 1.00 |
| Piedmont Virginia | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1.00 | 1.00 |
| Rappahannock | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 0.86 | 1.00 |
| Southside Virginia | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1.00 | 1.00 |
| Southwest Virginia | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 0.86 | 1.00 |
| Thomas Nelson | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1.00 | 1.00 |
| Tidewater | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 0.86 | 1.00 |
| Virginia Highlands | 1 | 1 | 1 | 1 | 1 | 0 | 1 | 0.86 | 1.00 |
| Virginia Western | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1.00 | 1.00 |
| Wytheville | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 0.86 | 1.00 |

Source: Individual VCCS websites, author's calculations

- **Advising Reach**: I do not have access to current advising utilization information at each college. Instead, I assess the ease of access and prevalence of each individual college's advising program through an array of characteristics likely to be associated with student advising use. I do this to proxy for how likely a given student is to encounter the new outcomes information in their regular use of student advising. The characteristics I assess, as well as their presence in each individual college's advising program, can be viewed in Table A2 below.

- These likelihoods are generally lower than website reach, as a minority of schools *require* new students to go through student advising, and students would then need to go out of their way to decide that they need advising, set up an appointment, and actually attend advising sessions.
- These likelihoods are ultimately subjective judgments on my part given the characteristics examined. For those colleges where advising is mandatory for new students, I set the likelihood of both the *Advising Data* and *Advising Expansion* alternatives equal to 1. For all other colleges, I use a simple average of the characteristics examined to generate the final likelihood, as there is not sufficient theoretical foundation to draw upon for any more complicated a model here.
- For the *Advising Data* alternative, where the outcomes information will be delivered via extant advising resources and systems, I generate this likelihood based on the observed characteristics of extant advising resources.
- For the *Advising Expansion* alternative, where advising resources would be greatly expanded, I generate this likelihood as a simple 33% increase from the reach of the *Advising Data* alternative. This is to bluntly reflect the expansion of advising access to students as part of the alternative, without making additional assumptions about exactly how that expansion of funding would be utilized by individual colleges.[12] Because the reach of *Advising Data* is already quite high, my final recommendation is not sensitive to increasing or decreasing the size of this 33% adjustment.

[12] I arrive at this 33% figure using a plug-in from my cost to VCCS methodology in **Appendix d**. For the *Advising Expansion* alternative, I propose that VCCS increases academic advising staff such that the student-to-advisor ratio is reduced from 200:1 to 150:1. This is then a 33% increase in advising staff, which can also be thought of as a 33% increase in advising time per student.

**Table A2. Advising Characteristics and Advising Reach by VCCS College**

| College Name | Is student advising **offered**? | Is student advising prominently **recommended** to new students? | Is student advising **required**? | Is student advising conducted by **dedicated staff**? | Is scheduling an advising appointment **easy and accessible**? | Are additional student **mentors** (e.g. older students, tutors, faculty, etc.) available? | Are there advising services **specifically for underserved or minority** populations of students? | Is **career-specific** advising available? | Is the **student-to-advisor ratio** below 100? | Percent of Students Reached by *Advising Data* | Percent of Students Reached by *Advising Expansion* |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Blue Ridge | 1 | 1 | 0 | 1 | 1 | 0 | 1 | 1 | 0 | 0.67 | 0.89 |
| Central Virginia | 1 | 1 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 0.89 | 1.00 |
| Dabney S. Lancaster | 1 | 0 | 0 | 1 | 0 | 0 | 1 | 1 | 1 | 0.56 | 0.74 |
| Danville | 1 | 1 | 0 | 1 | 1 | 0 | 1 | 1 | 1 | 0.78 | 1.00 |
| Eastern Shore | 1 | 1 | 1 | 0 | 0 | 1 | 1 | 1 | 0 | 1.00 | 1.00 |
| Germanna | 1 | 0 | 0 | 1 | 1 | 0 | 1 | 1 | 0 | 0.56 | 0.74 |
| J. Sargeant Reynolds | 1 | 1 | 1 | 0 | 0 | 1 | 1 | 1 | 0 | 1.00 | 1.00 |
| John Tyler | 1 | 1 | 0 | 1 | 1 | 1 | 1 | 1 | 0 | 0.78 | 1.00 |
| Lord Fairfax | 1 | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 0.78 | 1.00 |
| Mountain Empire | 1 | 0 | 0 | 1 | 0 | 1 | 1 | 1 | 1 | 0.67 | 0.89 |
| New River | 1 | 1 | 0 | 1 | 1 | 1 | 1 | 1 | 0 | 0.78 | 1.00 |
| Northern Virginia | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 1.00 | 1.00 |
| Patrick Henry | 1 | 1 | 1 | 1 | 0 | 1 | 1 | 1 | 1 | 1.00 | 1.00 |
| Paul D. Camp | 1 | 1 | 1 | 1 | 0 | 1 | 1 | 1 | 1 | 1.00 | 1.00 |
| Piedmont Virginia | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1.00 | 1.00 |
| Rappahannock | 1 | 1 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 0.89 | 1.00 |
| Southside Virginia | 1 | 1 | 0 | 1 | 0 | 1 | 1 | 1 | 1 | 0.78 | 1.00 |
| Southwest Virginia | 1 | 1 | 1 | 1 | 0 | 1 | 1 | 1 | 1 | 1.00 | 1.00 |
| Thomas Nelson | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 1.00 | 1.00 |
| Tidewater | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 1.00 | 1.00 |
| Virginia Highlands | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1.00 | 1.00 |
| Virginia Western | 1 | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 0 | 0.67 | 0.89 |
| Wytheville | 1 | 1 | 1 | 1 | 0 | 0 | 1 | 1 | 1 | 1.00 | 1.00 |

Source: Individual VCCS websites, author's calculations

- **Final Reach Scores**: By multiplying the number of students at each individual college with its reach statistic for each alternative, I can arrive at an aggregated number of students reached by each alternative. These calculations are displayed in Table A3, and summarized below.
    - Reach of *Online Data*: 94% (or 23,968 students out of 25,389 total)

- Reach of *Outcomes Explorer*: 99% (or 25,065 students out of 25,389 total)
- Reach of *Advising Data*: 93% (or 23,631 students out of 25,389 total)
- Reach of *Advising Expansion*: 98% (or 24,894 students out of 25,389 total)

**Table A3. Reach Calculations by College and Alternative**

| College Name | Number of First-Time Students | Percent of students reached by *Online Data* | Students reached by *Online Data* | Percent of students reached by *Outcomes Explorer* | Students reached by *Outcomes Explorer* | Percent of Students Reached by *Advising Data* | Students reached by *Advising Data* | Percent of Students Reached by *Advising Expansion* | Students reached by *Advising Expansion* |
|---|---|---|---|---|---|---|---|---|---|
| **Total** | **25389** | **0.94** | **23968** | **0.99** | **25065** | **0.93** | **23631** | **0.98** | **24894** |
| Blue Ridge | 620 | 1.00 | 620 | 1.00 | 620 | 0.67 | 413 | 0.89 | 550 |
| Central Virginia | 521 | 0.57 | 298 | 0.60 | 313 | 0.89 | 463 | 1.00 | 521 |
| Dabney S. Lancaster | 107 | 0.86 | 92 | 1.00 | 107 | 0.56 | 59 | 0.74 | 79 |
| Danville | 194 | 1.00 | 194 | 1.00 | 194 | 0.78 | 151 | 1.00 | 194 |
| Eastern Shore | 69 | 0.71 | 49 | 1.00 | 69 | 1.00 | 69 | 1.00 | 69 |
| Germanna | 1095 | 1.00 | 1095 | 1.00 | 1095 | 0.56 | 608 | 0.74 | 809 |
| J. Sargeant Reynolds | 1501 | 1.00 | 1501 | 1.00 | 1501 | 1.00 | 1501 | 1.00 | 1501 |
| John Tyler | 1180 | 1.00 | 1180 | 1.00 | 1180 | 0.78 | 918 | 1.00 | 1180 |
| Lord Fairfax | 832 | 0.86 | 713 | 1.00 | 832 | 0.78 | 647 | 1.00 | 832 |
| Mountain Empire | 173 | 0.86 | 148 | 1.00 | 173 | 0.67 | 115 | 0.89 | 153 |
| New River | 335 | 1.00 | 335 | 1.00 | 335 | 0.78 | 261 | 1.00 | 335 |
| Northern Virginia | 9475 | 1.00 | 9475 | 1.00 | 9475 | 1.00 | 9475 | 1.00 | 9475 |
| Patrick Henry | 290 | 0.43 | 124 | 0.60 | 174 | 1.00 | 290 | 1.00 | 290 |
| Paul D. Camp | 129 | 0.86 | 111 | 1.00 | 129 | 1.00 | 129 | 1.00 | 129 |
| Piedmont Virginia | 502 | 1.00 | 502 | 1.00 | 502 | 1.00 | 502 | 1.00 | 502 |
| Rappahannock | 236 | 0.86 | 202 | 1.00 | 236 | 0.89 | 210 | 1.00 | 236 |
| Southside Virginia | 192 | 1.00 | 192 | 1.00 | 192 | 0.78 | 149 | 1.00 | 192 |
| Southwest Virginia | 212 | 0.86 | 182 | 1.00 | 212 | 1.00 | 212 | 1.00 | 212 |
| Thomas Nelson | 1524 | 1.00 | 1524 | 1.00 | 1524 | 1.00 | 1524 | 1.00 | 1524 |
| Tidewater | 5070 | 0.86 | 4346 | 1.00 | 5070 | 1.00 | 5070 | 1.00 | 5070 |
| Virginia Highlands | 165 | 0.86 | 141 | 1.00 | 165 | 1.00 | 165 | 1.00 | 165 |
| Virginia Western | 804 | 1.00 | 804 | 1.00 | 804 | 0.67 | 536 | 0.89 | 713 |
| Wytheville | 163 | 0.86 | 140 | 1.00 | 163 | 1.00 | 163 | 1.00 | 163 |

Source: Author's calculations.

Following the calculation of reach, I assess the **degree of salience** for each alternative. That is, of the students who are *exposed* to the information, what percentage will actually notice it and understand it?

We can look to the business and advertising literature for evidence on which modes of providing information may be most effective. The advertising literature considers print and online as two separate, but complementary, modes of disseminating information. In general, the two are found to be equally effective when it comes to informational advertisements; individuals exposed to print ads recalled details from the ad at similar rates to individuals exposed to online versions of the ad (Wakolbinger, Denk, & Oberecker, 2009). Further, both forms of advertising benefit when the context of the ad is congruent with the ad (e.g. a travel ad in a travel blog or travel magazine) (Pelsmacker, Geuens, & Anckaert, 2002) or perceived as a useful resource to the consumer (e.g. a newspaper that the consumer enjoys reading) (Calder, Malthouse, & Schaedel, 2009).

However, most studies that directly compare the two modes utilize the same ads and ad layouts across media types, rather than leveraging the unique capabilities of online advertisements (e.g. animation, interactivity, etc.) (Ha, 2008). Researchers have found that the interactivity of an online ad can contribute to greater levels of effectiveness. For example, individuals who were actively engaging with a website felt that the advertisements within it were more useful and more memorable than otherwise (Calder, Malthouse, & Schaedel, 2009), and that interactivity with an ad itself made them more receptive to the message/branding of the ad presented by nearly 50% - especially when the interactive ad was already animated (Sundar & Kim, 2005).

Studies from behavioral and informational interventions can also tell us a bit more about the extent to which a student's understanding of the information is mediated by the way the information is delivered. The work of Hoxby & Turner (2014) and Page & Scott-Clayton (2016) suggest that providing students with *relevant*, *personalized* information can alter student college application behavior, so long as that information is carefully crafted and concise. In other words, students need to feel relatively certain that the information actually applies to them, otherwise they might easily dismiss it or assume it is not relevant to their circumstance.

I summarize these considerations into a set of characteristics that I can assess for each alternative, similar to my reach methodology. After determining whether each alternative fulfills each characteristic, I take a simple average of how many characteristics that alternative fulfills to arrive at its salience score - again, because there is not a sufficient research base to inform any more complex a formula. The results of this examination, and the corresponding salience scores, can be seen in Table A4 below.

**Table A4. Salience Calculations by Alternative**

| Alternative | Is the information provided **digestible and easy to understand?** | Is the context of the information **congruent** with the information provided? | Is the context of the information likely perceived as **useful** by the audience? | Is the informed provided **personalized and relevant?** | If online, does the **website context facilitate interaction?** | If online, would the **information itself be presented in an interactive format?** | Would students be able to quickly and easily access **support in understanding** the information provided? | **Overall Salience Score** |
|---|---|---|---|---|---|---|---|---|
| *Online Data* | 1 | 1 | 1 | 0 | 0 | 0 | 0 | **0.43** |
| *Outcomes Explorer* | 0 | 1 | 1 | 1 | 1 | 1 | 0 | **0.71** |
| *Advising Data* | 1 | 1 | 1 | 0 | 0 | 0 | 0 | **0.43** |
| *Advising Expansion* | 1 | 1 | 1 | 1 | 0 | 0 | 1 | **0.71** |

Source: Author's calculations.

As the last step in my influence score, I calculate the **degree of actionability**, or the likelihood that a student who has seen and understood the information acts on it to change their major.

I start my calculation of this figure using the research of Baker et al. (2017). In their experimental study, they find that a student's major enrollment decision is influenced by a variety of factors: a student's perceptions of the wages of program graduates, a student's beliefs about how much they would enjoy that major, and a student's prior disposition towards that major. Their results also indicate that the influence of wages on student major enrollment decisions was dependent on how *trustworthy* the students perceived the wage information they were provided. That is, the more trustworthy the information seemed, the more students were willing to weigh wage information.

While we know from their main findings that a 1% increase in perceived wages results in a 1.4% increased probability of students majoring in a given program, we do not necessarily know how much students weigh wage *relative to other factors* influencing the decision. Thus, we cannot say for certain from their main findings what proportion of students would be willing to change their major based solely on new wage information alone. Our best estimate for this value can still be derived from their analysis, though: they find that wage perceptions alone explain between 6% and 9% of the overall variation in students' major enrollment preferences (derived from the $R^2$ value) depending on the program of study being considered (p. 32). The rest of the variation is comprised of the aforementioned factors, plus several unobservable factors that the authors were not able to identify. We can *very roughly* interpret these results as a plug-in for what percent of student enrollment decisions might be sensitive to wage information. While this is not the most robust estimate, we do not presently have a better way of defining a base-level actionability percentage using extant literature. I split the difference between 6% and 9%, given that I am considering all programs of study together, and set the base actionability score of all alternatives to 7.5%.

To further adjust this actionability score by alternative, I assess each alternative on a vector of characteristics derived from the behavioral and informational intervention literature. As mentioned earlier, Hoxby & Turner (2014) and Scott-Clayton (2013) suggest that simple, relevant, and personalized information results in more behavioral change than otherwise. The work of Bettinger et al. (2012) helps us nuance this further; they argue that simple, relevant, and personalizable may be *necessary* characteristics for behavioral change, but not always *sufficient*. As part of their experiment, they tested to see whether providing families with personalized information on their estimated benefits of filling out the FAFSA and the costs of attending local colleges increased FAFSA completion, college application, and college attendance - but they found null results across the board for this experimental condition. The authors discuss that this is likely because the FAFSA itself is so difficult and confusing a process; just understanding it does not help the individual overcome the logistical hurdles to actually completing it. Likewise, changing a college major can, depending on context, be a daunting task. It requires meeting with academic advisors, assessing course requirements, filling out multiple forms, and even re-taking entrance exams.

In Table A5, I display the characteristics assessed and the performance of each alternative on each characteristic. I assume that the Baker et al. (2017) results represent a sort of theoretical maximum actionability - given that students were asked about their hypothetical major preferences in an isolated, experimental context - so I measure the percentage of characteristics that an alternative meets and multiply it with the 7.5% base actionability score to arrive at the final, mediated actionability score.

**Table A5. Actionability Calculations by Alternative**

| Alternative | Would the information be **perceived as reliable and true**? | Is the information provided **digestible and easy to understand**? | Is the informed provided **personalized and relevant**? | Would students be able to quickly and easily access **support in acting on** the information provided? | Percent of Characteristics Met | Base Actionability Score | **Overall Actionability Score** |
|---|---|---|---|---|---|---|---|
| *Online Data* | 1 | 1 | 0 | 0 | 0.50 | 0.075 | **0.038** |
| *Outcomes Explorer* | 1 | 0 | 1 | 0 | 0.50 | 0.075 | **0.038** |
| *Advising Data* | 1 | 1 | 0 | 1 | 0.75 | 0.075 | **0.056** |
| *Advising Expansion* | 1 | 1 | 1 | 1 | 1.00 | 0.075 | **0.075** |

Source: Author's calculations.

My **final estimates for the influence criterion** are then calculated as the product of total number of first-time, full-time students at VCCS, multiplied by the reach score, the salience score, and the actionability score. These calculations are displayed below in Table A6 as the total number of students influenced to change their majors as a result of each alternative. We see that the *Advising Expansion* alternative produces the greatest number of students influenced; this top result is not sensitive to any singular decision I articulate above, and so neither is my final policy recommendation. I do find that the relative positions of *Outcomes Explorer* and *Advising Data* can switch depending on certain decisions, such as the inclusion of additional characteristics in either the salience or actionability assessments.

**Table A6. Influence Score by Alternative**

| Alternative | Number of Students | Overall Reach Score | Overall Salience Score | Overall Actionability Score | Students Influenced Per Year |
|---|---|---|---|---|---|
| *Online Data* | 25,389 | 0.94 | 0.43 | 0.038 | 385 |
| *Outcomes Explorer* | 25,389 | 0.99 | 0.71 | 0.038 | 671 |
| *Advising Data* | 25,389 | 0.93 | 0.43 | 0.056 | 570 |
| *Advising Expansion* | 25,389 | 0.98 | 0.71 | 0.075 | 1334 |

Source: Author's calculations.

b. Net Benefit to Students Analysis Methodology

To assess the costs and benefits associated with changing the program enrollment of students, I break the process up into several discrete steps. Using the Influence metric I calculated, I have a rough estimate of how many students will be induced to actually change their major as a result of each alternative. In order to calculate the total costs and benefits associated with switching that number of students from their present major, I need to answer the following question: What is the expected net benefit of switching a single student, essentially at random, from their current intended major to a higher earnings major, just prior to their initial enrollment? I can then multiply the Influence metric by this expected value to arrive at the expected total net benefit of a given alternative (still also accounting for future discounting and other calculation details).

To illustrate this as clearly as possible, it is useful to imagine the chain of events that is likely to occur for a *single* student. Let's imagine that the *Online Data* alternative is implemented, such that newly enrolling students to VCCS have access to the average outcomes of all graduates for each college-by-program combination:

> Hannah identifies as a black woman and is currently slated to enroll at Tidewater Community College for Accounting in the fall. However, as a result of the earnings data she is provided, she is now reconsidering her major. Like most VCCS students, she is geographically constrained and cannot consider changing colleges. Because Hannah is a student sensitive to earnings data, her likelihood of switching into each other program offered at Tidewater is a function of the earnings of that program's graduates relative to Accounting graduates, such that she is more likely to switch into majors where graduates are earning much more than Accounting graduates do.

For simplicity, let's imagine Tidewater only offers Accounting (whose average graduate earns $40,000/yr), Nursing (whose average graduate earns $60,000/yr), and Business (whose average graduate earns $50,000/yr). Hannah is then twice as likely to switch her major into Nursing versus Business, because their graduates are earning $20,000 more versus $10,000 more. In this case, she decides on Nursing, though we know that other students in her position may still have chosen Business instead due to a combination of the earnings differential *and* other idiosyncratic preferences.

When Hannah now enrolls in Nursing, we assume that she will experience the same average outcomes and earnings as *other black women* who have historically *enrolled* in Nursing at Tidewater, even though Hannah made her decision based on the outcomes of *all graduates* from Nursing at Tidewater. Black women in Nursing at Tidewater have graduated at a certain rate, changed majors at a certain rate, accumulated a certain number of credits, paid a certain amount of tuition, and so on. We can benchmark these outcomes and earnings against what would have happened for Hannah if she had remained in Accounting, and had outcomes and earnings similar to other black women who historically enrolled in *Accounting* instead.

The net benefit (or net cost) of Hannah switching from Accounting to Nursing is then the difference between the dollar sum of these outcomes together.

This example of Hannah demonstrates that the expected value of switching a single student from one major to another is a function of:

- The expected benefits and costs for a student if they enrolled in their originally intended major, *unconditional* on graduation or other outcomes
- The expected benefits and costs for a student if they enrolled in a major with higher published earnings, *unconditional* on graduation or other outcomes
- The preferences a student forms for each major available to them, based on the published earnings data of *graduates* in each college-by-program combination

Importantly, the value of switching a student from one major to another is also dependent on the policy alternative, because students are provided different information that shapes their preferences for which majors they will choose to switch into. The above example mirrors the information Hannah would receive for both the *Online Data* and *Advising Data* alternatives, where average earnings of graduates for each college-by-program combination are averaged together regardless of student demographic. But for the *Outcomes Explorer* and *Advising Expansion* alternatives, earnings data would be reported for each subgroup of students in each college-by-program combination. In those cases, Hannah would have been provided with earnings data *specific to black women* graduating in each major, rather than all graduates together. We can imagine a case where the published outcomes of black women are markedly different than overall averages: say black women earned $50,000/yr for Accounting, $40,000/yr for Nursing, and $60,000/yr for Business. In this case, Hannah actually would switch into Business, and thus we would need to compare her outcomes for Business versus Accounting, as opposed to Nursing versus Accounting. This would then result in differential net benefit/cost, and so I account for this in my calculations.

I formalize my **cost-benefit calculations** in the following multi-stage process:

1. Calculate the **historical earnings over ten years** (in inflation-adjusted 2018 dollars) of all first-time, first-degree students in each college-by-program combination available at VCCS.

a. For each college-by-program combination, I calculate this value for every student who enters VCCS with intention to major in that program - whether or not they remain in that major, and whether or not they complete their program. This means I am calculating an expected earnings of *initially majoring* in that program (rather than, say, the expected earnings of *graduating* from that program), because any earnings calculated using this sample will automatically incorporate the probability that students transfer, change majors, drop-out, take excess credits, or take longer than expected to complete.
b. Using the historical earnings of students for each college-by-program combination, I can project the total average earnings over a ten-year period from the moment of a student's initial enrollment in a program. I use a future discounting rate of 5% to translate this into a total present value of initially majoring in a program.
c. To make my estimates as fine-grain as possible, I calculate all of the above for separate subgroups of students by sex and racial/ethnic minority status.[13] For example, I calculate the expected earnings of female non-white students in Nursing at Tidewater based on the historical earnings of prior female non-white students who initially majored in Nursing at Tidewater. I run this calculation for each permutation of these subgroups (female white, male non-white, male white). This is to better account for the possibility that students of different subgroups are served differentially by programs and colleges, and thus their expected earnings would also be different should they choose that major.
d. To illustrate what these earnings trajectories look like, Figures A1 and A2 display the average earnings per quarter since enrollment (in 2018Q1 dollars) of white male Wytheville students in Health and Business programs, respectively. Note that the actual observed earnings per quarter become less stable further along the x-axis; this is because I analyze data for enrollment cohorts starting in AY 2008-2009 through 2013-2014. Thus, there are relatively fewer students we can observe at a point ten years from enrollment, and so variation increases as the number of students being averaged into each data point decreases. For this reason, I make all my calculations using average *projected* ten-year earnings, rather than actual average earnings. I model this linearly, regressing earnings on quarters since graduation; for all programs with sufficient sample sizes, these trends are clearly linear. I also find that model fit is substantially worse and less realistic (e.g. zero, negative, and illogically high earnings per quarter) when I attempt to include a quadratic term (even in cases like A2).

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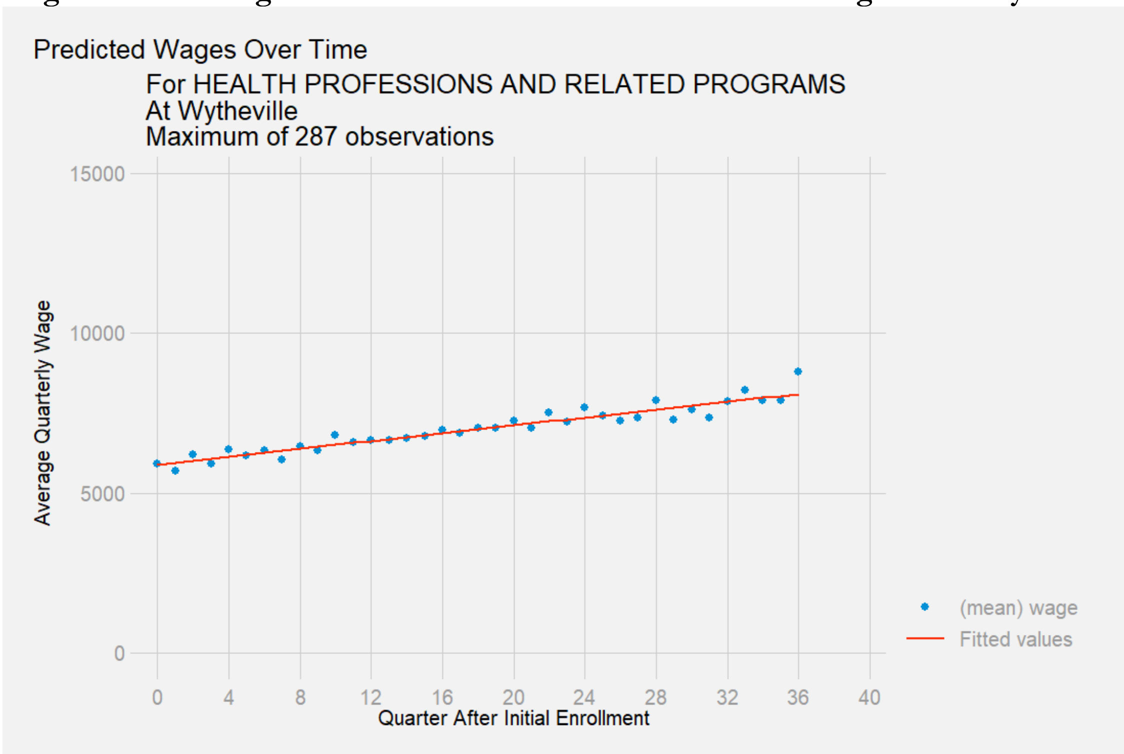
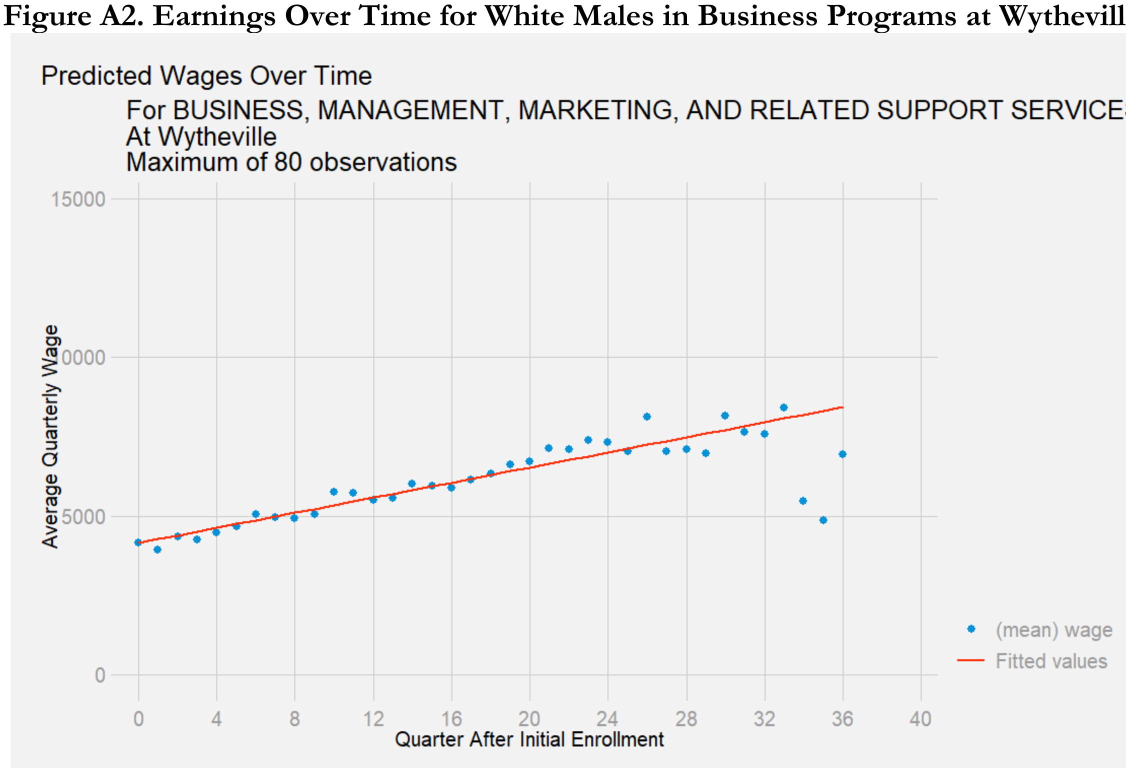
[13] I use only these two characteristics for subgroup analysis, because slicing the data by any additional characteristics increases the dimensionality of the data exponentially, reducing sample sizes of each subgroup of students at a similar rate. For example, as-is there might be only 18 students over six cohorts-years who were black, female, and majored in Nursing at Tidewater. If I were to split this further by low-income status, there will necessarily be at least one cell size of less than 10, making any earnings estimates unstable and less reliable. Thus, I use only sex and racial/ethnic minority status, as those are the two student-level covariates with highest correlation to earnings in my data.

**Figure A1. Earnings Over Time for White Males in Health Programs at Wytheville**




Source: Author's calculations, VCCS student-level data

**Figure A2. Earnings Over Time for White Males in Business Programs at Wytheville**




Source: Author's calculations, VCCS student-level data

2. Calculate the **historical tuition costs and missed earnings due to enrollment** (in inflation-adjusted 2018 dollars) for these same students, for each college-by-program combination.
    a. Using the same methodology as my earnings calculations, I do not condition on completion. This allows me to calculate the expected costs of initially majoring in a college-by-program combination, based on the average length of enrollment and average credit accumulation of students in that college-by-program combination - whether or not they graduate.
    b. To calculate missed earnings, I use the average earnings of a high-school graduate working full-time ($725/week) as calculated by the Bureau of Labor Statistics (Torpey, 2018). I adjust this value into an expected value by multiplying it with the probability of employment for high-school graduates from week-to-week (95.2%), which results in a final value of $691.65/week. I make this adjustment because we know that high-school graduates are unemployed at relatively high rates, and that should be accounted for in our expectation of how much a student could earn if not enrolled. I then multiply this wage rate with the average length of full-time enrollment for students in each college-by-program combination to create a proxy for how much students would have earned on average had they worked full-time instead of being enrolled in that college-by-program combination.
    c. To calculate tuition costs, I assume that students are in-state and use the in-state cost-per-credit value of $154.[14] I multiply this $154 by the average number of accumulated credits for each college-by-program combination to arrive at the average cost of tuition for students in each college-by-program combination.
    d. I assume that students are paying tuition at the beginning of each semester they are enrolled. This is to reduce the complexity of future discounting for students who will ultimately pay any loans they accrue outside of the study timeframe.[15]
    e. I can then project the total average tuition costs and missed earnings over a ten-year period from the moment of a student's initial enrollment in each college-by-program combination. This ten-year timeframe is especially useful in this case, as many community college students enroll, "stop-out," and re-enroll within only a handful of years. As above, I aggregate this into a total present value using a future discounting rate of 5%.
    f. Again, I calculate the above costs separately by student subgroups of sex and racial/ethnic minority status. This is to account for the fact that students of differing subgroups have vastly different rates of persistence and completion, and thus differential costs associated with each college-by-program combination.

[14] Roughly 97% of students in my employment data sample were in-state students; while I could easily use the expected cost of tuition by incorporating out-of-state tuition at a ratio of 97-3, my preferred method is to stick with an actual value when possible. Because this is such a small difference relative to all other monetary values in this cost-benefit analysis, my overall results and recommendation are not sensitive to this adjustment.

[15] Because current federal student loan interest rates are approximately 5% for both subsidized and unsubsidized undergraduate loans (Federal Student Aid, 2019), future discounting would essentially cancel out interest amounts into the lump sum present value anyway. In a sensitivity analysis, I assessed whether incorporating loan interest amounts into these semesterly lump sum tuition payments changes results in any substantive way; they do not, because these initial tuition costs are small relative to earnings over ten years.

3. Calculate a **net present value** using projected ten-year earnings (step 1) minus projected ten-year costs (step 2), for each subgroup of students within each college-by-program combination.
4. Calculate the **historical earnings of *graduates*** from each program, within each college, at VCCS. This acts as the earnings data that are released to the public, which students will then use to inform their program enrollment decisions.
    a. I use the earnings of students in the second year after graduation as the benchmark value. This allows me to maintain a reportable sample size for a larger number of programs and student subgroups; going to a longer time frame (similar to the 10-year timeframe of College Scorecard) means there are fewer students in my sample with that length of work history, while going to a shorter time frame means that there are fewer students in my sample employed due to the employment shuffle immediately after graduation.
    b. I condition on student employment, such that students who were unemployed in the second year after graduation are excluded from the average wage calculation (rather than include them and bias the estimate downwards towards zero earnings). This mirrors the methodology of SCHEV and the College Scorecard.
    c. To be as inclusive as possible, I look to see if a student was employed in the 5th, 6th, 7th, and 8th quarter after graduation. If a student was employed in at least one of those quarters, their earnings in those employed quarters are incorporated into the college-by-program average for those graduates. If a student was employed in more than one of those quarters, I average within students before averaging to the college-by-program level (such that every student, no matter how many quarters they were employed for in the second year after graduation, are weighted equally).
    d. For the *Online Data* and *Advising Data* alternatives, I calculate aggregated earnings for all students within that college-by-program combination, and I treat those aggregated values as what would be published. For the *Outcomes Explorer* and *Advising Expansion* alternatives, I calculate earnings separately by the student subgroups of sex and racial/ethnic minority status, and I treat those disaggregated values as what would be published.
5. Based on those published earnings values of graduates, **calculate how likely a student in one program will switch** to each other program offered at their college.
    a. I use the elasticity of program preference due to changes in perceived earnings found by Baker et al. (2017) because it is the best estimate we have from the community college context: approximately a 1.4% increased probability of majoring in a given program for each 1% increase in perceived earnings from that program.
    b. I take one program offered at a college and consider it a “home” program. I then find the difference in earnings of its graduates relative to graduates of each other program offered at this college. Using these differences and the elasticity from Baker et al., I can roughly calculate how likely a student in the home program is to change major to each other program. If the graduates of another program are reported to earn less than the home program, I set the probability of switching into that lower-earnings major as zero.
    c. I then calculate the *relative* probability that a student from the home program switches into each other program. To do this, I sum up the total probability of switching to any other major (which is often more than 100% because of large

differences in earnings between many majors) and set that as the denominator for each individual probability of switching into another major.

d. To illustrate, take again the example of Hannah. Her home program is Accounting, and she could go to either Nursing (whose graduates earn 50% more) or Business (whose graduates earn 25% more). She then has a raw probability of switching into Nursing of 70% (1.4 * 50) and a raw probability of switching into Business of 35% (1.4 * 25). I sum the overall probability of switching to create a denominator of 105% (70+35), and divide both 70% and 35% by 105% to arrive at the final probability of her switching into each major. Assuming Hannah *will* switch due to the earnings info, she has a 66.67% chance (70/105) of switching into Nursing, and a 33.33% chance (35/105) of switching into Business.

e. I run this same style of calculation for every program offered at every college, compared to every other program offered at the same college. This basically means that, for any given college-by-program combination, I know the probability that a student in that home program switches to any other program offered as a result of the earnings information they are provided.

f. For the *Outcomes Explorer* and *Advising Expansion* alternatives, I calculate these switching probabilities based on the *aggregated* all-student earnings that would be published for each program at each college. That is, every student (regardless of subgroup) will see the same aggregated outcomes and create identical preferences according to that information. For the *Outcomes Explorer* and *Advising Expansion* alternatives, I calculate these student preferences separately for each subgroup, because each subgroup will receive earnings information specific to their subgroup. So female non-white students would switch from one major into each other major at rates determined by the earnings they see for female non-white graduates in each major. These preferences are then separate from female white students, because female white students are provided different information by program and thus form different rates of switching from one program to each other program.

6. Based on the student major preferences calculated in step (5) and the net present value per major calculated in step (3), I calculate the ***expected net benefit* of switching** a student from each home major to each possible destination major.

   a. From step (5), I have a rough estimate for how likely a student in one major is to switch into each other major. I also know how much a student of a certain demographic is expected to benefit by staying in their home major, as well as how much a student is expected to benefit by switching into a different major, thanks to step (3). I subtract the expected benefit of the home program from the expected benefit of the destination program to arrive at a net expected benefit of switching from the home to the destination program (though, in some cases it is actually a net loss to the student, even if there is an increase in *published* earnings).[16]

   b. I can then multiply these net benefits for switching into each possible destination program by the probabilities of switching into each possible destination program. This value can be thought of as the expected net benefit of switching a student of a

[16] To illustrate, it may be the case that graduates of Nursing earn quite a bit more than graduates of Accounting. However, it may also be the case that black female students in Nursing rarely ever graduate, while black female students in Accounting almost always graduate. In such a case, even though Hannah switches into Nursing based on better *published* outcomes, her *actual* outcomes would be worse.

certain demographic out of the home program, irrespective of which destination program they actually end up in.

   c. Regardless of which set of student switching probabilities I use (those derived from the aggregated all-student earnings data as published in alternatives B and D, versus those derived from the subgroup-specific earnings data as published in alternatives C and E), I calculate this expected net benefit using the subgroup-specific 10-year earnings and costs data from step (3). This is because I assume students of each subgroup are expected to receive the same net present value as students of their subgroup on average for each major, no matter what kind of information they actually receive.

7. I use the present distribution of students enrolled at VCCS to calculate the **expected value of switching the major of a random student within VCCS** to a higher earnings major.
   a. I assume that each alternative influences students *at random* to change majors, to facilitate the use of these unweighted expected values. While I could construct a more complex weighting function by program type and college, perhaps using subcomponents of my influence metric, my preference is to make the simplest assumption possible here.
   b. Using the enrollment data from AY 2016-2017 (the most recent, complete year I have in my data), I calculate what percent of all enrolled, first-time first-degree students are students of a specific subgroup, enrolled in each program at each college. In other words, I want to know: if I were to pick a *random* student currently enrolled in a VCCS college, what is the probability that they are enrolled in a specific program, and of a specific student subgroup?
   c. I then take those probabilities and multiply them by the expected value of switching a student of a particular subgroup from a specific program to another, as calculated in step (6). This gives me the average expected value of switching a random student at VCCS, accounting for the fact that some programs are larger than others (and thus more likely to have a random student switch out of them), and for the fact that some subgroups are larger than others (and thus more likely to experience differential outcomes specific to that subgroup).
   d. I calculate this final expected value separately for the *Outcomes Explorer* and *Advising Expansion* alternatives, versus the *Outcomes Explorer* and *Advising Expansion* alternatives, given that I calculated separate probabilities for students switching majors in step (5)
8. Lastly, I calculate the **ten-year projected expected value of switching** the major of a single student per year.
   a. I assume that if an alternative is expected to induce one student in one cohort year to switch majors, it will induce one student *per cohort year* to switch majors. Because I am calculating a ten-year time horizon, that is ten cohorts of enrolled students to account for.
   b. An important wrinkle to consider is that a student induced to switch majors in the first year of an alternative's implementation will reap the expected value of ten years of earnings change. However, a student induced to switch majors in the *second* year of an alternative's implementation will only reap the expected value of *nine* years of earnings change. My future discounting also then needs to account for the fact that these earnings are one year further in the future relative to the first cohort.

c. Thus, if an alternative is expected to induce one student per cohort year to change majors, I adjust the expected benefit according to cohort year. I then arrive at a *total* expected benefit for switching one student per cohort-year, in net present value. These are the values I report in the main narrative.

d. Table A7 below displays my net benefit estimates by the type of information provided (aggregated versus subgroup-specific), separated by student subgroup and the cohort year of a given student. For example, if the *Online Data* alternative were implemented, it would provide aggregated data to students. For the sake of illustration, let's imagine that it influences only one student per cohort. If we picked a student in the first cohort at random to change their major (based on the present distribution of students, as my methodology assumes), we would expect them to experience a net benefit of $25,839.73 over the course of ten years. The next year, *another* random student would be influenced to change their major; over nine years (i.e. until the end of the ten-year time frame considered), we would expect them to experience a net benefit of $22,148.34 *separately* from the net benefit we calculated for the first student. Aggregating these benefits across all the ten cohorts influenced in the ten-year time frame, we arrive at an expected total net benefit to students of $123,626.50.

e. I also display net benefit estimates disaggregated by student subgroup. That is, if instead of selecting a random student from the present distribution of VCCS students, what if we selected a random *white male* student? Or *non-white male* student? This helps me assess whether subgroups are benefitted differentially by certain types of information, which will feed into my Equity analysis. As we see below, white male students uniformly benefit more regardless of what type of information is provided; this is a function of them generally having higher variation in their earnings trajectories, such that switching from a low-earnings major to a high-earnings major produces very large differences. However, we also see that other subgroups increase their benefit relative to white males when subgroup-specific information is provided.

**Table A7. Net Benefit to Students by Information Provided, Student Subgroup, and Student Cohort Year Relative to Policy Implementation**

| Information Provided | Student Group | Net Benefit of Influencing One Student Per Cohort | Cohort 1 | Cohort 2 | Cohort 3 | Cohort 4 | Cohort 5 | Cohort 6 | Cohort 7 | Cohort 8 | Cohort 9 | Cohort 10 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Aggregated (*Online Data* and *Advising Data*) | **Random Student** | **123626.50** | **25839.73** | **22148.34** | **18749.92** | **15624.93** | **12755.05** | **10123.05** | **7712.80** | **5509.15** | **3497.87** | **1665.65** |
| | White Male | 207308.80 | 43330.55 | 37140.47 | 31441.67 | 26201.39 | 21388.89 | 16975.31 | 12933.57 | 9238.27 | 5865.56 | 2793.13 |
| | Non-white Male | 88291.34 | 18454.17 | 15817.86 | 13390.78 | 11158.99 | 9109.38 | 7229.66 | 5508.32 | 3934.51 | 2498.10 | 1189.57 |
| | White Female | 67061.54 | 14016.83 | 12014.43 | 10170.95 | 8475.79 | 6919.01 | 5491.28 | 4183.83 | 2988.45 | 1897.43 | 903.54 |
| | Non-white Female | 129814.80 | 27133.18 | 23257.01 | 19688.47 | 16407.06 | 13393.52 | 10629.78 | 8098.88 | 5784.91 | 3672.96 | 1749.03 |
| Subgroup-Specific (*Outcomes Explorer* and *Advising Expansion*) | **Random Student** | **125419.40** | **26214.48** | **22469.55** | **19021.84** | **15851.54** | **12940.03** | **10269.87** | **7824.66** | **5589.04** | **3548.60** | **1689.81** |
| | White Male | 200032.00 | 41809.59 | 35836.79 | 30338.02 | 25281.69 | 20638.11 | 16379.45 | 12479.58 | 8913.99 | 5659.68 | 2695.08 |
| | Non-white Male | 89140.90 | 18631.74 | 15970.07 | 13519.63 | 11266.36 | 9197.03 | 7299.23 | 5561.32 | 3972.37 | 2522.14 | 1201.02 |
| | White Female | 78487.47 | 16405.02 | 14061.45 | 11903.87 | 9919.89 | 8097.87 | 6426.88 | 4896.67 | 3497.62 | 2220.71 | 1057.48 |
| | Non-white Female | 132694.20 | 27735.02 | 23772.88 | 20125.19 | 16770.99 | 13690.60 | 10865.56 | 8278.52 | 5913.23 | 3754.43 | 1787.82 |

Source: Author's calculations, VCCS student-level data

This is a complicated process, and I necessarily operate under several assumptions to arrive at my final values. In addition to the assumptions I note in the process above, I also make the following assumptions:

- That the proportion of students enrolling in each *college-by-program combination* is stable for each year in the ten-year time horizon. Put another way, I do not dynamically model changing program enrollments over time. Instead, I assume that the distribution of students across colleges and programs is exactly the same as it is in 2016-2017, for each of the following ten years.
- That the proportion of students of each *demographic group* are stable each year in the ten-year time horizon - essentially the same as the above assumption.
- That there are no students whose response to the provided outcomes information is to leave VCCS entirely, rather than potentially change majors. Put another way, I assume that overall student enrollment at VCCS is static across the ten years.
- That the marginal student who switches from one program into another is, on expectation, the same as the average student already in that program. In other words, that there are no unobservable differences related to both student outcomes and intended program of study, which would cause these newly-switched students to have systematically different outcomes.
- That all students, regardless of subgroup, respond to earnings information in the same manner. The research on "stereotype threat" suggests that minority students may be impacted by this earnings information in a more negative way, especially relative to majority students (Steele & Aronson, 1995). However, it would be difficult to incorporate these stereotype threat effects in a robust way in this net benefit analysis. Instead, I consider stereotype threat within my Equity analysis (**Appendix c**).

Additional analytic decisions and notes:

- To analyze employment and wage data (steps 1-4 above), I examine the data from enrollment cohorts between AY 2008-2009 and 2013-2014.
    - I found that the wage and earnings behavior of students enrolling in 08-09 (just on the tail-end of the Great Recession) do not seem to be meaningfully distinct from those of later cohorts, and decided to keep them as part of my analytic sample.
- To limit the complexity of this analysis (and improve our ability to find stable averages, i.e. bigger cell sizes), I collapse programs down to their high-level CIP code. This is the same methodology utilized by SCHEV, for the same reasons. So all health-related programs offered at a college are lumped together, as are all business-related programs, and so on. This is because individual college-by-program combinations often have enrollments too small to be analyzable in this fashion.
- Within a college, if a category of programs has fewer than 5 students graduating from that category per cohort year on average, I collapse them into an "Other" category specific to that college. For instance, Tidewater might have Automotive Technology in its "Other" category because only two students graduate from it per year, but at Southwest where it is more popular, it is not lumped into the "Other" category and considered on its own.
- I focus specifically on students who are first-time, first-degree at VCCS, as I did with the Influence Analysis (**Appendix a**). Of this sample of students, I exclude students who are dual-enrolled in high school concurrently. I also exclude students who are seeking any credential besides an associate's degree, as certificate programs are historically less stable and far smaller in their enrollment over time.

c. Equity Analysis Methodology

I assess Equity for each alternative by examining their measured and conceptual performance on the Influence and Net Benefit to Students criteria. That is, I consider an alternative more equitable if it *reaches* and *benefits* traditionally underserved, underrepresented, or otherwise minority populations in a way that addresses the unique barriers and disadvantages that they face. Given data and analytic constraints, my assessments will most closely examine equity as it relates to the demographics of first-generation college, racial and ethnic minority, female, and low-income students. I acknowledge that there are many other student groups that VCCS and other educational institutions should strive to serve more comprehensively, to include differently abled, gender non-conforming, immigrant, and English-language-learning students.

I evaluate Equity in a manner similar to my Influence methodology, examining a series of characteristics that reveal whether an alternative is more or less equitable. I score each alternative on a range of 0.5 - 1.5, beginning at a base level of 1. The literature makes clear that there is a difference between *not harming* underserved students in their college aspirations and experiences, and explicitly *supporting* them (Hurtado, Inkelas, Briggs, & Rhee, 1997; Page & Scott-Clayton, 2016). Thus, I create five characteristics that indicate whether an alternative may actually harm or not harm underserved students; each one will reduce an alternative's equity score by 0.1. Conversely, I create five characteristics that indicate whether an alternative may support or not support underserved students; each one will increase an alternative's equity score by 0.1. These resulting scores will then be multiplied by each alternative's Net Benefit to Students to arrive at an adjusted total net benefit to students, such that equity scores below one are penalties, and scores above one are bonuses.

I derive the assessment characteristics from the results of my influence and net benefit analyses, as well as insights from the psychology and college access literatures. For example, the literature on college advising shows that underserved students benefit in a variety of important ways from advising and mentorship. The thinking goes: formal mentor relationships with vulnerable students helps to bolster their sense of belonging, confidence, emotional health, and ability to navigate academic issues - all things help them succeed in college contexts (Bettinger & Baker, 2014; Crisp, Baker, Griffin, Lunsford, & Pifer, 2017). Similarly, literature from psychology suggests that the way a student is perceived by society, and the way a student perceives themselves, as a function of their demographics can negatively impact their academic performance in a variety of contexts (Steele & Aronson, 1995). Reminding students of these perceptions by providing them with subgroup-specific outcomes data can then detriment students in meaningful ways that we must consider. Lastly, I again reference the behavioral insights of Hoxby & Turner (2014) and Page & Scott-Clayton (2016) to establish that personalizability and relevance of information is especially important for vulnerable populations.

I form my final characteristics for assessment by contextualizing these dynamics to the alternatives presented. The final set of characteristics, and my assessment of each alternative, can be seen in Table A8 below.

**Table A8. Equity Score by Alternative**

| | Potential Supports for Underserved Students | | | | | Potential Detriments to Underserved Students | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **Alternative** | Is the information delivered through a medium with **explicit supports** for underserved students? | Does the alternative provide information that facilitates **additional equity interventions** at VCCS? | Is the information provided **personalized and relevant**? | Does the alternative otherwise **improve the overall college experiences** of underserved students? | Does the information provided create **additional net benefit** to underserved students? | Could the data released to students **deter or discourage** their conscious decision-making? | Could the data released to students **reinforce unconscious psychological barriers** for students (e.g. stereotype threat)? | Could the data released to students **reinforce negative stereotypes** in our society more broadly? | Is the information delivered through a medium that may have **barriers of accessibility** to particular subgroups? | Could the information **potentially mislead students** due to aggregating data across different subgroups? | **Equity Modifier** |
| *Online Data* | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 1 | 1 | **0.7** |
| *Outcomes Explorer* | 0 | 1 | 1 | 0 | 1 | 1 | 1 | 1 | 1 | 0 | **0.9** |
| *Advising Data* | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 1 | 1 | **0.8** |
| *Advising Expansion* | 1 | 1 | 1 | 1 | 1 | 0 | 1 | 0 | 0 | 0 | **1.4** |

Source: Author's calculations.

d. Feasibility Analysis Methodology

As the first stage of the feasibility criterion, I assess the cost of implementing each alternative to VCCS over a ten-year time-span. To simplify this analysis, I make the following assumptions:

- VCCS's current staffing allocation is inflexible, and so any additional labor necessary to implement an alternative would require increased staffing. While this assumption is unlikely to hold across all institutions and alternatives, it means that my cost estimates will reliably act as upper bounds.
- VCCS member institutions would prefer to hire full-time staff for any labor involving close contact with students or handling personally identifiable student-level data. This is to minimize the logistical and administrative costs related to background checks, data access permissions, training, employee turnover, and so on. VCCS will otherwise fill labor requirements through the hiring of part-time employees.
- Staff at each VCCS member institution, by virtue of being state employees, are paid identically regardless of which particular institution they work for. This assumption is supported through examination of employee salaries across each VCCS institution using the Virginia budgetary explorer ("Virginia State Salaries," 2019).

Other methodological notes that span across alternatives:

- I use a future discounting rate of 5%.
- I estimate the costs of any proposed staff using the following process:

a. Locate the appropriate staff position using faculty and staff directories on each VCCS member institution website (e.g. Webmaster, Academic Advisor, etc.). Find a specific employee whose position matches the position I propose to increase staffing of.
b. Use the publicly available database of Virginia state employee salaries (Hansen, 2017) to find how VCCS classifies that employee for salary purposes (e.g. Academic Advisors are uniformly classified as "education support specialists")
c. Use the publicly available budget explorer of state agencies in Virginia to find the salaries of all staff with that classification within VCCS ("Virginia State Salaries," 2019).
d. Take the average salary of positions with that classification. There is variation in how much these positions are paid due to seniority, experience, etc., and so an average seems like the most parsimonious way to find the expected cost of employing an individual for this position.
e. I assume that the ratio of salary-to-benefits for full-time employees at VCCS is 62.5-37.5. This reflects the averages from BLS in 2018 for state and local employees specifically (Bureau of Labor Statistics, 2019). I then derive the cost to VCCS of providing benefits to full-time employees using this ratio and incorporate them into my cost estimates accordingly - but only if proposed staff is to be employed full-time.
f. For any part-time labor that would need to be hired, I take the salary for the appropriate position from (d) and divide it by 2087 hours. This number mirrors the methodology used by the U.S. Office of Personnel Management for their calculation of hourly wages ("Computing Hourly Rates of Pay Using the 2,087-Hour Divisor," n.d.). I then multiply this hourly wage with a rough estimate for how many hours the labor would take.
g. While VCCS may choose to fill part-time labor requirements through contractors, extant data on payments to contractors are difficult to tie to particular positions and responsibilities. As a result, I argue that the hourly wage equivalent of full-time employees (excluding the cost of benefits) is the most robust way to estimate the cost of part-time labor.

- **Costs to VCCS for *Online Data*:**
  - Because SCHEV has already generated the statistics to be incorporated into each institution's program pages, the only costs for this alternative are the labor required to create salient graphics representing the data, and the labor required to update each program-specific webpage with the appropriate data/graphics. Because this alternative only requires using publicly available outcomes data, institutions would prefer to hire part-time staff for both roles.
  - There are 487 unique college-by-program combinations at VCCS, meaning 487 unique webpages to adjust and up to 487 graphics to create each year (an average of 21 per college).[17]

[17] To mirror my Net Benefit to Students methodology, I consider only associate's degree programs for the time being. SCHEV does not currently have strong coverage of outcomes data for other credential types, again because of less stable and generally smaller enrollment sizes.

- The average salary of graphic design staff at VCCS (classified as "Media Specialist II") is $47,537/year, which results in an hourly wage of $22.78/hr.
- I estimate that it would take a graphic designer approximately 5 hours to create the first graphic for each institution.[18] However, these graphics would be easily adjustable to accommodate any subsequent programs, such that each following graphic at an institution would only take approximately 1 hour. Because these would be created at the institution level, I multiply 5 by 23 to arrive at 115 hours for the first graphic created at each college. After the first graphic per college, there are still 464 programs remaining, resulting in another 464 hours of labor to complete the graphics for all programs. In sum, it would take approximately 579 hours of labor to complete the graphics the first year. In all subsequent years, I assume it will take only one hour per program to update the graphics with the most recent data, resulting in 487 hours of labor for each year after the first.
- Using a discount rate of 5% per year, the final cost over ten years in present value for the graphic designer is **$92,042.80.**
- The average salary of website management staff at VCCS (classified as "Information Technology Specialist II") is $84,098/year, which results in an hourly wage of $40.30/hr.
- I estimate that it will require 1 hour of labor per institution, per program, per year, to update the websites.[19] The final cost over ten years in present value for the website management staff is **$159,124.92.**
- Because these graphics will be placed on a pre-existing website, and I do not attempt to model an increase in traffic to these websites as a result of these graphics, I assume there are no additional operational costs to VCCS.
- **Total cost: $251,167.72**

- **Costs to VCCS for *Outcomes Explorer*:**
    - This alternative would require VCCS to hire its own full-time data analyst to construct the relevant outcomes metrics using its own student-level data.[20] In addition, it would require the work of a graphic designer to style the resulting outcomes explorer platform, and it would require the dedicated time of website management staff to ensure stable and intuitive integration into VCCS web services.
    - The average salary of data analysts at VCCS (classified as "Policy Planning Spec II") is $71,588.21. Incorporating the cost of benefits for full-time employees brings the overall cost to VCCS to $119,314 per year. Over ten years, this sums to a present value of **$967,376.64**
    - Because neither the graphic designer nor the website management staff need access to the individual data, they can be hired only on a part-time basis. I use the same hourly wages for these positions as in the *Online Data* cost analysis.
    - I estimate it would take a graphic designer approximately 40 hours to develop the graphical style of the outcomes explorer platform. In all years following the first, I

[18] This estimate is informed by my prior experience working as both a graphic designer (specifically, making data-driven infographics).

[19] This estimate is informed by my prior experience as a web designer.

[20] Having worked extensively with this data, I do not anticipate VCCS needing to hire more than one full-time staff to manage and maintain the outcomes explorer analysis.

estimate it would only take about 10 hours per year to update the style and accommodate any aesthetic changes. Over ten years, this sums to a present value of **$2,530.36**
    - I estimate it would take a website management staff approximately 100 hours to develop the actual platform itself. This is to include multiple tests, stakeholder meetings, and design iterations.[21] In all years following the first, I estimate it would only take 10 hours per year to maintain the code and update it as necessary for new data. Over ten years, this sums to a present value of **$6,894.45**
    - **Total cost: $976,801.45**

- **Costs to VCCS for *Advising Data*:**
    - This alternative would only require VCCS to hire the same estimated graphic designers as in the *Online Data* alternative. Because these materials are to be incorporated in the typical advising materials at each institution (which are often already organized into informational handouts for individual programs), it would not necessitate separate printing. However, a data analyst would still be required to write up an accompanying explanation of the materials (most likely disseminated electronically) and field potential questions from advisors on an on-going basis. I assume that the amount of advising that students request on a regular basis will not change.
    - Cost of the graphic designers: **$92,042.80**
    - Because the data analyst would only be working with publicly available data through SCHEV, VCCS would hire them only part-time. The average salary for data analysts at VCCS, as above, is $71,588.21. This equates to $34.30/hr without benefits.
    - Writing up the explanatory memo each year would take approximately 10 hours (to account for general interpretation of the data and trends each year), and I estimate that the analyst would need to field questions from advisors for approximately 20 hours per year immediately after the rollout of new materials. Over ten years, this would cost **$5,904.97** in present value.
    - **Total cost: $97,947.76**

- **Costs to VCCS for *Advising Expansion*:**
    - This alternative would require VCCS to hire the same data analyst as in the *Outcomes Explorer* alternative, as well as the graphic designers for the *Advising Data* alternative. In addition, VCCS would need to fund more full-time advising positions at each college to increase their capacity to have one-on-one student advising.
    - Cost of the data analyst: **$967,376.64**
    - Cost of the graphic designers: **$92,042.80**
    - The average salary of an academic advisor at VCCS is $40,953.44. Adjusting this figure for benefits paid increases the cost per advisor, per year, to $68,255.73. In terms of hourly pay (still including benefits), this translates to $32.71/hr.
    - It is difficult to get an accurate, comprehensive count of the number of dedicated advisors currently employed at each VCCS institution (to exclude faculty members acting as departmental advisors). To arrive at a rough estimate, I searched through

[21] This estimate is informed by my prior experience developing interactive, online data visualization platforms.

each institution's faculty and staff directories for positions related to academic advising (sometimes referred to as "academic counselors" and "student success counselors"). This produces a count of 127 full-time advisors, though I suspect this is an underestimate.

- There is not a clear correlation between student-to-advisor ratio and whether an institution mandates advising meetings with students (as surfaced in my Reach calculations). Further, I do not have a clear way to estimate what level of staffing would allow each institution to mandate one-on-one advising for all incoming students.
- Across all VCCS institutions, the student-to-advisor ratio is 200:1. As a rough estimate, I find that it would take an additional 43 advisors, dispersed across all institutions, to reduce this ratio down to 150:1.[22] Over ten years, this would cost VCCS **$23,796,427.35** in present value.
- Lastly, all new and existing academic advisors would need to be trained in the use of the outcomes data for student advising. I estimate this would require about 5 hours of dedicated training time per staff member in the first year. For all following years, I estimate it would require an additional hour per staff member to update them on any new trends or data points. With a new total of 170 advisors, this amounts to **$67,327.96** in present value over ten years.
- **Total cost: $24,923,174.75**

VCCS is a publicly funded institution, and I assume that the current allocation of funding throughout VCCS is fixed and inflexible. For this reason, any additional funding that an alternative requires will need to be requested through the General Assembly. In concept, I attempt to create a **feasibility modifier** as a function of how difficult it might be to successfully request the funds required for an alternative. I give alternatives with lower likelihood of successful funding a score of greater than 1; I give alternatives with a very high likelihood of successful funding a score as low as 1. I then multiply that feasibility score with the estimated costs to VCCS, to arrive at a *penalized* cost score. Intuitively, high-cost alternatives would require more political lobbying and argumentation while navigating the budget proposal process, and the overall *conceptual* cost to VCCS (in dollars, political capital, energy, etc.) ends up being actually much higher than the raw dollar costs I estimated above. This feasibility score modifier is my attempt to quantify that additional conceptual cost on top of the estimated dollar cost.

Budgetary decisions in Virginia are generally made on an agency-by-agency basis (The National Association of State Budget Officers, 2015). Further, Virginia utilizes an "incremental" budget system, which implies that an agency must justify any proposed changes to the previous year's budget request. In other words, the likelihood that a new line item request by VCCS is ultimately approved is determined by *how well* it is justified.

To operationalize this concept, I use the following formula:

$$feasibility\ modifier = 1 + \frac{cost\ to\ VCCS}{benefit\ to\ students}$$

[22] As a sensitivity check, I assess whether my recommendation would be different if I attempted to reduce the student-to-advisor ratio down to 100:1. Even though this represents an additional 127 advisors and a ten-year cost of $70,282,471.47, it still does not change my recommendation.

In this formula, the higher the ratio of costs to benefits, the higher the penalty multiplier becomes. Conversely, the lower the ratio of costs to benefits, the lower the penalty multiplier becomes. For example, an alternative with a 1:1 cost-to-benefit ratio would have a penalty multiplier of 2, which reflects that it would be quite difficult to justify a budget increase that just barely pays for itself, and that getting such a budget passed would require substantial effort on behalf of VCCS *beyond* just the dollar costs. An alternative with a 1:100 cost-to-benefit ratio would have a penalty multiplier of 1.01, which reflects that it would probably be easy to justify to outside audiences in the budgeting process, and require relatively little extra work by VCCS to get the budget approved. With this formula, there are also diminishing returns to better cost-benefit ratios - a phenomenon we would imagine exists in actual budgetary processes as well.[23] Note that I use the *unmodified* total net benefit to students in this calculation, without incorporating the Equity score.

The costs to VCCS, net benefits to students, feasibility scores, and modified costs to VCCS can be seen to Table A9 below.

**Table A9. Feasibility Score by Alternative**

| Alternative | Cost to VCCS Over 10 Years | Total Net Benefit to Students Over 10 Years | Feasibility Modifier | Adjusted Cost to VCCS Over 10 Years |
|---|---|---|---|---|
| *Online Data* | $251,167.72 | $47,620,643.96 | 1.01 | $252,492.46 |
| *Outcomes Explorer* | $976,801.45 | $84,203,225.71 | 1.01 | $988,132.86 |
| *Advising Data* | $97,947.76 | $70,427,036.77 | 1.00 | $97,947.76 |
| *Advising Expansion* | $24,923,174.75 | $167,261,222.99 | 1.15 | $28,636,914.42 |

Source: Author's calculations.

I intended to incorporate several miscellaneous feasibility concerns as part of this criterion, but I was not convinced that there were any substantial enough to include. For example, I considered whether hiring the proposed staff for each alternative would present an issue. The *Online Data*, *Outcomes Explorer*, and *Advising Data* alternatives required only 2-3 new staff being hired per institution - many of them part time, and none of them with particularly rare qualifications. Even the *Advising Expansion* alternative only calls for an average of 2 more advising positions per college, in addition to the graphic designers and a centralized data analyst. I also intended to weigh poor Equity scores against an alternative's feasibility as well. However, there are no alternatives that are conceptually so detrimental to underserved students that they would be made less feasible, especially given that the less equitable alternatives are also far less expensive. Lastly, *every* alternative involves

[23] To illustrate, a cost-to-benefit ratio of 1:100 is probably just as easy to justify to the General Assembly as a cost-to-benefit ratio of 1:1000. Both arguments are just as convincing in many contexts.

VCCS leveraging strong authority over member institutions to improve the transparency of student outcomes. While *Advising Expansion* exercises this authority far more than the other options, it does so while providing each college with significantly more resources - something that will likely mitigate pushback.

e. Limitations

I believe my calculations are generally robust, and I have conducted a number of sensitivity analyses throughout to validate my work (as noted in the various methodology sections). However, while I feel my results may be internally consistent, I make a large number of critical assumptions that may limit the actual applicability of these results. In the interest of transparency, I articulate these limitations to the best of my ability below.

- I do not consider broader state-wide economic implications of this analysis. For example, it may be the case that altering the overall distribution of student majors actually causes a "mismatch" between graduating student skills and the job positions that firms in the state are looking to fill (e.g. too many of one skill set and not enough of another). In such a case, student outcomes would differ substantially from the historical data I base my analysis on. This level of economic modeling is outside the scope of this analysis, despite its importance to VCCS. Further, note that relatively few students are estimated to actually change their major even in the *Advising Expansion* alternative; 1334 students is about 5% of all first-time, first-degree students enrolling from year-to-year. It seems unlikely that this scale of major switching would cause the problems noted here.
- I make the strong assumption that the earnings history of *past* students in a given college-by-program combination are representative of *incoming* students. In other words, that the correlations we see between student outcomes and major are causal and generally time-invariant. For this assumption to hold, that there can be no unobservable student characteristics associated with both student major selection and student outcomes later on. This is unlikely to be the case, but lacking better evidence for the causal effects of student major at this granular a level (within-college, in Virginia, etc.), it is the best I can do.
- My frame of consideration for costs and benefits is limited to only enrolling students of VCCS and VCCS itself. This excludes firms in Virginia, firms outside Virginia, the state government of Virginia, and even currently enrolled students. While these other stakeholders are important, incorporating them would have introduced many additional layers of complexity and uncertainty that would compromise the robustness of my results.
- I do not consider whether overall student enrollment could change as a result of providing students with outcomes information. Especially in the college choice market, it could be that these outcomes information actually deters students from enrolling in VCCS versus other institutions, or from enrolling in any post-secondary education at all.
- These alternatives have the potential to influence students at different stages of the enrollment process. *Online Data* and *Outcomes Explorer* are more likely to reach students prior to them declaring any major, or in the application process. *Advising Data* and *Advising Expansion* are more likely to reach students after they have formally declared a major, and they would need to go through the paperwork to switch. However, I am not able to model how this differential time of exposure to the information would change outcomes.
- I must assume that students are influenced at random. It is much more likely the case that there are systematic trends in how students are influenced for each alternative. For example,

(race, college, etc. etc.). However, these myriad differences in likelihood of switching would make this analysis exponentially more complex and rely on a large number of plug-in values.

- I only model the influence of student *earnings* information, rather than a larger vector of student labor market outcomes like employment rates, graduation rates, and so on. This is because there are fewer robust estimates of the impact of these data on student major decisions, and because earnings tends to be the most pervasive statistic available across college contexts.