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The Role of Social Media Networking Communities in Transfer Student Success

A dissertation submitted in partial satisfaction of the

requirements for the degree Doctor of Philosophy

in Education

by

Leesa M. Beck

Committee in charge:

Professor Karen Nylund-Gibson, Co-Chair

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September 2016

The dissertation of Leesa M. Beck is approved.

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Beck, L., & Cook, S. (2015, March). Keeping the momentum going: Finding opportunities
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ABSTRACT

The Role of Social Media Networking Communities in Transfer Student Success

by

Leesa M. Beck

For decades researchers have observed the relationship between college students' social integration, and college persistence and other student success outcomes (Cabrera, Castaneda, Nora, & Hengstler, 1992; Tinto, 1993). With social media having become such an important component of college students' social lives, many new possibilities to engage students through these media have emerged in recent years. Studies show both that colleges are increasingly utilizing these tools (NACAC, 2009), and that students who use them demonstrate higher levels of engagement (Valenzuela, Park, & Kee, 2009), which could ultimately lead to improved student success outcomes. Transfer students are a particularly vulnerable population, having consistently been shown to struggle more with social integration than their peers who enter institutions as freshmen (Bauer & Bauer, 1994; Rhine, Milligan, & Nelson, 2000; Laanan, 2007). They, therefore, might stand to benefit from the engagement opportunities offered by social media, which can be utilized before students ever set foot on campus, thereby easing the initial transition, and positioning students for both short- and long-term success. However, little information exists on the relationship

between students' participation in social media and student success. This study examines that relationship for transfer students admitted to a major public research university. Two sets of analyses look at whether students who participate in the university's social media community are more likely to matriculate, and whether they exhibit better student success outcomes. The first set of analyses provide some evidence that social media networking significantly influences the matriculation decisions of students who choose to participate, β = .323, p < .001. While the second set of analyses reveal no significant differences for student success outcomes, both graduation rates and GPAs are slightly higher within the treatment group than the control group, a promising result that may indicate further study is warranted.

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The Challenges Associated with Attracting and Retaining Students

How to attract and retain the best possible student body is a dilemma with which most colleges struggle. In addition to seeking academic excellence, the current social and political climate dictates that institutions must also create a class that is both demographically and geographically diverse, a goal this is complicated in many states by laws that prohibit affirmative action in college admissions.

According to recent reports from the National Association for College Admission Counseling (NACAC) and the National Student Clearinghouse Research Center (NSC), colleges are receiving record numbers of applications, but actual college enrollment in the United States is on the decline. Though over 70% of colleges reported increases in their numbers of applications during ten of the past 15 years (NACAC, 2015), the recent decrease in actual enrollments for U.S. colleges can be seen in Figure 1. This seeming paradox is likely driven by several factors. The proliferation of online applications has greatly streamlined the college admission process, making it quicker and easier for students to submit applications than in past decades, and decreasing the barriers to applying to multiple institutions. This phenomenon is exacerbated by the fact that many university systems allow students to apply to multiple campuses by submitting a single application. A similar trend can be seen due to the increase in schools using the Common Application, which first went online in the late 1990s, and now serves over 500 institutions (Common Application, 2015). This rise in applications has naturally meant a decline in the percentage of applicants admitted at many institutions even in cases where the actual enrollment numbers remain

steady, creating a perception of increased selectivity by institutions, which, ironically, encourages students to apply to yet more schools (Hoover, 2010). Rising college costs (see Figure 1) also likely contribute to the phenomenon, since many students are unsure about where they might get the most competitive financial aid package, and apply to multiple schools in an effort to find the most affordable option.
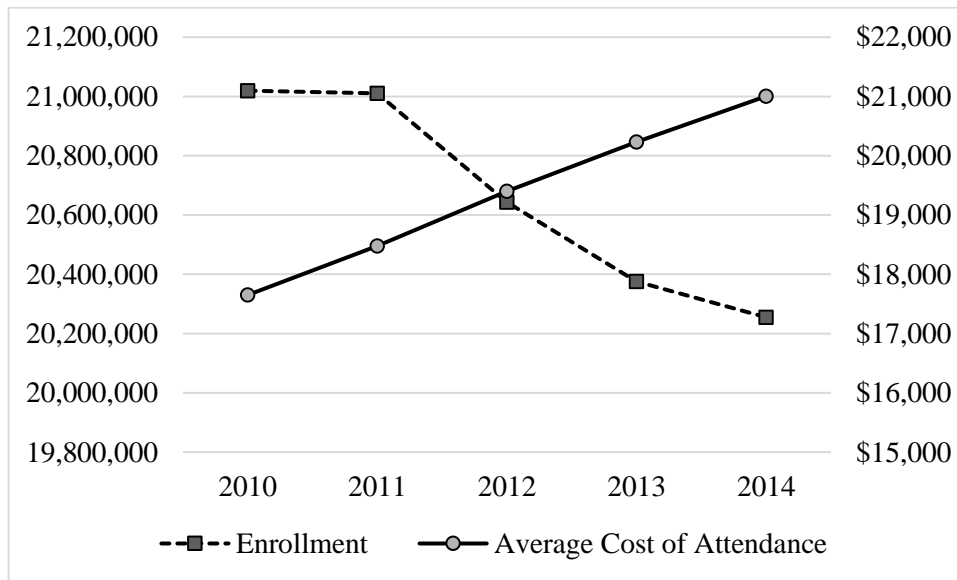
Figure 1. Total enrollment versus undergraduate cost-of-attendance at degree-granting postsecondary institutions in the U.S. Created using data from the 2013 Digest of Educational Statistics, Table 303.

Despite the increase in number of applications submitted, the decrease in actual enrollments can be attributed to a variety of factors. Rising cost-of-attendance is almost certainly an influence. Another cause may be a shrinking pool of high school graduates (U.S. Department of Education, 2014), which yields fewer college-eligible adults. Some higher education professionals have also postulated that the trend may be related to improvements in the economy, since many individuals who may have gone back to school

when unable to find work are now re-entering the workforce. This theory is largely borne out by the fact that the sharpest enrollment declines have been seen in students over the age of 24 (NSC, 2013).

These changes to the college recruitment landscape have made the jobs of Admissions directors very difficult, as traditional formulas for predicting yield may no longer prove accurate (NACAC, 2015). This means that it is no longer sufficient to bring in large numbers of applications. Admissions offices now face increasing pressure to ensure that as many acceptances as possible materialize into students filling seats in classrooms. Unfortunately, state budget cutbacks have hit public institutions hard, and many private schools saw sharp declines in their endowments and in donations during the recession. Data compiled by the Center on Budget and Policy Priorities shows that, after accounting for inflation, 47 states spent less per student in the 2014/2015 academic year than in the 2007/2008 academic year (Mitchell & Leachman, 2015). As a result, recruitment dollars may not be abundant and must be spent wisely.

This, combined with the fact that Generation Z students (the oldest of whom are currently in college) are digital natives who have grown up using the internet, makes social media marketing an attractive option, as it tends to be relatively inexpensive and can quickly reach a broad audience. That said, messages conveyed through social media can easily become diluted or distorted. A 2010 study by communications firm Burson-Marsteller that looked at 158 messages delivered by 16 different companies found a 48% gap between the intended messages communicated by companies, and the resulting messages conveyed through the media. The gap was even larger when messages were conveyed through social

media (Clary, Gioia, Cartwright, & Cheong, 2010). According to a 2009 study by NACAC, "Survey data indicate that most college admission offices consider social media outlets (i.e. blogging, podcasting, social networking, message boards, etc.) to be important tools for student recruitment, and consequently, are rapidly adopting these tools" (p. 1). Despite this belief on the part of college recruiters, little data exists to prove its efficacy in reaching prospective students or improving yield rates.

Social Media as a Recruitment and Retention Tool

Though reports of its effectiveness are largely anecdotal, it is little wonder that the possibilities of social media capture the imaginations of college recruiters and administrators. Social media allows for a much more meaningful and interactive recruitment experience than many of the more traditional channels. Rather than simply filling students' mailboxes with pages of colorful and expensive marketing materials that they may never look at, and hoping for the best, social media offers the opportunity to invite prospective students into a dialog, to get them thinking about and asking questions about the school. Then whether they engage and their level of engagement can be monitored.

It also offers a great deal of flexibility. There are countless ways to use social media in recruitment – targeted ads, webinars, targeted communities, activities such as web scavenger hunts, surveys, hashtags, etc. And in many of these cases the students themselves become part of the promotional process, a source of information that other students might perceive as less biased and more reliable than the school itself (though relying on this has its own drawbacks, as the Burson-Marsteller study highlights). A 2009 study of college students in Texas found students' use of social media to be positively associated with

4

attitudes of social trust and levels of civic engagement (Valenzuela, Park, & Kee), and

college recruiters are increasingly trying to tap into this seemingly trustworthy resource for

generating interest in their schools (NACAC, 2009).

Moreover, for decades researchers have observed the relationship between student

engagement and integration, and college persistence (Cabrera, Castaneda, Nora, &

Hengstler, 1992). Tinto's longitudinal model of institutional departure (1993), shown in

Figure 2, emphasizes the importance of peer group interactions in contributing to students'

social integration, and ultimately their decisions to persist. Social media offers a meaningful

opportunity for colleges to extend these interactions, on a large scale, to prospective

students, encouraging them to create relationships early, promote a sense of belonging, and

develop loyalty to the school and their peers who attend or plan to attend. This could have

implications not only for students' initial choice of college, but also for their level of long-

term engagement with the campus, and ultimately their success in terms of persistence and

graduation.
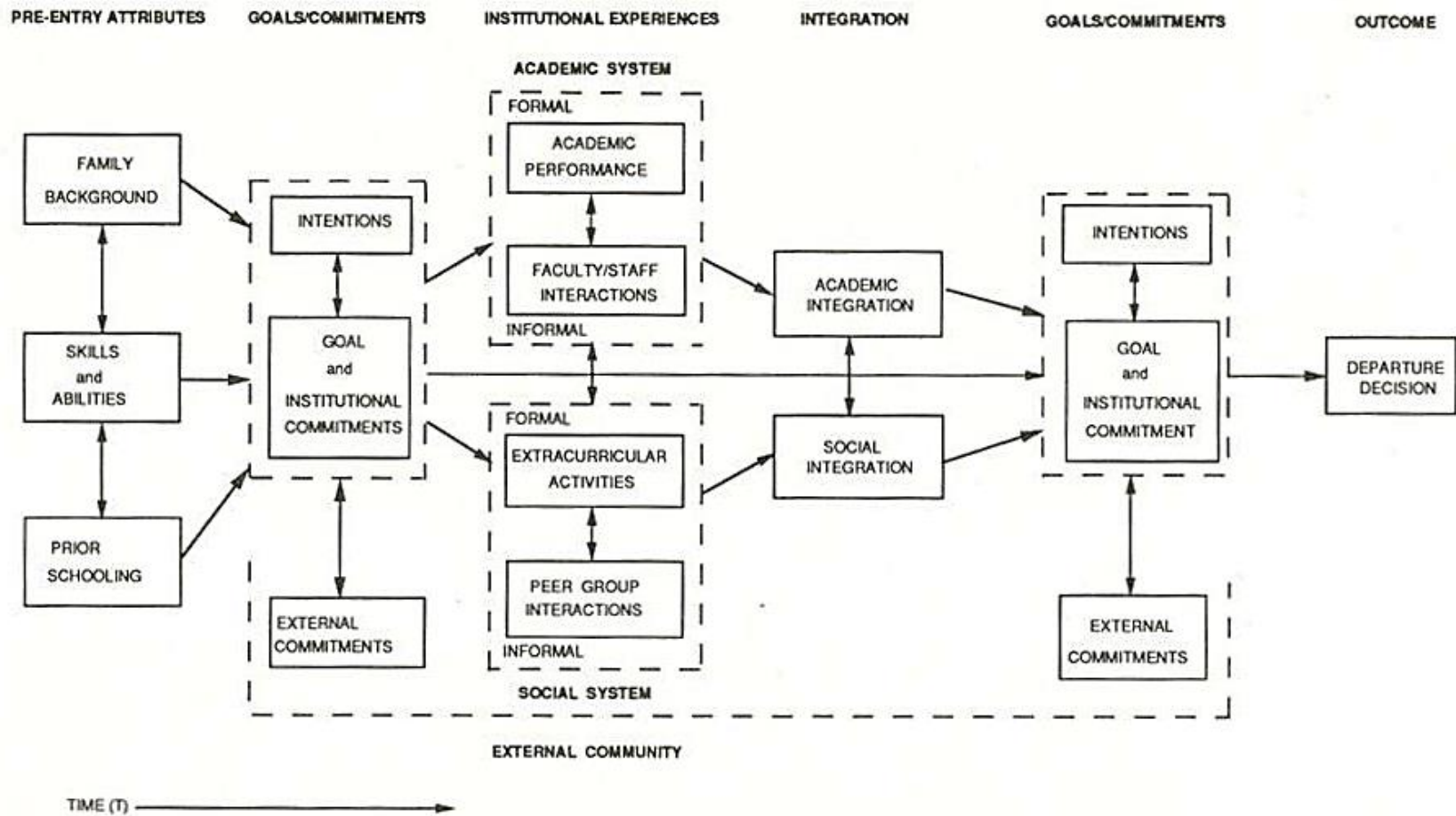
Figure 2. Tinto's longitudinal model of institutional departure (1993). Reprinted with permission.

Transfer Student Adjustment

These possibilities are perhaps even more exciting when considered in terms of transfer students. Transfer students have long been shown to have a particularly difficult time adjusting to life on a new campus as they suffer from "transfer shock" from which they may have difficulty recovering, impacting not only the outcomes tracked and reported by the university, such as grade-point-average (GPA), retention, and graduation, but also less easily measured outcomes such as level of involvement and social satisfaction (Laanan, 2007, p. 38). By engaging them prior to the point of matriculation, schools may be able not only to encourage their decision to attend, thus improving yield rates, but also ease their initial transition and ultimately improve their long-term outcomes. This also opens up the possibility of engaging students through this medium over the duration of their college careers, thereby enabling an ongoing dialog between the institution and the students being served.

Given the myriad challenges faced by transfer students, this population makes a particularly compelling subject in terms of early research into the efficacy of social media as a tool for both college recruitment and retention. This section will examine these challenges in more detail by reviewing the available literature, as well as consider some possibilities for how they might be mitigated through the use of social media and other online resources.

Transfer Student Heterogeneity

Transfer students can be a difficult population to define. According to Leonard Goldfine of the University of Minnesota, "Given their disparate backgrounds, transfer students are more easily defined by what they are not (not direct from high school, not first-

time enrollees, not indoctrinated to [campus] culture and norms by the orientation experience available to traditional first-time full-time freshmen) than what they are" (2009). However, this eclectic group makes up a growing portion of the overall college-going population. According to the National Student Clearinghouse, 37.2% of all U.S. undergraduates who began college in 2008 transferred institutions at least once (Shapiro, Dundar, Wakhungu, Yuan, & Harrell, 2015). Further, while studies have historically focused on students who transfer from community colleges to four-year institutions, data now shows that nearly 20% of students who begin at four-year institutions will transfer laterally to another four-year institution, and over 15% will actually "reverse" transfer back to a two-year college (Goldrick-Rab & Pfeffer, 2009). It seems safe to assume that these numbers will grow as barriers to attendance and transfer decrease.

The shift to online applications and shared (common) applications has dramatically simplified the college application process leading to record numbers of applications, both freshman and transfer, at colleges nationwide, and an explosion in the average number of colleges to which students apply (NACAC, 2015). This streamlined application process has likely resulted in a sense of empowerment for students, giving them the impression that, if they feel dissatisfied with their choice of college, applying to another college is easy. In addition, since they are applying to more schools as freshmen, they may have a better sense of the breadth of institutions to which they might be accepted later as transfers.

Rising college tuition has also likely contributed substantially to the growing numbers of college transfers. Middle- and lower-class students who cannot afford to attend their institution of choice right out of high school might instead choose to attend college

locally or attend a community college to save money during the first two years, and then transfer to a four-year or more prestigious four-year. This option may seem even more attractive to students as the Pell Grant program is phased out, and federal student aid transitions more fully toward the provision of student loans (American Association of Community Colleges, 2016).

The proliferation of alternative learning options, such as online courses, evening programs aimed at working adults, and summer-only programs has made it possible for many individuals, who in past decades might not have been able to complete their education, to transition back into academia. According to data from the National Center for Education Statistics (NCES), students over the age of 24 made up 41.7% of all U.S. college students in 2012, and this population is growing much faster than traditional-aged college students (Hussar & Bailey, 2016, p. 25). Post-9/11 educational benefits for veterans and active-duty military have also lead to an influx of service members at many institutions. Data from the Department of Veterans Affairs shows that the number of students receiving veterans' educational benefits more than doubled between 2000 and 2012, with the largest increase coming between 2009 and 2010, when the number of beneficiaries jumped up by 42% (2014). At the same time, many states have implemented laws related to the acceptance of transfer credit, such as Senate Bill 1440 in California or the Comprehensive State-wide Transfer Agreement (Lampitt Bill) in New Jersey, in an effort to decrease the difficulties faced by these and other students of getting work completed at two-year institutions to apply to a four-year degree.

These rapid changes in technology, economics, and policy have contributed to a growing, and growingly eclectic, transfer population. In addition to the traditional community college transfers, schools are now expected to serve four-year (lateral) transfers, reverse transfers, re-entry students (who may work full time, have families, or belong to another population with special needs, such as veterans), and some students who have never actually attended school full-time before, but have rather picked up a few courses here and there, possibly in a mix of community college and online settings.

Because transfer students are older, and in some cases much older, than most freshmen, college leaders may expect a higher level of self-sufficiency. However, studies have long shown that college completion rates are lower, overall, for transfer students than for students who begin and remain at a single four-year institution (Lee & Frank, 1990). Even for those who complete the degree, the time-to-degree is often much longer, and it is not uncommon to see a drop in students' academic performance during the first year after transfer (Laanan, 2001). In a 2006 qualitative study by Townsend and Wilson, one student observed that universities needed to, "realize that transfers are a pretty sizable chunk of the incoming class each year… and we need to extend things out to them. They're going to need as much of a hand hold for a little bit as the freshman."

Supporting the Transfer Student Population

This highlights the importance of providing services to support a diverse student body. A recent simulation study found that increasing spending on student services would have a significantly greater impact on institutions' graduation rates than an equivalent increase in either instructional or research spending (Webber & Ehrenberg, 2009, p. 12).

Unfortunately, the growing heterogeneity of the student body (not just among transfer students) can make the "hand holding" recommended by Townsend and Wilson difficult, since institutions are now faced with the dilemma of providing appropriate support for students of all types on budgets that are becoming stretched thinner and thinner, due to decreases in institutional resources (because of declining state and federal support as well as poorly performing endowments) and a need to share those dollars among more services. IPEDS data collected over the ten-year period between 2001 and 2011, and compiled by the American Institutes for Research showed that at institutions of all types, the percentage of institutional budgets spent on student services increased, while the percentage spent on operational and instructional expenses stayed consistent or decreased (Desrochers & Hurlburt, 2014, p. 11). This section will outline a number of needs frequently observed within the transfer student population, and how institutions are choosing to address these needs. The cost implications of providing this growing number of services will also be considered briefly.

Though the focus of the current study is on a particular set of social supports for transfer students, Tinto's model suggests that both students' academic systems and social systems offer a variety of formal and informal factors that influence the decision to persist, and that these factors are not entirely distinct. It is therefore important to understand both the academic and social challenges faced by this population.

Academic supports. Many transfer students struggle academically during their first year post-transfer (Luo, Williams, & Vieweg, 2007). This can sometimes be attributed to poor academic preparation at the college from which the student is transferring, particularly

in the case of community college transfers (Koker & Hendel, 2003). As a result, many schools are offering summer "bridge" programs or transfer student success courses aimed at helping transfer students make the academic transition to their new institution (Ackermann, 1991). These programs often cover study skills and provide supplementary coursework that will fill in gaps in students' prior learning. Many institutions also offer robust tutoring programs that can help transfer students to catch up in areas where their previous coursework may have been insufficient. Social media and online education are beginning to broaden the possibilities for these types of programs, as they no longer have to be offered in person. Some institutions are beginning to experiment with virtual bridge programs, and many now offer robust online tutoring and gap assessment through companies such as ALEKS and Khan Academy.

Another academic issue of which transfer students complain is the inability to get the courses they need to complete their degree. Transfer students often register for courses long after their counterparts who have been attending the same institution since they were freshmen, and spaces may no longer be available. They also face issues with having to provide documentation that they have met the proper prerequisites, which can further slow their registration (Rhine, Milligan, & Nelson, 2000, p. 449). Providing robust and timely articulation mechanisms for transfer coursework, and ensuring that spaces in gateway courses are made available to transfer students is key to preventing delays in their academic progress.

Finally, transferability and applicability of previous coursework to major and degree requirements can often hinder timely degree completion (Lee & Frank, 1990). Though some

recent state laws have required broader acceptance of transfer coursework and clearer rules for transferability, units toward a degree do students little good if they do not satisfy specific requirements for degree completion. In fact, in some cases they prevent the student from completing a degree, as they push students' unit totals toward a maximum, leaving them with insufficient open units to satisfy all degree requirements. Schools that are transfer-friendly should be as explicit as possible about their rules for transferability, and provide academic advising in order to help students to understand, before matriculation, how previous coursework will apply to their degree requirements. This is another area where social media is opening up new options for transfer students, as many schools are now able to offer remote advising sessions to students who do not live near the campus.

Social supports. Adjusting to the social environment of a new college can be a particularly difficult aspect of college transfer, especially for students transitioning from a 2-year to 4-year institution, where environments often differ substantially (Rhine, Milligan, & Nelson, 2000, p. 444). Making friends at their new institution is frequently one of the greatest concerns faced by transfer students (Bauer & Bauer, 1994). According to the 2008 National Survey of Student Engagement, transfer students report fewer interactions with peers than students entering as freshmen.

Freshman cohorts are typically larger and more cohesive. Often freshmen live together and get to know one another in dorms or other university housing. They meet one another and learn about campus opportunities at freshman orientation. They are generally at a similar age and experience level. Transfer students, by contrast, often do not live in university owned housing at all. They often do not attend orientation, or attend an

abbreviated orientation. Their cohorts are smaller, and there tends to be a much wider

spread in age and experience. In many cases these challenges are exacerbated by the fact

that transfer cohorts contain more minority, low-income, and non-traditional students

(Shulock & Moore, 2005) – all populations that may feel more isolated or alienated than

college students in general. One student described the problem of making friends as a

transfer student this way:

> "Coming as a transfer student… it just kind of seems like there're already groups,
>
> you know, that have been established since like freshman year and there's this kind
>
> of bond, and sometimes there doesn't seem to be too much of an interest… in adding
>
> some more people." (Townsend & Wilson, 2006)

Just as summer bridge programs and transfer student success classes can help

students to adjust academically, they can also help students to adjust socially. These

programs offer opportunities for students to get to know their peers, as well as for campus

faculty and administrators to make students aware of resources and opportunities available

to them. In a qualitative study conducted by Velasquez in 2002 of students in a summer

bridge program offered by the University of California, San Diego, he found that, "they

formed diverse, close networks of peers during Summer Bridge that contributed to their

social integration," as well as, "supportive relationships with UCSD staff … that enabled

them to negotiate the institution" (p. 3).

Unfortunately, not all students have the necessary time or resources to participate in

such programs. Offering opportunities to connect through social media might be another

way to fill this need. Though transfer cohorts tend to be small compared with freshman

cohorts, finding peers with similar interests and situations can be easier online. This also

provides an opportunity for administrators to connect with students by putting out messages

and advertising services that can be of use to them.

Strong counseling services may be helpful, particularly to students with special

mental health needs or students who face specific stressors, such as student veterans

(Ackerman, DiRamio, & Garza Mitchell, 2011) and student parents (Cameron, 2005). This

is crucial given the rapid rise colleges nationwide have seen in students seeking mental

health services in recent years (Center for Collegiate Mental Health, 2016). Both individual

and group counseling, and particularly the combination of the two, have been shown to be

effective in improving retention for new freshmen and transfer students (Lee, Olson, Locke,

Michelson, & Odes, 2009). While social media cannot take the place of in-person

counseling services, this may be a good platform through which to advertise and normalize

these services. In addition, by providing an additional channel for social support, social

media may help to reduce the anxiety associated with transitioning to a new college, thereby

mitigating this need.

Resource centers that focus on the needs and experiences of specific groups can be a

great way to provide students with necessary support and build a sense of community. This

is particularly important among smaller student groups that may feel marginalized, such as

students of color (Turner, 1994). One student mother described her experience this way:

"In the community college there were a lot more people like myself that were either

working and going to school or coming back to school after a long break. I feel very

old and out of place here sometimes… I might find one or two other people that have

15

kids or are returning after a break from school, so this is a very different age group."

(Townsend & Wilson, 2006)

Many campuses, in addition to having resource centers for students of particular ethnicities or cultural identities, also have resource centers for other groups, such as non-traditional students, LGBTQ students, veterans, former foster youth, undocumented students, etc. Social media can offer another avenue for students to build these connections, or to stay connected with these communities. In addition, some students may feel more comfortable connecting with these resources online than in person, where they feel a higher level of scrutiny, and experience greater levels of social anxiety (Yen, Yen, Chen, Wang, Chang, & Ko, 2012).

Practical supports. In addition to the academic and social challenges of transferring between colleges, transfer students also face a variety of practical concerns. Many may have spent their first two years at a community college for financial reasons, and may be faced with a four-year college bill for the first time. Others may have difficulty finding housing, since many colleges do not offer dormitory housing to upper classmen. Student parents may struggle to find and pay for childcare (Marandet & Wainwright, 2010). About 40% of traditional-aged full-time U.S. college students work at least part-time (NCES, 2015), and these students may have severe scheduling constraints. A variety of services may be needed to support these students.

While social media may not offer direct solutions for problems of this type, it can provide students with a broader set of options, by giving them the ability to find and connect with other students facing similar concerns. The social media community studied in this

dissertation included a roommate-finder feature to assist students with finding suitable and affordable housing options, as well as the ability for students to post and respond to a variety of needs, including childcare sharing.

Fiscal considerations. Providing adequate services to support a diverse transfer population can be a struggle for colleges. Recent declines, nationally, in per-student spending, particularly at state-supported institutions (Mitchell & Leachman, 2015), may exacerbate this challenge, as does the fact that transfer students represent a relatively small portion of the total student population at most schools (Shapiro et al., 2015), and other students have needs as well. Fortunately, many resources that benefit transfer students can also benefit other students, such as good tutoring programs or access to psychological services.

According to Townsend and Wilson (2006), "Student affairs staff may need to lead the way in fulfilling four-year institutions' responsibility for integrating… transfers into the fabric of the institution." Unfortunately, at many institutions funding for student affairs divisions and the types of services they provide is being cut, particularly in situations where college leaders are faced with the choice of either cutting student services or cutting academic programs, and often students are being asked to pick up the tab in the form of new or increased student service fees, despite already paying rapidly rising tuition costs (Romano, Hanish, Phillips, & Waggoner, 2011). Many schools may not find this sustainable over time, and as a result, even those with a strong vision for contributing to the success of transfer students, and of all students, may find this vision increasingly difficult to realize.

Once again, social media may come to play an important role in filling this gap. Because virtual resources are often more economical to provide than physical resources, institutions may be able to use social media or other online offerings to supplement their existing infrastructure.

Improving Transfer Student Outcomes

The factors affecting success of transfer students are complex and start well before the point of transfer. According to Lee and Frank (1990), even when comparing students with similar characteristics and abilities, those who began at a community college and later transferred to a four-year institution were 10-20% less likely to receive a bachelor's degree than those who spent all four years at the same institution. This implies that factors inherent to being a transfer student, possibly in the transfer process or in the post-transfer adjustment, hinder students' academic attainment. This section will review, in more detail, several specific institutional factors that the literature indicates may be able to positively impact transfer students' long-term educational success – academic advising before and during the transfer process, academic assistance such as remedial coursework, tutoring, and study groups, relationships with faculty, and the institutional environment.

Academic advising before and during transfer. The transfer process itself can be confusing and frustrating for students. Even for those who began their college career with the intention to transfer have difficulty understanding which courses they need to take to prepare them for their longer-term education goals, and which courses will give them credit toward their degree at their transfer institution. Most community colleges offer academic advising services aimed at students planning to transfer to a baccalaureate institution, but

research shows that these programs are often limited and may not be effectively structured (Karp, 2013). In addition, academic advising positions are often low-paid and subject to high turnover, so the quality of advising may be poor. According to nationwide data on 1,267 college academic advisors collected by PayScale, a private company that specializes in using big data to assess salaries by job title, "The average salary for an Academic Advisor is $39,626 per year.... Pay for this job does not change much by experience, with the most experienced earning only a bit more than the least." In a 2006 qualitative study of community college transfers by Townsend and Wilson, 13 of the 19 students they interviewed said they felt they received no help in the transfer process from their community college. One student described his experience:

> "I felt like you were on your own, as far as making a decision to see an advisor, or set up a program of study, and if you go see an advisor, they could give you advice, but the most practical advice they'd give you was to call [the university], or wherever you were looking to transfer to.... I recall feeling frustrated they couldn't help me any more than they could."

This indicates that providing better advising resources to students before and during the transfer process may improve their experience, smooth the transition, and ultimately pave the way for long-term success. Interestingly, however, one recent study found that receiving advising from community college counselors before and during the transfer process was significantly negatively related to transfer adjustment (Laanan, 2007). There could be several reasons for this. It is possible, as mentioned above, that the quality of the advising was poor, causing students to have incorrect information or feel frustrated, and

possibly making them less likely to seek advising help from their transfer institution. If this is true, then improving the quality of advising at community colleges could still benefit transfer students. It is also possible that the students most likely to seek advising help are those least able to navigate systems on their own, and thus the ones who might be most likely to struggle in degree attainment. Finally, it is possible that these students, used to a greater level of personal attention in the community college setting, felt lost after transitioning to a four-year institution. If the last is true, it may indicate a need for improved academic advising to transfers at the transfer institution as well as the original institution.

As mentioned above, this is an area where social media and other online resources may be able to improve the student experience, and many institutions are now offering some form of online academic advising. According to a recent article in Campus Technology, this has a number of advantages, including allowing students easier and more convenient access to academic advisors, and a greater degree of transparency into their academic records and the ways in which courses are being used to fill degree requirements (Schaffhauser, 2014).

Academic assistance. Students transfer between institutions for a variety of reasons, but often academics play a role. In general, students who begin at a community college and later transfer to a four-year institution were less academically prepared at the end of high school than those who began their academic careers at a four-year institution (Lee & Frank, 1990). Students who begin at four-year institutions and engage in lateral or reverse transfer may also do so because they are struggling academically (Goldrick-Rab & Pfeffer, 2009). This seems to indicate a need for academic assistance for transfer students, but academic

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assistance might take a variety of forms, and it is important for institutions to understand which prove most effective.

Many institutions, particularly community colleges, offer remedial courses in math and English, generally aimed at that population of students who are interested in attaining a bachelor's degree, but who were academically unprepared to enter a baccalaureate institution after high school graduation. The hope is that, by helping them to bridge the gap in their educational attainment, schools will help to move them back on track for degree completion. However, in a 2009 study by Xueli Wang, she found that students who had taken remedial coursework in math were only about a third as likely to complete a bachelor's degree as those who had not. She postulates that enrollment in remedial work may reinforce negative self-perceptions, causing students to perform more poorly rather than to rise to the level of their more academically prepared peers. But there are a variety of other possible explanations for her findings. It is possible that the students most likely to enroll in remedial coursework also have the most difficulty keeping pace in these subject areas (leading to their having fallen behind during high school), and that even after having been caught up in subject matter, they will continue to struggle to keep pace in those subjects. If this is true, it is possible that without remedial coursework, even fewer of these students would ultimately have achieved bachelor's degrees. Wang's study also does not take into account the students' areas of study, so it is possible that these students are pursuing academic tracks for which they are poorly suited, possibly due to parental pressure or a perception that certain fields will lead to greater long-term financial gain. For instance, a student who struggles with math may be better suited to pursuing a degree in history or

political science than in economics. If they are taking remedial math in an effort to prepare them for a math-heavy academic career, they might benefit more from improved academic advising.

Another form of academic support that is likely to impact the success of transfer students is access to tutoring in subject areas and study skills. Particularly for students moving to a larger institution, the change in the classroom environment can be dramatic. According to one student, "Probably the most helpful would have been something to tell you the study habits of community college versus the university are a lot different" (Townsend & Wilson, 2006). By providing assistance that allows transfer students to be successful in the same courses as their peers who did not move between institutions, as opposed to segregating them with remedial work, it is possible that some of the negative psychological effects postulated by Wang could be avoided.

A third possibility alluded to in the Townsend and Wilson study is the formation of study groups. This option blurs the line somewhat between social and academic supports. Several of the students they interviewed lamented how much more difficult it was to get fellow students to form study groups with them after moving from a community college to a university. This could be partially related to the social difficulties transfers experience (i.e. the groups have already been formed, and they do not feel welcome to join in), and it could indicate a difference in study habits or expectations among university students versus community college students. Professors might be able to aid students in the formation of study groups by encouraging the practice in their classrooms, or providing space, such as

through the class's learning management system, where students can post information about study sessions.

The internet has broadened opportunities in all of these academic support areas. Services such as ALEKS and Khan Academy are being adopted by institutions nationwide to expand on or replace existing remedial education and tutoring services. McGraw-Hill Education, originally formed in 1917, is the producer of the ALEKS software, and recently announced that in 2015 unit sales of digital platforms and programs exceeded those of print in its U.S. Higher Education Group. This attests to the popularity of this medium of delivery. While social media may not be able to fill this specific niche, it can offer an opportunity for students to connect to form study groups and request help from peers.

Relationships with faculty. Research has shown that the quality of students' relationships with their faculty can substantially impact their overall satisfaction, academic performance, and persistence. The results of one quantitative study indicate that, "if students perceive that faculty are not difficult to approach they will also experience a smoother academic adjustment" (Laanan, 2007). Qualitative research agrees with this finding. Townsend and Wilson (2006) noted hearing numerous comments from community college transfer students such as, "Here you kind of feel like you're a number because the professors don't know you," and, "Sometimes I think it's harder to get to know a faculty member at a big university." This indicates that students might perceive professors at universities as less approachable than professors at smaller institutions or community colleges, which in turn could make it more difficult to ask for help when needed. Because

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students who spend their entire academic careers at four-year institutions would not know any differently, they may be less likely to feel intimidated by their professors.

Social media and other online tools can, once again, expand on and enhance the existing opportunities for faculty to engage students. A recent exploratory study into why students choose not to take advantage of faculty office hours found that students' perception of the convenience of the office hours' time and location significantly impacted their likelihood to attend (Griffin, Cohen, Berndtson, Burson, Camper, Chen, & Smith, 2014). Online office hours can be held at any time and from anywhere, which could make them a more attractive option for busy students. In addition, Yen et al. discovered that young adults experience significantly less social anxiety when interacting online rather than in person (2012). This, too, might make online office hours less intimidating for transfer students, particularly given that some tools used for delivery of online office hours actually allow the students seeking help to remain anonymous (Hooper, Pollanen, & Teismann, 2006). It is important to remember, however, that online office hours (like all office hours) are only useful to students if they are structured in such a way as to effectively facilitate learning. Griffin et al. also found that, while incorporating an online option did not, in and of itself, significantly impact students' propensity to attend office hours, the effectiveness of that component did.

It should be noted that none of the needs discussed above – the need for good academic advising, the need for academic assistance, or the need for positive relationships with faculty – are unique to transfer students. However, the lower rate of baccalaureate attainment among transfers and the specific issues voiced by these students indicate that the

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needs may be stronger among this population, and that the specific flavors of help they require are slightly different than for students who do not transfer (e.g. assistance with transfer and transferability, assistance to bridge gaps in knowledge and skills, etc.). A combination of quantitative and qualitative research is necessary to give a true and robust picture of how transfer students' needs differ from those of other students.

Environmental factors and sense of belonging. In addition to the formal institutional factors mentioned above, there are also a variety of informal factors that contribute to transfer student outcomes. Hoffman, Richmond, Morrow, and Salomone postulate that fostering a "sense of belonging" among students during their first year of attendance is critical to their long-term success (2002), as this enables and encourages them to persevere through the rigors of baccalaureate attainment. Hausmann, Schofield, and Woods found sense of belonging among first year college students to be positively related to intentions to persist, and also found some evidence that institutions could successfully improve students' sense of belonging through targeted intervention (2007).

Unfortunately, fostering a sense of belonging among the transfer student population can be particularly difficult, since they do not have the same shared experiences as freshman cohorts – attending orientation together, the bonding experience of being away from home for the first time, living in dorms together, etc. As a result, colleges must find other ways to integrate transfer students into the campus community successfully.

Colleges can begin this early in their relationship with students by setting expectations appropriately. Students entering as freshman are expected to be unused to the post-secondary setting, and a great deal of energy is expended to acclimate them to their

new environment. But the same care is rarely taken with transfer students, who presumably already know how to navigate their way through the complexities of higher education, despite the fact that research shows that the types of issues faced by transfer students during the orientation process are often more complex than those faced by incoming freshmen (Jacobs, 1992; Eggleston & Laanan, 2001). One student expressed his desire for help with this transition:

> "They could help by letting people know more about the campus, not just the buildings and what goes on, but what types of services are available and also like different hidden fees… I didn't know I had to pay for parking. I didn't know I had to park off campus." (Townsend & Wilson, 2006)

By helping transfer students to have a clearer idea of what to expect in their new setting, colleges may be able to set a tone that will reduce students' anxieties and enable them to focus more successfully on academics. Unfortunately, though data from the Policy Center on the First Year of College's (now Gardner Institute) 2000 National Survey of First-Year Curricular and Co-Curricular Practices shows that most four-year institutions offer specialized orientation programs for transfer students, students may not be taking full advantage of this resource. This could be because the students themselves believe that they have already been sufficiently oriented to college. As a result, Flaga (2006) suggests that transfer orientations may need to be renamed and marketed to students differently. This is another area where social media could provide some relief. Students who lack the time or resources to attend an on-campus orientation may yet be willing to attend online orientation sessions. Social media could also be used to supplement an in-person orientation,

facilitating continued networking with other new students, providing an additional avenue

for institutions to convey and reinforce important messages, and giving students an alternate

medium to ask questions and seek out resources.

Research and anecdotal evidence has long shown that transfer students struggle to

make connections with peers at their transfer institution (Townsend & Wilson, 2006;

Laanan, 2001, 2007). This lack of connection may be particularly troublesome for the

current college-going generation, who have grown up with close and constant access to

peers through social media, and often believe information conveyed through peers to be

more reliable than information garnered from official channels. As one student expressed, "I

would have liked to have heard from someone that had actually gone through or is going

through [being a transfer student]… versus someone that is teaching about it" (Townsend &

Wilson, 2006). This indicates that colleges may need to do a better job of helping transfer

students to connect with other students. This can be done in a variety of ways, but social

media offers a particularly appealing option, given its relatively low cost and broad reach. It

also offers students the somewhat unique opportunity to connect before arriving on campus,

thus potentially allowing for a smoother transition.

Students with strong peer networks also have the advantage of being able to use that

avenue to fill in gaps in their knowledge or understanding of the university. According to

one student,

> "I had to find everything on my own. I had to find where the shuttle picks people up,
>
> where they leave, and that was intimidating. I had a friend who went here and he
>
> took me around and he showed me." (Townsend & Wilson, 2006)

This implies that students rely on peer networks for more than just social and emotional support. Strong relationships with peers also provide a valuable practical resource, giving students a trusted channel through which to get questions answered, hear pertinent information, and even get academic assistance (as in the case of study groups).

Another proven way to help students increase their sense of belonging is through extracurricular activities. According to Wang (2009), participation in school-sponsored activities, including performing arts, college newspapers, student governments or politics, social clubs, and fraternities and sororities, has a significant positive relationship with baccalaureate attainment, with transfer students who participated in one or more activities being nearly twice as likely to graduate as students who did not. Interestingly, Wang does not include participation in sports in her list of activities which constitute college involvement, and the omission is not explained, but it seems probable that this type of involvement would exhibit a similar trend. It should be noted that this relationship is not necessarily causal, so it cannot be said that encouraging or requiring involvement in extracurriculars will make students more likely to graduate, since it could simply be that students who are more driven and feeling more comfortable with their academics are more likely to participate in other school activities. However, this type of information could be used by institutions as an early warning sign of students who might be at risk of becoming disenfranchised and ultimately dropping out.

As with the more formal institutional factors, it should be pointed out that none of these issues is entirely unique to transfer students. Most students sometimes struggle with issues related to building connections with peers and finding a sense of belonging.

However, freshman matriculants (students who have successfully enrolled in a college or university) have more resources, formal and informal, available to help them overcome these early obstacles, as well as more time to learn to successfully navigate the institution. By beginning to build relationships with transfer students prior to matriculation, and offering regular and meaningful opportunities for involvement and engagement with peers both prior to and after matriculation, institutions may be able to improve educational outcomes for this growing and still largely underserved population. Though data on the role that social media can play in this process is currently sparse, it is clear that a great deal of potential exists, and that the possibilities warrant further study.

Chapter 2: General Purpose and Background of the Study

Purpose

This dissertation consists of two distinct sets of analyses, all of which examine the relationship between social media networking communities, and proximal and distal outcomes for college transfer students. The previous chapter examined the importance of social supports and fostering a sense of belonging in order to enable transfer student success. However, most of the existing research on this topic focuses on physical rather than virtual resources and communities. The ability to build strong social networks prior to establishing a physical presence on the campus is a relatively recent development, and little is known about its effectiveness at improving outcomes for college students. Thus, a better understanding of how social media tools might enhance or coordinate with existing campus services would represent a useful contribution to the literature.

Though different methodologies are utilized for each of the analyses described here, the two are thematically similar, and use the same dataset. Specific research questions include, does participation in school-sponsored social media networking opportunities impact students' decisions to matriculate? Does participation have longer lasting impacts on students' academic careers, such as improving the likelihood of graduating or decreasing the time to degree? To what degree does participation influence these outcomes?

The specifics of each analysis, including the methodologies and data subsets used, are discussed is greater detail in this and the following chapters. However, a summary can be seen in Table 1.

Table 1

Summary of the Analyses

	Focus	Research Questions	Data Subset	Methods
First Set of Analyses	Social media and transfer recruitment	Does participation in a social media networking community impact transfer students' decisions to matriculate? If so, how effective is this tool? Is it more effective for certain sub-populations than for others?	Control Group, all Treatment Group 1, all	Treatment-on-the-treated (TOT) framework Instrumental variable (IV) regression and propensity scoring (PS)
Second Set of Analyses	Social media and transfer retention	Does participation in social media networking communities prior to matriculation contribute to transfer students' academic success? Do students who participate persist longer, have higher GPAs, or greater likelihood of graduating? Do these results vary based on observable characteristics, such as gender, ethnicity, and type of major?	Control Group, matriculated students Treatment Group 1, matriculated students	MANCOVA for continuous outcomes Binary logistic regression for binary outcomes

Given the influence that social integration has on student outcomes, as evidenced by the literature, the researcher hypothesizes that social media participation will have a small but measurable impact both on the proximal outcome of matriculation, and on the distal student success outcomes. A substantial impact is not expected, because the factors contributing to decisions about college choice and persistence are numerous and complex, which will necessarily limit the degree to which this specific component can influence student behavior.

It is also predicted that different sub-populations of students will choose to participate in school-sponsored social media at different rates and that it will influence them to different degrees. This is based on an assumption that people of different demographics may use or respond to social media differently, and that different types of students may be exposed to different or different degrees of competing influences. For example, prospective students who live further from campus may be more likely to participate in school-sponsored social media for the purpose of networking, as they may have fewer opportunities to network with other prospective students in person.

Practical and Policy Implications

Implications for college administrators. The answers to the research questions outlined above are important in terms of practical decision-making by college administrators. All colleges seek to improve yield rates, decrease stop-outs and drop-outs, and increase the number of degrees awarded. If the use of social media can assist with some of these goals, particularly for student populations, such as transfers, who historically perform more poorly than their peers on attainment metrics, then decision-makers should be

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aware of this potential. At the institution from which the data was collected, though transfer students make up only about a quarter of their undergraduate population, a full 41% of students who fail to obtain their degree in their declared graduation term are transfers.

Budget is another serious consideration for administrators. The first decade of the 2000s saw unprecedented increases in college costs-of-attendance. According to the National Center for Education Statistics (2014), the average cost of tuition, fees, room, and board at 4-year institutions in the U.S. went up by nearly 70% between the 2001-2002 academic year and the 2011-2012 academic year. Even after accounting for inflation, this represented an increase of nearly one third. Both the public, and federal and state governments have begun putting increasing pressure on institutions to keep costs down. At the same time, state support for public institutions was cut dramatically during those years, and even at private institutions the nation's economic downturn caused sharp declines in endowment and other operating funds. As a result, many institutions now face the reality of having less money on hand with which to provide services, and greater scrutiny in how that money is spent. While social media may appear at first glance to be an inexpensive option for connecting with students, its cumulative costs can be surprising. In addition to the direct costs associated with creating and maintaining social media communities or other social media tools (which often involve third party vendors and/or consultants, and hefty annual fees), there are also numerous indirect costs, including staff time spent monitoring these channels, and time spent crafting messages to be delivered via multiple media. When the wrong messages get distributed through social media, schools may also face costly clean-up.

Administrators also struggle with how to best reach the current college-going generation of technically savvy but often data-saturated students. Though making information available is easier than ever before, getting the intended audience to consume this information has perhaps become more difficult. Students are so constantly inundated with information, and the channels they use and trust to receive information from change so rapidly, that many administrators feel at a loss as to how to communicate with them effectively. Though the use of social media for this purpose has become relatively commonplace, its actual effectiveness is unclear. It is also unclear whether all students respond similarly to this medium, or whether it advantages certain types of students over others.

Implications for transfer students. The answers to these questions are also important in terms of improving outcomes for transfer students. The previous chapter briefly discussed the works of Hoffman et al. (2002), and Hausmann et al. (2007), who found students' "sense of belonging" during their first year at an institution to be positively correlated with their intention to persist, and ultimately with their baccalaureate attainment. Hausmann et al. also found that institutions could successfully foster sense of belonging among students through the use of targeted interventions. From the works of Laanan (2001, 2007) and Townsend and Wilson (2006), it was clear that transfer students have a particularly difficult time building the necessary social supports (presumed by the researcher to be closely related to the concept of sense of belonging) as they transfer to a new institution halfway through their college careers, and that this has been seen to hinder their adjustment. Finally, the work of Wang (2009) indicates that participation in school-

sponsored activities has a strong positive correlation with baccalaureate attainment for transfer students.

Overwhelmingly the literature supports Tinto's model of institutional departure (1993), which emphasizes the longitudinal impact of social systems, both informal systems manifested through peer interactions, and formal systems manifested through institutionally sponsored mechanisms such as extracurriculars, on students' choice to persist. In a broader sense, this implies the importance of students building strong social networks early in their college careers in order to improve their success in educational outcomes. Though there is no indication that this is more important for transfer students than for other students, the literature does strongly suggest that they struggle more to do so. There is, however, no literature to indicate whether social media can be viable tool for helping students to foster that sense of belonging, and ultimately contribute to improved educational outcomes. Even the work of Wang focuses solely on student participation in physical, rather than virtual, activities. Therefore, this dissertation is intended to contribute to the literature by examining the relationship between social media networking via a school-sponsored medium, and educational outcomes for transfer students.

Conceptual Model and Assumptions

An underlying assumption of the study is that any impact social media participation has on these outcomes is through the mechanism of helping to foster a sense of belonging, and thereby initiating or improving social integration, among the participating students. A conceptual model can be seen in Figure 3. The model incorporates elements of Tinto's model for institutional departure, shown in Figure 2, but builds on Tinto's model in two

important ways. First, it assumes that valid peer group interactions, as described by Tinto, can take place in virtual spaces in addition to, or possibly even in lieu of, physical spaces. It also suggests that, if this is true, these interactions can begin to take place prior to matriculation, thus potentially influencing not only the student's decision to persist, but also their decision to attend.

It should be noted that social media is a broad concept. Wikipedia describes it as, "computer-mediated tools that allow people, companies and other organizations to create, share, or exchange information, career interests, ideas, and pictures/videos in virtual communities and networks" (2016). Sources discussed in chapter 1 may have looked at a variety of different types of tools that could fall under this heading. However, many of these channels are unidirectional, such as Twitter, or anonymous, such as Yik Yak, or manifest other qualities that may not lend themselves well to the development of meaningful interactions with peers. For this reason, social media, as it is referred to in the context of the current study, is intended to specifically refer to social media networking communities, which allow free dialog between participants.
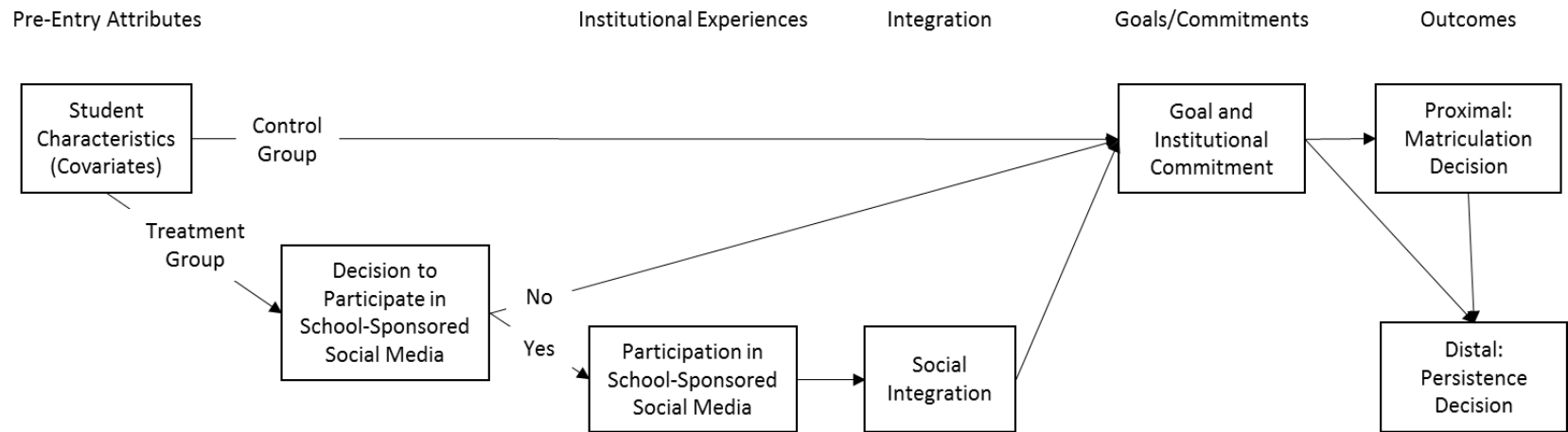
Figure 3. Conceptual model of a mechanism for school-sponsored social media to influence student outcomes through promoting social integration.

The Data Set

The analyses utilize a data set that contains information on over 6600 prospective junior-level transfer students admitted to a major public research university for Fall, 2012. (Not all analyses utilize the same subset of the data.) The researcher worked in collaboration with the university's Division of Student Affairs to design and conduct the study, which was used internally for program assessment purposes. All data contained within the data set was collected in the course of normal institutional business and stored as a part of the students' applicant and/or educational records.

Approximately one third of the prospective students were randomly selected to be invited to join the university's social media community at the point when they were offered admission, one third were selected to be invited at the point of matriculation (if they did matriculate), and the final third were never invited to join, thereby serving as a control group. The purpose of dividing the sample into three groups, rather than simply a treatment and control group, was to observe whether the timing of the intervention impacted either uptake or distal outcomes.

The community was available to prospective students only by invitation, and only those who had joined could post and view posts within the community. Students could access the community in a variety of ways, but the most common was via a closed Facebook app, not viewable by other Facebook users or discoverable by search. Those who were invited to join the community at the point of matriculation received their initial invitation via email several days after receiving their offer of admission. Those who were invited at the point of matriculation received their initial invitation via email during their first week of the

Fall, 2012 academic term. The community was promoted as a convenient and secure place to connect with other prospective and current students and learn more about the university. Invitees who did not join were sent several reminders. Once prospective students had joined the community, no special effort was made to encourage participation within it, though they had the ability to opt into email alerts on specific topics of interest or a more general community digest. Monitoring of activity within the community by university administrators was minimal, and only for the purpose of maintaining a safe and open environment.

Matriculation data was collected for all prospective students in the study. Data on longer-term academic outcomes was also collected for those students who matriculated to the University. In order to observe not only how effective the community was as a recruitment and retention tool, but also for whom, several covariates were included in the data set – gender, ethnicity, highest parent education level, residency classification, transfer GPA, and STEM major classification. This is consistent with the literature, which suggests that different populations, such as men versus women, use social media differently (Correa, Hinsley, & de Zuniga, 2010, p. 247), making it reasonable to assume that they might exhibit different patterns of responsiveness to social media networking opportunities. It was also hypothesized that some groups might be more unsure of their choice to attend a particular school than others, or might face greater difficulties in transitioning between colleges. If so, these subpopulations could be more likely to seek out online social networks to gain information or build community. Historically marginalized groups, such as ethnic minorities, might use social media to meet students of similar background. Students whose

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parents are less educated might have more difficulty navigating the transition to a four-year institution, and use social media to gain insights from peers. Non-resident students might rely more than resident students on the use of social media in deciding where to attend due to the differences in tuition rates for these populations or due to differences in familiarity with the university and its environment.

Sample

The full sample consisted of 6606 prospective junior-level transfer students offered admission to a major public research university in southern California for the Fall of 2012. (Because not all of the analyses use the full sample, the subsamples used in each set of analyses will be described in the appropriate chapters.) Students were randomly assigned to three roughly equal groups – one group of students who would be offered access to the university's official social media community at the point they were offered admission (treatment group 1), one group who would be offered access to the community at the point they matriculated in Fall 2012 (treatment group 2), and a third who would never be offered access (control group). The purpose of having multiple treatment groups was to study the impact of time on the distal outcomes. Students in the control group who learned of the community through other means and asked to have access were given access, but remained a part of the control group. This happened only twice. Descriptive statistics for the full sample and all three groups appear in Table 2.

Table 2

Descriptive Statistics for the Treatment and Control Groups

	Full Sample		Treatment Group 1 (offered treatment at admission)		Treatment Group 2 (offered treatment upon matriculation)		Control Group	
	%	*n*	%	*n*	%	*n*	%	*n*
Total		6606		2237		2191		2178
Gender								
Male	49.1	3241	49.2	1101	49.6	1086	48.4	1054
Female	49.5	3273	49.6	1110	49.0	1073	50.0	1090
Ethnicity								
White	37.3	2466	38.7	866	37.6	824	35.6	776
Hispanic	18.2	1202	18.8	420	17.6	386	18.2	396
Asian	37.1	2449	35.7	798	37.2	814	38.4	837
Other	3.9	253	3.7	82	4.0	87	3.9	84
Parent Education								
College Grad	52.3	3456	51.4	1149	53.1	1164	52.5	1143
Some College	19.8	1311	20.8	465	18.6	408	20.1	438
HS Grad	14.9	983	14.3	320	15.9	349	14.4	314
Less than HS Grad	10.2	672	10.8	242	9.9	216	9.8	214
Residency Class								
Local	5.8	384	5.3	118	5.9	130	6.2	136
CA Resident	70.2	4635	70.9	1586	69.9	1532	69.7	1517
Non-Resident	24.0	1587	23.8	533	24.1	529	24.1	525

Variables

Inputs. Both sets of analyses focus on student participation in the university's official social media community, and its influence on educational outcomes. Though not all inputs are used in all analyses, the following represent all inputs available in the data set.

Invitation category. Students fell into one of three invitation categories – those who were invited to join the community at the point of admission (treatment group 1), those who were invited to join at the point of matriculation (treatment group 2), and those who were never invited to join (control group). Treatment groups 1 and 2 were each coded dichotomously with "not invited to join" serving as the reference group.

Participation category. Participation category was coded dichotomously to represent whether individuals "joined" the community or "did not join" the community, with not joining serving as the reference category.

Registered for Fall 2012. Students were assigned a binary indicator based on whether or not they had ever registered for the Fall 2012 academic term, thus showing intent to matriculate. However, this variable is not used as an indicator of matriculation, which is described below.

Covariates. Five categorical covariates were included in the data set: gender, ethnicity, highest parent education level, residency classification, and STEM major classification. In addition, one continuous variable, transfer GPA, was included. Each of these was chosen both because they have historically been shown to have a bearing on college students' outcomes and in addition some were hypothesized to impact the decision to participate in the university's social media community.

Gender. Gender information was taken from prospective students' applications for admission to the university. It was a dichotomous variable consisting only of male and female, with male being treated as the reference group.

Ethnicity. Ethnicity data was also self-reported by students on their admission applications. Though more robust ethnicity information is housed by the university, for the purposes of these analyses, the categories were collapsed into White, Hispanic, Asian, and other minority. This was done primarily to simplify the analyses and render the results more interpretable, but also serves to protect the identities of students from ethnic groups with very small cell sizes, and increase the statistical power of these groups. Hispanic, Asian, and other minority were each coded as dichotomous variables with White being used as the reference group.

Highest parent education level. Highest parent education level was derived from mother and father education levels as reported on students' admission applications. Categories were collapsed by the researcher into Less than High School Graduate, High School Graduate, Some College, and College Graduate. This was done both to simplify the analyses and because conventional wisdom in college attainment suggests that first generation college students face much greater barriers to matriculation and persistence than students with a parent who attended college (London, 1992). However, students with a parent who has an advanced degree have no substantial advantage over students for whom neither parent has more than a bachelor's degree. Less than High School Graduate, High School Graduate, and Some College were each coded as dichotomous variables, with College Graduate serving as the reference group.

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Residency classification. Residency classification was based on a combination of students' home address and residency classification for tuition purposes. Originally the researcher divided residency into four categories: Locals, defined as living within 50 miles of the campus and qualifying for in-state tuition, Non-Local California Residents, defined as living more than 50 miles from the campus but still qualifying for in-state tuition, Domestic Non-Residents, defined as living within the United States but not qualifying for in-state tuition, and International Non-Residents, defined as living outside of the United States. Fifty miles was chosen as the radius for defining a Local, due to the geographical elements of the surrounding region and the availability of transportation networks, as it encompasses the community in which the University is located, as well as possible nearby commuter communities.

The original four categories make logical sense given the different challenges each group faces. Locals have the fewest barriers to attendance, given that they pay in-state fees, know the area, and even have the option of commuting. Non-local California Residents may not know the area and do not have the option of commuting, but they still pay far lower fees than non-residents. Domestic Non-Residents pay substantially higher fees than residents, but face no language or visa issues. International Non-Residents face the greatest barriers to attendance, because their fees are very high, they may face language and/or cultural issues, and they must contend with the visa process. However, after a close examination of the data, it was determined that Domestic Non-Residents and International Non-Residents should be collapsed into a single Non-Resident category, due to there being such small numbers of Domestic Non-Residents in the data set. This is unsurprising given that most

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domestic students who choose to attend a state school outside their home state do so as freshmen. Transferring to a state school outside one's home state is uncommon. The University of California publishes admission statistics for all nine of its undergraduate campuses, and between 2011 and 2013, domestic non-residents made up less than 3% of the systemwide transfer applicant pool, with most of these students applying to UC Berkeley or UCLA.

Among the remaining three groups, Non-Local California Residents and Non-Residents were each coded as dichotomous variables, while Locals served as the reference group. Though this was the smallest of the groups, it was hypothesized that these students were most likely to matriculate, making them a logical group against which to compare the others.

Transfer GPA. Transfer GPA was included in the data set to be used as a control for prior academic performance. It was calculated by the University on a traditional 4.00 scale based on self-reported grade data from the admission application. The values ranged from 1.74 to 4.00, with a strong negative skew.

STEM major classification. Major information for matriculated students was collapsed into a binary indicator of STEM (science, technology, engineering, and math) majors, and non-STEM majors. Classification of Instructional Programs (CIP) code as defined by the National Center for Education Statistics was used to determine whether majors should be considered STEM or non-STEM. Non-STEM majors served as the reference group.

Outcomes. Several outcomes of interest were included in the data set. The proximal outcome of matriculation to the University is used for the first set of analyses, and the distal outcomes of persistence, degree status, and overall GPA are used for the second set of analyses.

Matriculation. Matriculation, within this data set, was a binary indicator determined by registration status at the beginning of the Spring 2013 term. This was believed to be a more accurate reflection of true matriculation than registration status during the Fall 2012 term, given that a number of college students drop out during or soon after their first term (Hoffman, Richmond, Morrow, & Salomone, 2002).

Persistence. Persistence was a continuous variable ranging from 0-6 representing the number of quarters over which the student persisted at the University. Summer terms were considered optional, and thus excluded from the calculation. Though 152 students (about 2.3% of the full data set) received a degree in fewer than six quarters, all students who received a degree were assigned a value of 6 in order to differentiate them from students who dropped out after fewer than six quarters (considered the normative time-to-degree for junior-level transfer students).

Degree status. Degree status was a simple binary indicator representing whether or not the student had received their bachelor's degree by the end of the Summer 2014 term. Students who did not receive the degree served as the reference group.

Overall GPA. In contrast with the transfer GPA mentioned among the covariates above, overall GPA represents the GPA achieved by the student after matriculating to the

University. It was calculated on a traditional 4.00 scale, covered the period from Fall 2012 through Spring 2014, and ranged from 1.82 to 4.00.

Intrinsic variables. It should be noted that in addition to the variables included in these analyses, a variety of unmeasured factors are known to influence student recruitment and retention. While effort was made to include the as many relevant inputs as was practicable, often only a small overall portion of the variability in the data is explained by the models presented. Where possible, R^2 values are included to give a sense of the completeness of the model.

Variables not included in the analyses are covered in more detail in the Discussion section.

Chapter 3: Social Media and Transfer Student Matriculation

Description of the Analyses

The first set of analyses addresses the use of social media for transfer student recruitment. Specifically, does participation in a social media networking community impact transfer students' decisions to matriculate? If so, how effective is this tool? Is it more effective for certain sub-populations than for others? (In other words, are there differences in effectiveness based on gender, ethnicity, or other factors?)

Based on indications in the literature that sense of belonging is closely correlated with a variety of transfer student outcomes, it was hypothesized that participation in the community would have a modest impact on transfer students' decisions to matriculate.

These analyses focus on Treatment Group 1 and the Control Group described in the previous chapter. Of those assigned to Treatment Group 1, only 27.6% chose to join the University's social media community when offered at the point of admission. Therefore, in order to control for imperfect compliance with treatment, the data was examined within a treatment-on-the-treated (TOT) framework, using both an instrumental variable (IV) approach and propensity scoring for data analysis. The results of these two analyses will be compared, and the merits of each method discussed.

Explanation of Treatment-on-the-Treated Research Designs

In random assignment studies where compliance with treatment is imperfect, two possible frameworks can be used for analyzing the data: intention-to-treat (ITT) and treatment-on-the-treated (TOT).

ITT research designs compare a group that was offered treatment against a control group that was not offered treatment. They do not attempt to control for acceptance of treatment or adherence to treatment. A simple example would be to examine a group of four children, all at the same spelling level. A researcher tells two of the children that she will teach them to spell ten new words if they would like. The other two do not get the offer, and serve as the control group. Of the two who are offered the learning opportunity, only one decides to do it. The other would just prefer to go play (or is out sick that day, or get stuck in a "time-out," or one of many other things that could get in the way of treatment being properly administered). So the researcher successfully teaches the one who takes the offer the ten words. Then she gives each of the four children a spelling test on those words, and finds that the two control children get no words correct, the one ITT child who did not take the offer gets no words correct, and the ITT child who took the offer gets all ten words correct. Comparing the ITT group to the control group would render an average treatment effect (ATE) of five words (ten total words correct divided by two children, compared with no words correct divided by two children).

This might seem like a poor way to judge the effectiveness of a treatment. After all, if you know one child did not actually receive the treatment, why not exclude them from the analysis? However, in social science research (as well as in clinical trials, where this technique originated), things are not always as straightforward as in this example. The researcher may not have a way to monitor treatment uptake, or the treatment might be administered differently by different people (e.g., one teacher understands the teaching technique well and uses it properly, while another does not), or some people might withdraw

from treatment early and as a result, receive some but not all of the benefits of treatment. A researcher who tried to account for all of these scenarios could have a difficult job ahead of them. In addition, treatment uptake is affected by a variety of factors. Some people might want to uptake and properly adhere to treatment, but be unable. By excluding these people from the study, one ignores the fact that, in practice, treatment is imperfect, and thus the "clinical" effectiveness of the treatment may be overestimated (Hollis & Campbell, 1999).

That said, there are times when the researcher truly wants to know how effective a treatment is if given and properly adhered to. For example, birth control pills have been shown to be about 90% effective overall, but this is because many people do not remember to take them daily. Among people who do take them daily as directed, they have been shown to be about 99.5% effective. For consumers to know and understand both numbers is important in helping them to decide whether this treatment is appropriate, and the expected consequences of imperfect adherence to treatment.

For this, researchers must conduct a treatment-on-the-treated analysis. TOT analyses attempt to account for actual treatment uptake, not just the offer of treatment, to give a more realistic picture of how much impact the treatment actually has on those who receive it, thus preventing an underestimation of the treatment's actual effectiveness. Going back to the hypothetical spelling example, one would take the overall ATE calculated above – five words (ten total words correct divided by two children, compared with no words correct divided by two children) – and then divide that number by the percentage of children in the ITT group who actually received the treatment, 50%. Because five words divided by 50% is

equal to ten words, it becomes clear that the actual treatment effect on those who *received* the treatment, the local average treatment effect (LATE), is ten words.

While this is not the only method for calculating TOT, this method, known as the Wald estimator, is probably the simplest (Brookhart, Rassen, & Schneeweiss, 2010), and thus useful for illustrative purposes. However, in practice, there are a variety of methods that can be used, and each might render slightly different information. For instance, some take into account levels of treatment received (such as when a participant leaves a study early, or complies partially with treatment), or try to approximate likelihood of treatment uptake. They are all similar in that they attempt to logically control for treatment uptake in order to better understand the true effectiveness of the treatment.

There are a variety of reasons that someone might choose to use ITT over TOT or vice versa, but it depends upon what the researcher wants to know and why. In fact, in many cases (such as the birth control example above), knowing both numbers and understanding the difference can be crucial, and it is not uncommon to see researchers report both if they have sufficient data to calculate the TOT. In general, proponents of ITT argue that it gives a more realistic picture of how effective the treatment will be when applied in practice rather than under ideal experimental conditions. They contend that since people can choose whether or not to accept treatment, and how faithfully to follow treatment, you could expect similar results if the same choice were given to a control group or to the wider population, and thus ITT avoids overestimation of the treatment's effectiveness. Conversely, proponents of TOT argue that ITT does not give a true picture of a treatment's impact, and thus using only ITT could cause a treatment's actual value to be overlooked.

TOT might be especially useful when the researcher has a theoretical understanding of when and why participants choose to accept or not accept treatment, as he can then predict how effective treatment will be and for what population(s).

In situations where most of those offered treatment do, in fact, take up the treatment, there may be little additional value to gain by trying to estimate the effect of TOT. However, in situations where treatment uptake is low, and particularly in situations where you can infer why uptake is low and who is likely to uptake, estimating TOT can provide you with a lot of valuable additional information. In a study published in 2003 by Tama Leventhal and Jeanne Brooks-Gunn, the researchers looked at the effects on children's mental health of providing low income families with opportunities to move into middle class neighborhoods. For a variety of reasons, only 40% of those offered treatment actually moved to better neighborhoods (which actually exceeded the researchers' expected rate of 25%). The researchers presented the results of both the ITT and TOT analyses. In that situation, because treatment uptake was so low, the ITT analysis showed no significant results, but the TOT analysis showed substantial positive results. A policy-maker, unfamiliar with the limitations of ITT, might look only at the ITT results and conclude that there is no compelling reason to help low income families to try to better their living situations, whereas, in reality, the potential benefits for children whose families take up this offer can be profound.

In the case of the current study, an ITT analysis would dramatically underestimate how participation within the social media community influenced students' decisions to matriculate, because, of those in the treatment group, only 27.6% actually joined. As a

result, any observable effects of participation would likely be heavily mitigated by the 72.4% of invited students who did not choose to join the community. This suggests that a TOT analysis will render the most useful results.

Instrumental Variable Estimation Using Two-Stage Least Squares

One method for obtaining a reliable TOT estimate is to use an instrumental variable approach, in which the randomly assigned invitation category can be used as an instrument to predict the probability of students self-selecting into a participation category. In this context, an instrument, or instrumental variable, is a variable that is correlated with the predictor variable of interest, but uncorrelated with error. These predicted values would then be used to predict students' likelihood of matriculating, thus controlling for self-selection bias by using only the portion of participation category that is related to the randomly assigned invitation category in the final regression, and parsing out the portion that is related to self-selection. Because an instrumental variable approach specifically controls for bias in this way, perfect compliance with treatment is not necessary, making it a strong quasi-experimental alternative for situations in which a random assignment study suffers from imperfect compliance.

The instrumental variable framework can be applied using a variety of different analytical techniques, including two-stage least squares (2SLS), limited-information maximum likelihood (LIML), simultaneous equation modeling (SEM), jackknife IV estimation (JIVE), and three-stage least squares (3SLS), among others. By far the most common among these is 2SLS. LIML, which has actually been in use slightly longer than 2SLS, is also somewhat common, and some evidence suggests that LIML is more accurate

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with smaller samples or weaker instruments (Bekker, 1994). However, its adoption has not been nearly as widespread as that of 2SLS, possibly because LIML is "more difficult to implement and harder to explain" (Cameron & Trivedi, 2005). Given the study's relatively large sample and strong instrument (discussed below), 2SLS was deemed the most appropriate analytical method.

Assumptions of instrumental variable estimation. In order to be considered a valid instrument, a variable must meet two specific criteria – relevance and exogeneity. Relevance is the degree to which the instrument is related to the predictor variable. In this study, invitation category is used as an instrument to predict participation category. Thus, relevance must be proved by showing a strong relationship between these two variables, which can be done by conducting a simple bivariate correlation. Within the data set used for this study, the correlation between the instrument and the predictor is $r(4413) = 0.396$, $p < 0.001$.

Exogeneity is the assumption that the instrumental variable is not correlated to the unobserved effects (residuals) impacting the outcome variable. In other words, the only viable path between the instrument and the outcome is through the predictor variable. This is key, because if the instrument is correlated with the residuals, it cannot control for the predictor variable's bias. In this case, because the instrument, invitation category, was randomly assigned, it is known to be uncorrelated with the residuals, thus meeting the exogeneity assumption.

Propensity Scoring

Propensity scoring (PS) is another possible method that can be used to control for selection bias in the form of imperfect treatment uptake. However, there are a variety of ways that propensity scores can be used for this purpose, and each has slightly different advantages and disadvantages. Murnane and Willet's *Methods Matter* (2011) outlines three common approaches: using propensity scores to create comparable strata, individual matching based on propensity scores, and weighting treatment effect results using inverse propensity scores.

All three methods are similar in that they begin with the calculation of a propensity score for each participant in the data set. The propensity score represents the participant's probability of accepting treatment, based on what is known of their individual characteristics. The decision of which variables to include in the calculation of the propensity score should be based on theory, but, in practice, might also be limited by the dataset available. If the resulting set of scores ranged from .05 to .30, this would indicate that among participants least likely to accept treatment, about 5% do so, and among participants most likely to accept treatment, about 30% do so. If histograms were then compared of propensity scores for those who accepted treatment versus those who did not, this would be reflected. For instance, propensity scoring could be used to compare students who attended private school versus those who did not. The histograms would have nearly identical ranges, but the lower end of the range (less likely to enroll in private school) would appear thicker or fatter among the public school students, and the higher end of the range

(more likely to enroll in private school) would appear fatter among the private school students. This new data could then be used to apply one of the techniques described next.

Comparing strata. The first technique, stratifying based on propensity score, essentially entails breaking the propensity scores down into score ranges, or blocks, and comparing participants within each block, then creating a weighted average of the results. The width of the blocks is somewhat arbitrary, and essentially at the discretion of the researcher, though studies have shown that accurate results can often be obtained with as few as five blocks (Murnane & Willet, 2011). If, as suggested above, the scores ranged from .05 to .30, the researcher might choose propensity scores of .05-.10, .10-.15, .15-.20, .20-.25, and .25-.30. This results in groupings of presumably similar participants based on their propensity to accept treatment. The researcher would then test for mean differences between those who did and did not actually receive treatment within each block, both on the propensity scores themselves, and on all variables used to create the propensity scores. If significant differences are found, smaller blocks may be necessary. The researcher would continue to break the data into smaller blocks until no significant mean differences were found. If certain variables continued to exhibit mean differences even as the blocks became smaller and smaller, particularly if these differences pooled in the higher or lower blocks, it might be necessary to perform a transformation on that particular variable and recalculate the propensity scores.

Once the blocks were successfully created such that no significant mean differences existed in either the propensity scores themselves or the variables comprising them, mean differences in outcomes could be compared. These could then be combined into a weighted

average using all participants within each block to create an average treatment effect (ATE), or using only participants receiving treatment within each block to create an average effect of treatment on the treated (ATT).

This method has many advantages. Because balance, in numbers, between control and treated groups within each block is not required, data on all participants can be used, increasing statistical power, and potentially allowing for more robust results than would be rendered by the propensity score matching technique which will be described next. It can also help to highlight incorrect assumptions about the relationship of the variables making up the propensity scores, in cases where certain blocks consistently fail to render non-significant results when these variables are compared. However, it can be a highly iterative and sometimes frustrating process, particularly when dealing with covariates yielding significant results.

Individual matching. Another possible technique would be to individually match participants based on propensity scores, essentially taking all participants in the treatment group, matching each one with the participant in the control group with the closest propensity score, discarding data for any unmatched participants, and then comparing outcomes between the two resulting groups. This technique is sometimes referred to as nearest-neighbor matching.

While in some ways simpler and potentially less time consuming than creating stratifications, the approach introduces different problems. The researcher must decide how to deal with situations where one treatment individual matches equally well with several control individuals and vice versa. She must also decide how to deal with situations where

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no good match can be found for a particular treatment individual, particularly when dealing with smaller datasets. The fact that many participants could be discarded may result in a less robust analysis and lower statistical power than other propensity score approaches. In addition, incorrect assumptions about the relationship of the variables making up the propensity scores can cause biased estimates (Heinze & Juni, 2011).

      Inverse propensity scores. The final technique, weighting treatment effect results using inverse propensity scores, sometimes referred to as inverse probability of received treatment weighting (IPTW), eliminates some of the issues inherent in propensity score matching. It is performed by assigning each participant in the sample a weight equal to the inverse of their probability of having ended up in that group. In other words, for a participant receiving treatment whose propensity score (likelihood of receiving treatment) was .25, their weight would be 1/.25 or 4. For a participant not receiving treatment with the same propensity score, their weight would be 1/.75 or 1.33 (since their likelihood of not receiving treatment must have been .75 given that their likelihood of receiving treatment was .25). This will ultimately result in even weights for the control and treatment groups, even if they differ substantially in size, and is intended to reduce the impact of selection bias by giving less weight to those who behave in a more predictable manner based on their propensity scores.

      IPTW has been shown to be highly effective at mitigating bias, and recent studies have shown that it is better able to control for systematic differences between treatment and control groups than stratification (Heinze & Juni, 2011). It is also relatively easy to perform, and allows for inclusion of all participants, resulting in the potential for a more

robust analysis. However, unlike stratification, it cannot help to identify potential incorrect assumptions about the variables, so choice of this model may be influenced by how confident the researcher feels about the choice of these variables and the assumptions made about their relationships.

Propensity scoring to compensate for imperfect compliance in a randomized study. Each of the techniques described above, and, indeed, the traditional use of propensity score matching, assumes that all participants in the study had the option to receive treatment, regardless of whether they exercised that option. However, participants in the current study were randomly assigned to be offered treatment. As a result, traditional propensity scoring techniques present several problems. If propensity scores were calculated using the entire data set without incorporation of invitation category as an input, propensities would be underestimated. Using this method would also be problematic in that it would result in a comparison of participants who chose to uptake versus similar participants who did not choose to do so, but the intended comparison, in this circumstance, is participants who were offered and accepted treatment versus similar participants who were not offered treatment. If, on the other hand, invitation category was incorporated into the generation of the propensity score, those who were and were not offered treatment would not end up with comparable score distributions. In a 2007 study incorporating a Monte Carlo simulation and two empirical examples, Bhattacharya and Vogt found that, "When a researcher uses an instrumental variable in the construction of a propensity score, the estimates become more inconsistent than with a naive estimator." Thus, directly employing any of the comparison techniques described above would yield flawed results.

Follmann (2000) suggests a solution to this problem, utilizing data from the treatment group to calculate propensity scores for the entire population, and then modeling an interaction effect between treatment category and the propensity score. Sagarin, West, Ratnikov, Homan, and Ritchie (2014) summarize Follmann's technique in this way:

> This approach begins by regressing the dichotomous compliance measure on the set of baseline covariates in the treatment group. The coefficients from this logistic regression model are then used to calculate estimated propensity scores for each participant in both the treatment and control groups. Finally, outcomes are regressed on condition (treatment vs. control), estimated propensity scores, and the condition by propensity score interaction.

Jo and Stuart (2009) also describe Follmann's approach, and further go on to discuss its subsequent use in educational research:

> Follman used the propensity score approach to estimate treatment effects accounting for levels of compliance. Follman estimated a model of treatment receipt using the treatment group members (the propensity score model), and then used the predicted probabilities of treatment receipt in outcome models. In particular, he treated the propensity score as a baseline covariate and included an interaction of it and treatment assignment in the outcome model, essentially estimating a subgroup effect with the subgroup defined by predicted level of treatment receipt. Hill et al. used a similar approach to look at the effects of high levels of participation in an early intervention for high-risk children, and found that higher-levels of participation led to stronger and longer-lasting effects.

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In the same paper, Follmann also proposed a second approach, in which non-compliers from the treatment group and would-be non-compliers from the control group were excluded from the analysis, thus resulting in a true TOT comparison. However, he ultimately advised against this method due to the complications associated with trying to accurately predict the probability of compliance within the control group.

Given the nature of the data being used for this study, Follmann's approaches seem more appropriate than the three traditional propensity scoring techniques discussed above. Due to the issues associated with Follmann's second approach, his first approach, which incorporates a treatment group by propensity score interaction effect, were ultimately chosen for this study.

Methods

Sub-sample

The sub-sample used in this study consisted of Treatment Group 1 and the Control Group described in the previous chapter, for a total of 4415 prospective junior-level transfer students. Four-hundred ninety-seven students were missing data on one or more of the predictor variables, and were thus excluded from the analysis, leaving a total of 3918 participants. While there is no definitive statistical test capable of proving data to be missing at random (Rubin, 1976), examination of the missing data showed no indication that this assumption was violated. Given the relatively large overall sample size, and that missing data was spread evenly across the treatment and control groups, data imputation was deemed unnecessary.

Statistical Analyses

Analyses were conducted using SPSS version 22.0. Initially a simple calculation of

effect size was performed using the Wald estimator, which has been used successfully to

calculate TOT effect size since 1940 (Bowden & Turkington, 1990, p. 39). The Wald

estimate can be found by obtaining the difference in probability of matriculation between the

ITT and control groups, and then dividing this number by the difference in probability of

participation between the ITT and control groups. It can be represented using the following

formula:

$$TOT = \frac{E(Y|Z = 1) - E(Y|Z = 0)}{E(D|Z = 1) - E(D|Z = 0)}$$

where Y represents the outcome, Z the assigned treatment, and D the actual treatment

(compliance). While the Wald estimate is of limited value, given the small amount of

information it yields, and its strict assumption that the treatment and control groups are

identical in all ways other than the offer of treatment, it does give an easily interpretable idea

of the magnitude of impact the intervention (in this case participation in the community) has

on those who self-select into it versus a similar sample who was not given that option. In a

program evaluation this is important, because it gives decision-makers a sense of the

practical impact of their program, which has value regardless of the statistical significance.

For instance, a program having a small but statistically significant impact may not be worth

pursuing when resources are tight. Conversely, a program with a statistically insignificant

impact may be worth continuing and reassessing at a later time if that small difference is of

value to the institution.

Instrumental Variable Analysis. After the initial calculation of effect size, a 2SLS

regression was performed incorporating the instrumental variable (invitation category), the

predictor variable (participation category), and the covariates believed to be relevant in

predicting matriculation to the University – gender, ethnicity, parent education level,

residency status, and transfer GPA. However, in the first model no interaction terms were

incorporated. The first stage equation can be represented as follows:

$$X_i = \eta_0 + \eta_1 Z_i + \eta_2 W_{1i} + \cdots + \eta_{11} W_{10i} + \mu_i$$

where X_i represents the predictor variable, Z_i represents the instrumental variable, and W_{1i} –

W_{10i} represent the covariates. The second stage equation can be represented as follows:

$$Y_i = \beta_0 + \beta_1 \hat{X}_i + \beta_2 W_{1i} + \cdots + \beta_{11} W_{10i} + \varepsilon_i$$

where Y_i represents the outcome variable.

A second 2SLS regression was then performed incorporating the two-way

interactions between the instrumental variable and all relevant covariates into the first stage

regression:

$$X_i = \eta_0 + \eta_1 Z_i + \eta_2 W_{1i} + \cdots + \eta_{11} W_{10i} + \eta_{12}(Z_i)(W_{1i}) + \cdots + \eta_{21}(Z_i)(W_{10i}) + \mu_i$$

The second stage regression remained the same, effectively causing the interaction terms to

behave as additional instruments in predicting participation in the community.

Finally, a third 2SLS regression was performed incorporating the two-way

interactions between the instrumental variable and all relevant covariates into the first stage

regression, as well as the two-way interactions between the predictor variable participation

category and all relevant covariates into the second stage regression.

The latter two models were run to determine whether the social media networking community affected some subpopulations differently, either due to differential uptake or differential participation, as the literature indicates differences in social media use and impact based on gender among other traits. Fit statistics for each model were examined to determine whether it represented a significant improvement over the previous model.

Propensity Score Analysis. To serve as a comparison to the instrumental variables analysis, the same data was also analyzed using the propensity scoring technique originally proposed by Follmann in 2000 and described above.

The first step in any propensity scoring technique is to estimate the propensity scores, which is normally done using either a probit or logit function. When the treatment variable is binary, neither technique presents a strong advantage over the other (Heinrich, Maffioli, & Vazquez, 2010), so logistic regression was used in this case, given that this is the default in SPSS. Initially, propensity scores were calculated for the treatment group only using the equation:

$$e(x_i) \ = \ P(Z_i = 1 \mid X_i)$$

where $e(x_i)$ is the propensity score for participant i, P a probability, $Z_i = 1$ a treatment indicator with values 0 for those who did not uptake treatment and 1 for those who did, the "|" symbol stands for conditional on, and X_i is a vector for the set of covariates being used to predict treatment uptake, in this case gender, ethnicity, parent education level, residency status, and transfer GPA.

The resulting coefficients from this logistic regression model were then used to calculate propensity scores for the control group, resulting in analogous propensity score estimates for the two groups.

Finally, a regression analysis was fit using the calculated propensity scores, where $e(x_i)$ is used as a covariate that has an interaction with treatment. Though Follmann used a Cox regression when originally developing this technique, due to the time-dependent nature of his outcome variable, this analysis instead employed a binary logistic regression, due to the binary nature of the outcome variable. Logistic regression is "relatively free of restrictions… with the capacity to analyze a mix of all types of predictors (continuous, discrete, and dichotomous)," (Tabachnick & Fidell, 2007, p. 441) making it an appropriate choice given the mix of continuous and categorical predictor variables. The functional form of binary logistic regression is as follows:

$$\ln\left(\frac{\widehat{Y_i}}{1 - \widehat{Y_i}}\right) = A + \sum B_j X_{ij}$$

where $\hat{Y}_i$ represents, in this case, the estimated probability that student i will be registered in Spring, 2013. A is constant and B_j is the coefficient for variable X_{ij}. (Tabachnick & Fidell, 2007) Because changes in B_j represent changes to the log odds of the outcome variable rather than to the outcome variable itself, it can be difficult to interpret. Therefore, odds ratios are also included in the SPSS output, and can be calculated using the formula:

$$R_j = e^{B_j}$$

where R_j is the odds ratio associated with predictor variable j, or the change in odds that a student will be registered in Spring, 2013 based on a one-unit change in the predictor variable j (Szumilas, 2010).

Because the covariates of interest could have impacts on the outcome (matriculation) above and beyond their influence on treatment uptake, the regression was performed sequentially, with only propensity score, treatment group, and their interaction being incorporated in block 1, and with the covariates being added to the analysis in block 2. Fit statistics and 95% confidence intervals were examined for both models.

Results

Of the 4415 students comprising the sub-sample, only 983, or 22.3%, fully matriculated (were registered as of Spring, 2013). Within the treatment group, 23.0% of students matriculated, whereas in the control group 21.5% of students matriculated. Using the Wald estimator to calculate a local average treatment effect (LATE) revealed an overall effect size of 5.3%, indicating that students who participated in the social media community matriculated at a rate 5.3% higher than did students who were not invited to participate, but otherwise likely would have.

Instrumental Variable Analyses

The results of the first stage regression were examined to determine whether the instrumental variable, covariates, and interactions functioned as strong predictors of social media community participation. These results appear in Table 3. Overall R^2 for the first stage, incorporating interactions, was .388, indicating that the model accounted for nearly 39% of the variability in the data.

Table 3

Stage 1 Regression to Predict Social Media Community Uptake

$R^2 = .388$	Unstandardized		Standardized		
	B	SE	β	t	p
Constant	0.030	0.072		0.419	0.675
Invitation Category	1.571	0.102	2.236	15.404	<.001*
Gender	0.002	0.013	0.004	0.198	0.843
Ethnicity					
Hispanic	0.018	0.019	0.020	0.943	0.345
Asian	0.002	0.016	0.003	0.132	0.895
Other Minority	0.002	0.033	0.001	0.048	0.961
Parent Education					
Less than HS Grad	-0.039	0.022	-0.034	-1.721	0.085
HS Grad	-0.039	0.019	-0.039	-2.102	0.036*
Some College	-0.130	0.012	-0.152	-10.815	<.001*
Residency Class					
CA Resident (non-local)	0.007	0.026	0.010	0.278	0.781
Non-Resident	0.003	0.030	0.004	0.114	0.909
Transfer GPA	-0.001	0.020	-0.001	-0.050	0.960
Gender Interaction	-0.007	0.018	-0.009	-0.398	0.691
Ethnicity Interactions					
Hispanic	-0.019	0.026	-0.016	-0.733	0.464
Asian	-0.048	0.023	-0.053	-2.093	0.036*
Other Minority	-0.049	0.047	-0.019	-1.040	0.298
Parent Ed Interactions					
Less than HS Grad	0.013	0.030	0.008	0.420	0.675
HS Grad	0.034	0.026	0.025	1.312	0.190
Some College	0.780	0.029	0.378	27.251	<.001*
Residency Interactions					
CA Resident (non-local)	-0.207	0.039	-0.282	-5.361	<.001*
Non-Resident	-0.296	0.044	-0.277	-6.725	<.001*
Transfer GPA Interaction	-0.316	0.028	-1.576	-11.471	<.001*

*Denotes a significant result, $p <= .05$.

    The results of the three instrumental variable analyses were examined and overall

model fit was compared using F and R^2. These results can be seen in Table 4. It should be

noted that, unlike with ordinary least squares regression, the R^2 value calculated for 2SLS does not have a straightforward statistical interpretation. Due to the multi-stage nature of the regression, and the fact that the second stage results are based upon predicted inputs, R^2 cannot be assumed to directly represent the portion of variability explained by the model, and can, in fact, sometimes result in a negative number. However, Pesaran and Smith (1994) demonstrated that R^2 can still be used as a valid criterion to evaluate the relative fit when comparing models.

The first model, which incorporated the instrument, predictor, and covariates, but no interaction effects, showed reasonable model fit, $F(11, 3907) = 45.000, p < .001$. Despite this, the R^2 value was only .112, indicating that only a small portion of the variability in the data could be explained by the model. In addition, the predictor of interest, participation category, was non-significant. This could imply that the instrument and covariates were insufficient to adequately predict student participation in the community.

Interaction terms were incorporated in the second and third models. This was done to test for possible interactions between invitation category and the other five predictors – gender, ethnicity, highest parent education level, residency classification, and transfer GPA – since the literature indicated that differences may exist in how these various groups use social media in general, implying that there could be differences in how social media influences their decisions about college selection.

The second 2SLS model, which incorporated interaction effects into the first stage of the regression model only, showed a substantial improvement in fit over the previous model, $F(11, 3907) = 75.446, p < .001$. In addition, a much larger portion of the variance was

explained, $R^2 = .175$. This indicates that interactions between invitation category and the covariates played an important role in the prediction of participation category. In other words, different types of students responded differently to the invitation to join the social media community, which in turn influenced the decision to matriculate. An inspection of the first stage regression results showed that four interactions significantly contributed to the prediction of participation in the community: the interaction with a highest parent education level of some college, $\beta = .38$, $t(3897) = 27.25$, $p < .001$, the interaction with being a non-local California resident, $\beta = -.28$, $t(3897) = -5.36$, $p < .001$, the interaction with being a non-resident, $\beta = -.28$, $t(3897) = -6.73$, $p < .001$, and the interaction with transfer GPA, $\beta = -1.58$, $t(3897) = -11.47$, $p < .001$.

By examining the results in Table 4 it becomes evident that, in addition to the variable of interest (participation category), ethnicity, highest parent education level, residency status, and transfer GPA were all statistically significant predictors of matriculation. Gender was not a significant predictor, but this was unsurprising given that men and women generally matriculate to the university at similar rates.

The third 2SLS model incorporated interaction effects into both the first and second stage regressions. However, a comparison of this model against the previous model showed that incorporating interaction terms into the second stage lead to significantly poorer model fit, $F(21, 3897) = 40.182$, and almost no additional variance was explained, $R^2 = .178$. This implies that, while interactions between invitation category and the covariates impacted students' decisions to participate in the social media community, once students had made the decision to participate, no additional variance could be explained by differences in their

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participation. It is interesting to note that participation category ceases to be a significant predictor in this model, and the sign changes from positive to negative. This is likely because incorporating interaction effects in the second stage regression causes a parsing of the impact of participation category among its many interactions with the covariates. Though the overall effect of participation is positive, as indicated by the other 2SLS regressions, after accounting for all possible stage two interactions, the residual effect is negative.

Table 4

Instrumental Variable Analyses Examining Social Media Communities and Matriculation

	IV Model 1		IV Model 2		IV Model 3	
	$F(11, 3907) = 45.000$		$F(11, 3907) = 75.446$		$F(21, 3897) = 40.182$	
	β	*p*	β	*p*	β	*p*
Constant		< 0.001		< 0.001		< 0.001
Participation Category	0.059	0.106	0.323	< 0.001*	-0.005	0.951
Gender	0.002	0.876	0.003	0.847	-0.001	0.979
Ethnicity						
Hispanic	0.008	0.648	0.004	0.792	-0.004	0.856
Asian	-0.078	< 0.001*	-0.066	< 0.001*	-0.096	< 0.001*
Other Minority	-0.043	0.005*	-0.042	0.002*	-0.051	0.015*
Parent Education						
Less than HS Grad	-0.036	0.024*	-0.029	0.043*	-0.047	0.044*
HS Grad	-0.059	< 0.001*	-0.053	< 0.001*	-0.099	< 0.001*
Some College	-0.024	0.115	-0.018	0.183	-0.123	< 0.001*
Residency Class						
CA Resident (non-local)	-0.268	< 0.001*	-0.229	< 0.001*	-0.260	< 0.001*
Non-Resident	-0.317	< 0.001*	-0.263	< 0.001*	-0.303	< 0.001*
Transfer GPA	-0.200	< 0.001*	-0.154	< 0.001*	-0.184	< 0.001*
Gender Interaction					0.002	0.933
Ethnicity Interactions						
Hispanic					0.009	0.738
Asian					0.029	0.334
Other Minority					-0.002	0.925

Parent Ed Interactions		
Less than HS Grad	0.018	0.450
HS Grad	0.057	0.011*
Some College	0.297	< 0.001*
Residency Interactions		
CA Resident (non-local)	0.064	0.268
Non-Resident	0.037	0.446
Transfer GPA Interaction	-0.125	0.065

*Denotes a significant result, $p <= .05$.

Propensity Score Analysis

The distributions of propensity scores for the control and treatment groups can be seen in Figure 4. As anticipated, score distribution was nearly identical for the two groups, reflecting their balance in terms of the covariates used to generate the scores.

However, in addition to balance, propensity scoring relies on the assumption that correct and sufficient covariates have been used in the generation of the scores. The use of too few or irrelevant covariates renders the results suspect (Rudner & Peyton, 2006). Though no definitive statistical tests exist to indicate whether a set of covariates will produce strong propensity scores, a variety of criteria may serve as indicators (Caliendo & Kopeinig, 2008). In the case of the current study, the covariates included in the dataset were extremely limited, and literature was not available to indicate which covariates might be useful in predicting use of school-sponsored social media. Thus, all available covariates were included in the analysis. Among participants in the treatment group, propensity scoring correctly predicted service uptake in 73.8% of cases. This represents a statistically significant, but marginal, improvement over the intercept-only model, which correctly predicted 72.4% of cases. Among students who chose to participate in school-sponsored social media, the model predicted correctly in only 12.2% of cases. In addition, only three

variables contributed significantly to the prediction of service uptake, with Hispanic students having a slightly higher propensity, and both non-local residents and non-residents having a lower propensity. These issues call into question the overall validity of the propensity scores.
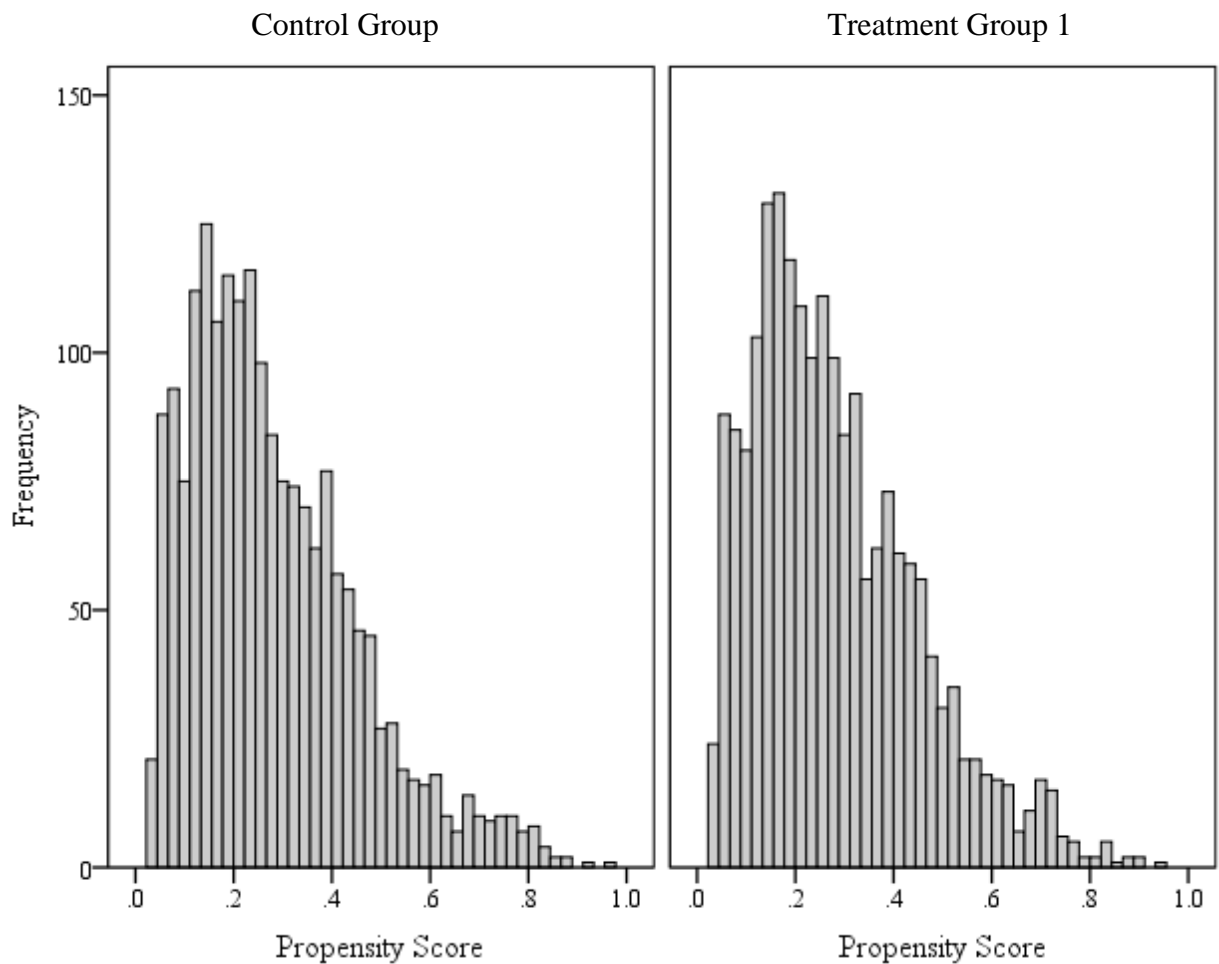
Figure 4. Distributions of propensity for service uptake within control and treatment groups.

Results of the propensity score analysis, including regression coefficients, Wald statistics, significances, and odds ratios, can be seen in Table 5. While the combined covariates were shown to be significant predictors of matriculation, neither participation category, nor the interaction between participation category and the combined covariates,

rose to the level of statistical significance. In fact, this model indicated even less

significance for the variable of interest than did the ITT model, $OR = 1.12$, $p = 0.14$, which

is considered to be quite conservative. This is not entirely unexpected, given that, as

mentioned earlier, this version of Follman's propensity scoring technique is not intended to

result in a true TOT estimation, and that his alternate version, which is intended to produce a

LATE, introduces other unreliabilities. The Nagelkerke pseudo-R^2 value was .083,

suggesting that only a small portion of the variability in the data could be explained by the

model. Hosmer and Lemeshow's goodness-of-fit test was significant, χ^2 (8, $N = 4124$) =

18.66, $p = .017$, indicating a rejection of the null hypothesis that the model predictions are

consistent with the data, and thus poor overall model fit.

Table 5

Propensity Score Analysis Examining Social Media Communities and Matriculation

	B	SE	Wald χ^2	df	p	OR
Constant	-2.602	0.143	332.318	1	<0.001	0.074
Invitation Category	0.031	0.204	0.023	1	0.880	1.031
Combined Covariates	4.350	0.426	104.495	1	<0.001*	77.472
Propensity Score Interaction	0.327	0.617	0.280	1	0.597	1.386

*Denotes a significant result, $p <= .05$.

Comparison of the Results

A comparison of all IV and PS models was conducted to determine which

represented the strongest overall model. Side-by-side results can be seen in Table 6.

Among the instrumental variable models, fit statistics strongly suggest the second, in

which covariate interactions were incorporated into stage 1, but not into stage 2, to be the

preferred model. As was indicated above, this suggests that covariate interactions with

invitation category play an important role in predicting participation category, but that once participation has been determined, covariate interactions with participation category play a less important role in predicting matriculation. In conceptual terms, this means that different types of students will respond differently to an invitation to participate in school-sponsored social media, but once they have decided whether or not to participate, there is little evidence to suggest that actual participation impacts these different types of students differently.

Several concerns arose over the strength and validity of the propensity score results. Due to the limited number of covariates, and the lack of available literature to indicate which covariates might impact service uptake, there was uncertainty as to the overall quality of the propensity scores. This model also exhibited generally poor fit, as was evidenced by significant results on the Hosmer and Lemeshow's goodness-of-fit test.

A direct comparison of the quality of the results between the preferred IV model and the propensity score model is not possible, given the different types of fit statistics used to measure each. However, given that the instrument used in the instrumental variable analyses (invitation category) was shown to be extremely strong, while the covariates used in the propensity score analysis were questionable in their ability to predict service uptake, and given that the preferred IV model demonstrated reasonable model fit, while the PS model demonstrated decidedly poor fit, the second instrumental variable model was deemed strongest overall, and considered to be the final model.

A more conceptual comparison of the instrumental variable and propensity scoring methodologies can be found in Appendix A.

Table 6

Results of All Analyses Examining Social Media Communities and Matriculation

	IV Model 1 $F(11, 3907) = 45.000$		IV Model 2 $F(11, 3907) = 75.446$		IV Model 3 $F(21, 3897) = 40.182$		PS Model		
	β	*p*	β	*p*	β	*p*		*OR*	*p*
Constant		< 0.001		< 0.001		< 0.001	Constant		< 0.001
Participation Category	0.059	0.106	0.323	< 0.001*	-0.005	0.951	Participation Category	1.031	0.880
Gender	0.002	0.876	0.003	0.847	-0.001	0.979			
Ethnicity									
Hispanic	0.008	0.648	0.004	0.792	-0.004	0.856			
Asian	-0.078	< 0.001*	-0.066	< 0.001*	-0.096	< 0.001*			
Other Minority	-0.043	0.005*	-0.042	0.002	-0.051	0.015*			
Parent Education									
Less than HS Grad	-0.036	0.024*	-0.029	0.043*	-0.047	0.044	Covariates	77.472	< 0.001*
HS Grad	-0.059	< 0.001*	-0.053	< 0.001*	-0.099	< 0.001*			
Some College	-0.024	0.115	-0.018	0.183	-0.123	< 0.001*			
Residency Class									
CA Resident (non-local)	-0.268	< 0.001*	-0.229	< 0.001*	-0.260	< 0.001*			
Non-Resident	-0.317	< 0.001*	-0.263	< 0.001*	-0.303	< 0.001*			
Transfer GPA	-0.200	< 0.001*	-0.154	< 0.001*	-0.184	< 0.001*			
Gender Interaction					0.002	0.933			
Ethnicity Interactions							Propensity Score Interaction	1.386	0.597
Hispanic					0.009	0.738			
Asian					0.029	0.334			

Other Minority	-0.002	0.925	
Parent Ed Interactions			
Less than HS Grad	0.018	0.450	
HS Grad	0.057	0.011*	
Some College	0.297	< 0.001*	
Residency Interactions			
CA Resident (non-local)	0.064	0.268	
Non-Resident	0.037	0.446	
Transfer GPA Interaction	-0.125	0.065	

*Denotes a significant result, $p <= .05$.

Chapter 4: Social Media and Transfer Student Retention

Description of the Analyses

The second set of analyses addresses the impact of social media on transfer students' longer-term outcomes, including persistence and overall academic performance. Does participation in social media networking communities prior to matriculation contribute to transfer students' academic success? Do students who participate persist longer, have higher GPAs, or greater likelihood of graduating? Do these results vary based on observable characteristics, such as gender, ethnicity, and type of major?

Again, based on indications in the literature that sense of belonging is closely correlated with transfer students' educational outcomes, it was hypothesized that participation in the community would have a small impact on transfer students' distal outcomes. The impact was expected to be smaller than that on matriculation, given that it would be somewhat mitigated by students' participation in other activities after arriving on campus.

Methodologically speaking, these analyses are somewhat simpler than those discussed in chapter 3. Rather than looking at all students in Treatment Group 1 and the Control Group, these focus only on the subset of those students who at some point registered for the Fall 2012 term, thereby expressing an intent to matriculate. This sample consists of a total of 1025 students, with 529 having received the invitation to join the social media community, and 496 not having received the invitation. Adherence to assigned treatment was nearly perfect for this subpopulation. Within the control group, only two students somehow heard about the community and asked to join. Within the treatment group, only

one student chose not to participate in the community. Due to the size of the sample, and

this extremely low rate of non-compliance, the ITT and TOT estimates would be nearly

identical. Mathematically, this could be conceptualized by dividing the ITT outcome by the

percentage in the ITT group who actually received the treatment (consistent with the Wald

estimator). In the case of perfect compliance, this would be 100% or 1. Because dividing

by 1 leaves the outcome unaltered, the ITT and TOT estimates would be the same. Thus,

the closer compliance is to 100%, the more similar the ITT and TOT estimates will be. In

the case of this study, given the compliance rate of 99.7% within the sample being

examined, an ITT framework can be utilized without resulting in a biased estimate of the

treatment's effectiveness.

Bias in Intention-to-Treat Research Designs

One of the key advantages of an ITT estimate is that it is ostensibly free from

selection bias, since it allows for the maintenance of "treatment groups that are similar apart

from random variation," and it "allows for non-compliance and deviations from policy by

clinicians" (Hollis & Campbell, 1999). However, in order for this to hold true, several

assumptions must be met:

1. There must be no non-random missing data, particularly outcome data.

2. There must be no "crossover" or "spillover" effect (i.e. no interference between
   units, particularly between the ITT group and the control group).

3. There must be no "false inclusions," or participants who were included despite
   not meeting the eligibility criteria.

4. There must be no non-random mediating effects.

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These assumptions will be examined individually to determine how well the data meets each one.

No non-random missing data. Any time missing data requires that some participants be left out of an analysis, it raises the question of introducing bias, since missing data is often systematic. In ITT studies, this comes up most often when participants in the treatment group drop out of or decline treatment, and then do not supply outcome data. This would cause the ATE to be overestimated, and runs counter to the whole philosophy of ITT designs, which holds that outcomes for all participants in the treatment group must be used regardless of whether or not they actually received treatment.

According to White, Carpenter, and Horton (2012), "there is confusion about how the ITT principle should be applied in the presence of missing outcome data." They suggest four steps for dealing with systematically missing outcome data in ITT analyses:

1. Attempt to follow up all randomized individuals, even if they withdraw from allocated treatment.

2. Perform a main analysis that is valid under a plausible assumption about the missing data and uses all observed data.

3. Perform sensitivity analyses to explore the impact of departures from the assumption made in the main analysis.

4. Account for all randomized individuals, at least in the sensitivity analyses.

In the case of the current study, all outcome variables of interest are available for all participants. However, because most input variables rely on self-reported data from the students, some inputs are missing for both the treatment and control groups. Luckily, this

data was collected from students prior to their being randomly assigned to treatment, so participants with missing data are randomly distributed across treatment and control groups. Thus, the missing data does not reflect a systematic flaw in the research design. In addition, missing data is minimal within the data set, so few participants needed to be excluded from analysis for this reason.

No spillover or crossover. Spillover happens when participants in the control group are influenced by participants in the treatment group, contaminating the results, and leading to an underestimation of ATE. Crossover describes the situation when participants in the control group end up receiving treatment. Both are common in social science research, and typically experiments are not designed in such a way as to allow for the measurement of spillover (Baird, Bohren, McIntosh, & Ozler, 2014), so in practice, this assumption may often be violated.

Estimating the degree of spillover between participants in the current study is impossible. Because many students within the treatment group had various interactions with students in the control group, possibly because they attended the same community college, because they attended orientation together, because they socialized through other social media channels, and ultimately because they transferred to the same University, it is certain that some contamination between the two groups occurred. However, the degree of crossover was extremely light, as is evidenced by the fact that only two students in the control group heard about the community and requested to join. This indicates that spillover contamination may also have been slight. In addition, though spillover does introduce some degree of bias into the ITT estimate, it is more likely, in this case, to mitigate or mask the

effects of treatment than to magnify them, due to the fact that students in the control group may have received some of the benefits of treatment second-hand through other types of interactions with peers. As a result, spillover should increase the likelihood of type II error, resulting in a more conservative estimate of treatment effects.

No false inclusions. False inclusions occur when participants who do not meet the eligibility criteria are included in the ITT and/or control group by mistake, leaving the researcher with the question of how to deal with these participants. Hollis and Campbell (1999) recommend that, "false inclusions should also generally not be excluded from an intention to treat analysis. Their exclusion can be justified only if the reascertainment of the entry criteria is applied identically in each group."

Because the only criteria for participation in this study was that the students must have been junior-level transfers matriculating to the University in the Fall of 2012, and all participants in both groups met that criteria, the assumption of no false inclusions has been met.

No non-random mediators. Non-random mediators represent situations in which an unaccounted-for interaction effect skews the results of a study. Educational studies are probably at greatest risk of non-random mediators when randomization occurs at a level other than that of the individual, such as at the classroom or school level, as the treatment may impact both the student and the classroom, which in turn impacts the student more. As a result, the actual effect of the treatment will be overestimated, because a portion of the ATE will be due to this interaction between the treatment and the classroom rather than due to the direct influence of the treatment on the student (VanderWeele, Hong, Jones, &

Brown, 2011). Because this mediator is systematically altered for the treatment schools

only, it ceases to be random.

In the case of this study, because treatment was assigned randomly at the individual

participant level, it is unlikely that any non-random mediators were introduced.

Mixing Binary and Continuous Outcomes

This study is complicated by the fact that it includes three different, related outcomes

– persistence, degree status, and overall GPA – which are each measured on different scales.

Both persistence and overall GPA can be considered continuous variables. Though

persistence is measured in discrete intervals within a wider range, while GPA is measured

more or less continuously within a narrower range, these two variables could easily be

incorporated into one MANCOVA analysis. Tabachnick and Fidell (2007) describe some of

the advantages to combining dependent variables (DVs) into a single multivariate analysis:

> With multiple DVs, a problem of inflated error arises if each DV is tested separately.
>
> Further, at least some of the DVs are likely to be correlated with each other, so
>
> separate tests of each DV reanalyze some of the same variance…. Multivariate
>
> statistics help the experimenter design more efficient and more realistic experiments
>
> by allowing measurement of multiple DVs without violation of acceptable levels of
>
> Type I error.

However, because degree status is a binary outcome, and MANCOVA assumes that

all outcomes are continuous, it could not be included in such an analysis along with the other

two outcomes.

One possibility is to perform separate analyses of each outcome, or separate analyses of the continuous and binary outcomes. Though this increases the risk of Type I error, and of the same variance being reanalyzed across multiple tests, Teixeira-Pinto and Mauri (2011) acknowledge that this is a common approach in studies with multiple outcomes. They also indicate that this method can provide relatively unbiased estimates of effect size, but may overestimate error:

> When the study outcomes have no missing values (or they are missing completely at random), analyzing each outcome separately will provide unbiased estimates for the treatment effects, even if the outcomes are correlated. In this case, the separate models for each outcome will give correct effect estimates of the covariates but some may have larger SEs than if the correlations among outcomes were considered.

They go on to describe a possible method for integrating "noncommensurate" outcome types into a single model. This involves incorporating a unifying latent variable, which specifies the correlations between the outcomes, into each individual regression equation. This serves to link the equations, and by controlling for the correlation between the outcomes, one can examine each outcome as independent of the others. However, they do acknowledge that the primary utility of such a method would be in situations where data is missing for some outcomes, and that "with sufficiently large sample sizes, investigators may not be concerned, so that the tradeoff between simplicity of the analysis procedure and larger errors might favor the simple one-outcome-at-a-time approach" (Teixeira-Pinto & Mauri, 2011).

Given the reasonably large sample size, and the fact that all outcome variables were present for all participants, performing two separate analyses was deemed sufficient. Thus, a binary logistic regression was performed on the binary variable, degree status, and a single MANCOVA analysis was performed on the two continuous variables, persistence and overall GPA.

Methods

Sub-sample

For the purposes of these analyses, only students who registered for the Fall 2012 term (thus demonstrating an intent to matriculate), and who were part of either Treatment Group 1 or the Control Group were analyzed, for a total of 1026 students. Seventy-six students were missing data on one or more of the predictor variables, and were thus excluded from the analysis, leaving a total of 950 participants. Examination of the missing data showed no indication that the missing-at-random assumption was violated, and data imputation was deemed unnecessary.

Statistical Analyses

All analyses discussed in this chapter were conducted using SPSS version 23.0.

Binary Outcome – Degree Status. The first analysis examined the dependent variable of primary interest, degree status. Due to the binary nature of the outcome, and the varied inputs, binary logistic regression seems most appropriate. A detailed description of this method can be found in the previous chapter. In the current context, the basic regression equation remains the same:

$$\ln\left(\frac{\widehat{Y}_i}{1 - \widehat{Y}_i}\right) = A + \sum B_j X_{ij}$$

Here $\widehat{Y}_i$ represents the predicted probability that student i will receive a bachelor's degree within six quarters.

Analyses were performed sequentially, with the independent variable of interest, treatment group, being introduced in block 1, the six covariates (gender, ethnicity, parent education level, residency status, transfer GPA, and STEM major classification) being introduced in block 2, and interaction effects between treatment group and the covariates being introduced in block 3. This allowed for the determination of whether treatment had a greater impact for some populations than for others, as the literature indicates differences in social media use and impact based on gender among other traits. Fit statistics and 95% confidence intervals were examined for all models.

Continuous Outcomes – Persistence and Overall GPA. The second analysis examined the two continuous outcomes, persistence and overall GPA. Due to the mix of both binary and continuous predictors, MANCOVA was used to conduct the analysis. MANCOVA is considered appropriate for situations in which some predictors are discrete and some continuous, and all outcomes are continuous. The analysis was performed using the General Linear Model (GLM) dialog in SPSS, as MANCOVA represents an expansion on the basic GLM in which more than one equation is required to relate all independent variables to the dependent variables. The required number of equations is usually equal to the number of input variables or the number of output variables, whichever is smaller (Tabachnick & Fidell, 2007).

Wilks' Lambda was examined to determine the significance and effect size of the relationships between the independent and dependent variables, and tests of between-subjects effects were examined to determine more specifically from where any significant results uncovered in the Wilks' tests stemmed.

Data Screening

As mentioned previously, binary logistic regression is relatively free of assumptions regarding the data and its distribution (Tabachnick & Fidell, 2007). However, preliminary data screening was performed to determine whether the assumptions of MANCOVA were violated, and this procedure revealed several issues with the data.

Examination of histograms revealed that while the distribution of GPAs was roughly normal, distribution of persistence showed a strong negative skew, as the vast majority of students persisted for a full six quarters. Due to the large sample size, and the robustness of MANCOVA to this type of assumption violation, this was not deemed to be problematic.

Examination of box plots revealed 13 subjects to be univariate outliers due to very low GPA, and due to the very strong negative skew, all students who failed to persist for six quarters were revealed to be univariate outliers. Calculation of Mahalanobis distance revealed 31 multivariate outliers, which included all students who persisted for two or fewer quarters, as well as one student who persisted for three quarters, but with an exceptionally low GPA. Given the fact that persistence was a variable of strong interest to the researcher, these outliers were not removed, but it is acknowledged that this could increase the probability of Type 1 error.

Box's M revealed no significant violation of the assumption of equality of covariance matrices. Levene's test of equality of variances was nonsignificant for both dependent variables.

Results

Degree Status – Binary Logistic Regression

Of the 1026 students in the sub-sample, 806, or 78.6%, received a degree within normative time (six quarters from the point of matriculation). Within the treatment group, 79.6% of students received their degrees, whereas in the control group 77.5% of students received their degrees, a difference that was not statistically significant.

After the removal of cases with missing data on one or more covariates, 950 cases were left in the sample, including 454 in the control group, and 496 in the treatment group.

The first block of the model, which included all seven predictors but no interaction effects, showed statistically significant improvement in model fit over an intercept-only model, χ^2 (12, N = 950) = 34.81, p = .001. In this block, using the default cut value of .5, 743 of 745 students who received a degree, or 99.7%, were correctly classified. However, only one of 205 students who did not receive a degree, or 0.5%, were correctly classified. Thus, the overall accuracy was 78.3%. The Nagelkerke pseudo-R^2 value was .056, suggesting that only a small portion of the variability in the data can be explained by the model. Hosmer and Lemeshow's goodness-of-fit test was non-significant, χ^2 (8, N = 950) = 4.05, p = .852, indicating adequate model fit.

Interaction terms were incorporated in the second block. Specifically, this was to test for possible interactions between treatment group and the other six predictors – gender,

ethnicity, highest parent education level, residency classification, transfer GPA, and STEM

major classification. A comparison of this block against the previous block did not show

statistically significant improvement in model fit, χ^2 (11, N = 950) = 16.236, p = .133. In

this block, 741 of 745 students who received a degree, or 99.5%, were correctly classified,

while only five of 205 students who did not receive a degree, or 2.4%, were correctly

classified, for an overall accuracy of 78.5%. This demonstrates that incorporation of

interaction terms leads to only a marginal improvement in the prediction of students who are

unlikely to receive their degrees within normative time. The Nagelkerke pseudo-R^2 value

was .081, indicating, again, that only a small portion of the variability in the data can be

explained by the model, though this actually represents a substantial improvement over the

previous block. Hosmer and Lemeshow's goodness-of-fit test was non-significant, χ^2 (8, N

= 950) = 5.161, p = .740, demonstrating adequate model fit. Despite the fact that fit was not

significantly improved by the incorporation of interaction terms, two covariates did exhibit

significant interaction effects, so the results are included in Table 7 for consideration.

Table 7 shows regression coefficients, Wald statistics, significances, odds ratios, and

95% confidence intervals for odds ratios for each of the seven predictor variables, as well as

the interaction effects between treatment group and the covariates. Within both blocks

gender and STEM major category emerged as statistically significant predictors of degree

attainment within normative time, with women being significantly more likely than men to

receive their degrees within normative time, and those in STEM fields significantly less

likely than their non-STEM peers to receive their degrees within normative time. Ethnicity

emerged as a significant predictor within block 1 only, with students falling into the "other

minority" category being significantly less likely to have received their degrees within normative time than white students. Because relatively few students fall into this category, its significance may also be underestimated.

Participation category did not emerge as a significant predictor in either block, indicating that participation in school-sponsored social media is unlikely to influence students' ability to complete their bachelor's degree within normative time.

Though block 2 did not exhibit significant improvement in fit over block 1, it is worth noting that several interactions did demonstrate statistical significance. This model indicated that Asian students who participated in school-sponsored social media were more likely than other students to graduate on time, while, interestingly, non-resident students who participated were less likely than other students to graduate on time.

Table 7

Logistic Regression Results of Social Media Participation and Covariates on Baccalaureate Degree Attainment within

Normative Time

	Block 1 (*N* = 950)							Block 2 (*N* = 950)						
	B	SE	Wald χ^2	*df*	*p*	OR	95% CI	*B*	SE	Wald χ^2	*df*	*p*	OR	95% CI
Constant	1.360	0.275	24.390	1	<0.001	3.895		1.364	0.351	15.108	1	<0.001	3.912	
Participation Category	0.137	0.161	0.718	1	0.397	1.146	0.836 - 1.573	0.029	0.540	0.003	1	0.957	1.029	0.357 - 2.965
Gender	0.603	0.164	13.456	1	<0.001*	1.828	1.324 - 2.522	0.690	0.237	8.498	1	0.004*	1.993	1.254 - 3.169
Ethnicity			6.869	3	0.076					4.035	3	0.258		
Hispanic	-0.289	0.219	1.740	1	0.187	0.749	0.488 - 1.151	-0.545	0.311	3.068	1	0.080	0.580	0.315 - 1.067
Asian	0.019	0.229	0.007	1	0.935	1.019	0.651 - 1.596	-0.485	0.325	2.231	1	0.135	0.616	0.326 - 1.164
Other Minority	-0.913	0.392	5.421	1	0.020*	0.401	0.186 - 0.866	-0.469	0.575	0.664	1	0.415	0.626	0.203 - 1.932
Parent Education			1.112	3	0.774					0.320	3	0.956		
Less than HS Grad	0.063	0.294	0.046	1	0.831	1.065	0.598 - 1.896	0.173	0.406	0.182	1	0.670	1.189	0.536 - 2.636
HS Grad	-0.133	0.261	0.261	1	0.609	0.875	0.525 - 1.460	-0.018	0.389	0.002	1	0.964	0.982	0.458 - 2.106
Some College	0.162	0.213	0.581	1	0.446	1.176	0.775 - 1.786	0.125	0.308	0.164	1	0.685	1.133	0.619 - 2.073
Residency Class			0.336	2	0.845					4.083	2	0.130		
CA Resident (non-local)	-0.058	0.241	0.057	1	0.811	0.944	0.588 - 1.515	0.103	0.329	0.097	1	0.755	1.108	0.581 - 2.114
Non-Resident	-0.198	0.353	0.316	1	0.574	0.820	0.410 - 1.638	1.023	0.558	3.358	1	0.067	2.780	0.931 - 8.300

	B	SE	Wald	df	Sig	Exp(B)	95% CI	B	SE	Wald	df	Sig	Exp(B)	95% CI
Transfer GPA	-0.001	0.004	0.095	1	0.758	0.999	0.990 - 1.007	-0.005	0.005	0.896	1	0.344	0.995	0.984 - 1.006
STEM Major Category	-0.524	0.165	10.100	1	0.001*	0.592	0.429 - 0.818	-0.705	0.237	8.870	1	0.003*	0.494	0.311 - 0.786
Gender Interaction								-0.097	0.334	0.085	1	0.771	0.907	0.471 - 1.747
Ethnicity Interactions										6.431	3	0.092		
Hispanic								0.478	0.442	1.169	1	0.280	1.612	0.678 - 3.833
Asian								1.009	0.473	4.545	1	0.033*	2.742	1.085 - 6.929
Other Minority								-0.694	0.805	0.744	1	0.388	0.500	0.103 - 2.418
Parent Ed Interactions										0.127	3	0.988		
Less than HS Grad								-0.058	0.603	0.009	1	0.924	0.944	0.289 - 3.079
HS Grad								-0.158	0.531	0.089	1	0.766	0.854	0.302 - 2.417
Some College								0.049	0.433	0.013	1	0.909	1.051	0.450 - 2.452
Residency Interactions										10.712	2	0.005*		
CA Resident (non-local)								-0.243	0.493	0.242	1	0.623	0.785	0.299 - 2.062
Non-Resident								-2.168	0.754	8.261	1	0.004*	0.114	0.026 - 0.502
Transfer GPA Interaction								0.007	0.009	0.589	1	0.443	1.007	0.989 - 1.025
STEM Major Interaction								0.398	0.335	1.406	1	0.236	1.489	0.771 - 2.873

*Denotes a significant result, $p <= .05$.

Persistence and Overall GPA – MANCOVA

Because the decision was made not to remove outliers from the sample, this analysis also included 950 subjects, with 454 being from the control group and 496 being from the treatment group. Four students removed for missing data were also among those considered to be outliers.

Wilks' Lambda revealed that a couple of the covariates demonstrated small but statistically significant relationships with the dependent variables. Alpha was adjusted to 0.004 to account for the fact that twelve multivariate tests were run. At this level, significant covariates included only gender, $F(2, 936) = 5.844$, p $= .003$, partial $\eta^2 = .012$, and an ethnicity of Asian, $F(2, 936) = 9.176$, p $< .001$, partial $\eta^2 = .019$. Participation category was not shown to have a significant multivariate relationship with the dependent variables, indicating that participation in school-sponsored social media is unlikely to influence the GPA or persistence of matriculated students.

Table 8 shows the univariate results for each dependent variable by all input variables, thus revealing the source of the significant results uncovered in the Wilks' test. In this case, to address the fact that 24 tests were run, alpha was adjusted to .002. Both gender and an ethnicity of Asian were found to be significantly related to GPA, but no covariates were found to be significantly related to persistence, likely due to the fact that nearly all students in the sample persisted for a full six quarters. Again, participation category was not shown to have a significant relationship with either of the outcomes.

Table 8

MANCOVA Between-Subjects Results of Social Media Participation and Covariates on GPA and Persistence

	Outcome	Type III SS	df	MS	F	p	Partial η^2
Intercept	GPA	891.464	1	891.464	3493.008	<0.001	0.788
	Persistence	2912.991	1	2912.991	3623.503	<0.001	0.795
Invitation Category	GPA	0.148	1	0.148	0.579	0.447	0.001
	Persistence	0.006	1	0.006	0.008	0.929	<0.001
Gender	GPA	2.900	1	2.900	11.362	0.001*	0.012
	Persistence	0.648	1	0.648	0.806	0.370	0.001
Ethnicity							
Hispanic	GPA	1.988	1	1.988	7.788	0.005	0.008
	Persistence	1.513	1	1.513	1.882	0.170	0.002
Asian	GPA	4.466	1	4.466	17.498	<0.001*	0.018
	Persistence	0.684	1	0.684	0.850	0.357	0.001
Other Minority	GPA	1.144	1	1.144	4.484	0.034	0.005
	Persistence	3.096	1	3.096	3.851	0.050	0.004
Parent Education							
Less than HS Grad	GPA	0.595	1	0.595	2.333	0.127	0.002
	Persistence	0.836	1	0.836	1.040	0.308	0.001
HS Grad	GPA	1.809	1	1.809	7.090	0.008	0.008
	Persistence	1.464	1	1.464	1.821	0.178	0.002
Some College	GPA	0.165	1	0.165	0.646	0.422	0.001
	Persistence	0.054	1	0.054	0.067	0.795	<0.001
Residency Class							
CA Resident (non-local)	GPA	0.142	1	0.142	0.557	0.456	0.001
	Persistence	1.328	1	1.328	1.652	0.199	0.002
Non-Resident	GPA	0.718	1	0.718	2.813	0.094	0.003
	Persistence	0.900	1	0.900	1.120	0.290	0.001
Transfer GPA	GPA	0.745	1	0.745	2.917	0.088	0.003
	Persistence	2.678	1	2.678	3.332	0.068	0.004
STEM Major Category	GPA	0.379	1	0.379	1.486	0.223	0.002
	Persistence	0.546	1	0.546	0.679	0.410	0.001

*Denotes a significant result, $p <= .002$.

Chapter 5: Discussion

Summary of the Study and Findings

This study is intended to explore the relationship between participation in school-sponsored social media and both proximal and distal outcomes for transfer students. While extensive literature exists on transfer student success factors, and social media is a rapidly emerging focus within social science research, at present little data exists to demonstrate how school-sponsored social media influences student decision-making and persistence, or whether such interventions are effective. Despite this lack of hard evidence, the use of social media within higher education is growing exponentially, for everything from recruitment to promoting involvement on campus to connecting with alumni. It seems clear that while the specific platforms may change, such tools are here to stay, and the current crop of digitally native college students have come to expect and rely on them. Having a more robust understanding of their impact can help administrators to make better decisions regarding how to use them effectively, as well as the type and amount of resources that should be expended to properly maintain them.

Specifically, the study was intended to bring about a firmer understanding of whether providing prospective college transfer students with the opportunity to network with their peers through social media would influence their decision to matriculate, and their academic performance post-matriculation.

This was tested using a random assignment study in which one group of admitted students were invited to join a school's official social media community and another was

not. Two years later, their matriculation rates, graduation rates, GPAs, and persistence toward degree were collected and examined.

Proximal Outcome – Matriculation

Because actual uptake of the service was low (27.6%), the matriculation data was analyzed through an instrumental variable framework using two-stage least squares regression. Three different models were tested – one incorporating no interaction effects between treatment and the covariates, one incorporating interactions in the first stage regression only, and one incorporating interactions in both the first and second stage regressions. The second model, incorporating interaction effects into the first stage regression only, resulted in the strongest overall model fit, and was thus retained. The data was also analyzed using propensity scoring, but this model was discarded due to poor overall fit, and uncertainty over the quality of the covariates used to calculate the scores.

Results (Table 4) revealed that the majority of factors influencing students' matriculation decisions were beyond the scope of the study (as evidenced by the modest R^2 value). Further, the low overall rate of uptake indicates that providing access to social media networking opportunities is unlikely to influence most students' behavior. However, the analysis did reveal that providing social media networking opportunities significantly influenced the matriculation decisions of students who chose to participate, with the Wald Estimator indicating an overall effect size of 5.3%. While not a large difference, when applied across thousands of students considering a particular school, this could produce a substantial increase in overall yield.

In addition to invitation category, five other predictors were incorporated into the model – gender, ethnicity, highest parent education level, residency classification, and transfer GPA. Of these, all but gender were found to significantly influence matriculation.

The study provided some evidence that access to social media networking opportunities influenced certain groups differentially. Specifically, interaction effects in the first stage regression between invitation category and highest parent education level indicated that students whose parents had some college were significantly more likely to participate in the social media community than students whose parents were college graduates, though the reason for this difference is unclear. Interaction effects between invitation category and residency class indicated that non-local residents and non-residents were significantly less likely to participate in the community than locals, which ran counter to the researcher's expectation that students living farther away would be more likely to join in an effort to build community. Students with higher transfer GPAs were also less likely to participate in the community. Both of these phenomena could be because students of these types are more likely to have made matriculation decisions based on other criteria, and are therefore less interested in engaging with the University or other prospective students through social media.

While the analysis indicated some difference in students' patterns of service uptake, it provided no evidence that, after joining the community, they benefitted differentially from participation within it. In other words, while different types of students may have been more or less likely to participate in the community when offered, there was no indication that, after joining, participation in the community impacted them differently.

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Distal Outcomes – Retention and Graduation

Degree attainment was analyzed using binary logistic regression, while both persistence and overall GPA were analyzed using MANCOVA. Neither analysis revealed significant results with respect to the variable of interest, participation category. This implies that, while participation in school-sponsored social media may have some modest effect on transfer students' decisions to matriculate, it has little or no longer-term impact on academic success post-matriculation.

Six other predictors were also incorporated into the analyses - gender, ethnicity, highest parent education level, residency classification, transfer GPA, and STEM major category. Both gender and ethnicity were found to significantly influence overall GPA and degree attainment. STEM major category was found to influence degree attainment only. Even with the incorporation of these additional variables, very little of the variability in the data was explained by these models.

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Discussion of the Findings

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Proximal Outcome – Matriculation

Prior to the running of any analyses, it was apparent from the low overall participation in the social media community even among those who were invited (27.6%) that most students make their matriculation decisions based on criteria that were not incorporated into the study, and that social media networking opportunities would have a limited ability to influence students' behavior. This was then borne out by the low overall R^2 of the preferred instrumental variable model, which indicated that only a small portion of the variance in matriculation was explained. In terms of college matriculation patterns, this

makes sense. According to the 2014 State of College Admission report published by

NACAC, 81% of freshman applicants in 2013 applied to at least three schools, a number

that has been rising steadily in recent years, and reflects a nearly 20% increase when

compared with 20 years earlier. Even more surprising is the number of applicants applying

to seven or more institutions, which has greater than tripled in the past 20 years, and now

reached 32%. This increase could be related to a perceived increase in college selectivity

(providing students with incentive to apply to multiple schools in order to increase the

chances of getting accepted to at least one), and the proliferation of online and common

applications (decreasing barriers to applying to multiple schools). It stands to reason that

most students applying to multiple colleges will have preferences among those to which they

applied, and will accept admission to the school they most prefer among those to which they

were offered admission. Thus, in terms of matriculation, students most likely to be

influenced in their choice of college by participation in a social media community are those

who have not yet made a definitive choice based on other criteria. However, the results do

provide evidence that for students in this situation, social media networking opportunities

can have a small but statistically significant impact.

Examination of the output from the preferred IV model (Table 4) shows a few other

interesting results. When compared with white students, Asian students were significantly

less likely to matriculate, $\beta = -.07$, $t(3907) = -4.01$, $p < .001$. This is interesting in that white

students and Asian students are generally believed to be similar in their college

matriculation patterns, given their socio-economic similarities. However, because no data is

available on what happened to students who did not matriculate, it is impossible to say

exactly what this difference represents. It may be that Asian students are more likely to choose to attend a different type of institution if given multiple options (for instance, more likely to attend a private college or more likely to attend a college with a larger Asian population). Another interesting finding was that Hispanic students matriculated at a rate nearly identical to white students, which is encouraging in terms of recruitment of traditionally underrepresented students, though this finding is likely highly contextual, and not representative of what would be observed among other populations or at other institutions. Unfortunately, other minority students were significantly less likely to matriculate than white students, $\beta = -.04$, $t(3907) = -3.12$, $p = .002$, indicating a need for further study of and possibly targeted intervention toward this group.

Results for highest parent education level were fairly predictable. Students whose parent had graduated college served as the comparison group as they were by far the most numerous. Students whose parent had some college did not differ significantly from the comparison group in their matriculation rate, which is unsurprising given that many of the factors which might be expected to influence whether a student matriculates to a certain school (e.g., knowledge of financing options, knowledge of school rank, understanding of college culture, etc.) would likely be similarly influenced by having any parent who attended college, regardless of whether that parent graduated. First generation college students, both those whose parent had graduated high school, and those whose parent had not, were significantly less likely to matriculate.

Results for residency status, while significant, were not unexpected. Both non-local California residents and non-residents were far less likely to matriculate than locals. Of

some interest is the fact that the betas for non-local residents and non-residents differed so little. This may be due to the fact that non-residents who did not have a serious interest in the university would not bother to go through the application process. Thus, more non-residents would be weeded out of the pool of possible matriculants at the point of application.

The negative relationship between transfer GPA and matriculation was expected, given that students who perform better at their previous institution will likely have more transfer options.

Distal Outcomes – Retention and Graduation

Though nearly all students who were offered access to the social media community at admission, and then later matriculated, chose to join, the data set did not include information on continued participation in the community post-matriculation. Therefore, it is impossible to know whether these students continued to use this resource after coming to the University, or whether its use subsided once students had the opportunity to network in other ways.

Both graduation rates and GPAs were slightly, but not significantly, higher within the treatment group than in the control group, with 79.6% of students in the treatment group receiving their degrees within six quarters, as opposed to only 77.5% in the control group, and students in the treatment group having an average GPA of 3.06, as opposed to an average GPA of 3.04 in the control group. Though non-significant, these results are encouraging in terms of promoting student success, and it is possible that the University could improve these results by using the community more proactively. Remember from

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Chapter 2 that University officials' participation in the community was minimal, and strictly to ensure the maintenance of a safe and open environment through which prospective students could interact with one another. However, many schools make more robust use of such communities, actively encouraging student participation through the incorporation of practical features like roommate-finder tools and direct access to campus resources, pairing new and prospective students with current student mentors, and hiring staff or student workers to answer postings and create seed postings. These tactics could help to improve student participation and foster a stronger early sense of belonging, as well as ease the transition between schools and put students in touch with needed resources, all of which the literature revealed to positively impact transfer student success. Given the minimal but generally positive results observed in this study, further investigation into these options could be worthwhile.

Factors shown by the analyses to impact degree attainment and overall GPA were not unexpected. Results from block 1 of the binary logistic regression (Table 7) show that women were more likely than men to graduate within normative time, $B = .60$, χ^2 (1, N = 950) = 13.46, p < .001. Students classified as "other minority" were less likely than white students to graduate within normative time, $B = -.91$, χ^2 (1, N = 950) = 5.42, p = .020. Both of these findings are consistent with current national trends as published by the National Center for Education Statistics (2015), which show that women are significantly more likely than men to successfully complete a bachelor's degree, and that minority students are significantly less likely than white students to successfully complete a bachelor's degree.

A similar picture emerged from the MANCOVA analysis in terms of GPA, with both gender and ethnicity having statistically significant impacts. A look at the between-subjects effects (Table 8) showed more specifically that women had higher overall GPAs than men, $F(1, 937) = 11.362$, p $= .001$, partial $\eta^2 = .012$, and that Asian students had higher overall GPAs than white students, $F(1, 937) = 17.498$, p $< .001$, partial $\eta^2 = .018$. GPAs for "other minority" students were substantially lower than for white students, though the result did not emerge as statistically significant, $F(1, 937) = 4.484$, p $= .034$, partial $\eta^2 = .005$. This is likely because the category had so few students, however, rather than because no difference exists, and thus is still worth noting, as it may warrant further study or a targeted intervention.

Students in STEM majors were significantly less likely than students in non-STEM majors to graduate within normative time, but this could simply reflect structural or institutional differences between STEM and non-STEM degree programs at the University, rather than differences in the students or their ability to complete the degree, given that no significant differences emerged in either GPA or persistence between STEM and non-STEM students. For instance, because STEM majors are impacted at many campuses, getting access to the necessary courses to complete the degree may be more difficult. STEM majors also often have greater overall or upper-division unit requirements than non-STEM majors, which could impact time-to-degree. In terms of transfer students specifically, completing all necessary lower-division major requirements at another institution may be more challenging for STEM than non-STEM majors, given the stratified nature of these programs, in which

readiness for upper-division coursework may depend heavily on the specific content of lower-division coursework.

Other Findings

One interesting finding emerged directly from the creation of the dataset. As described in Chapter 2, the initial sample was divided into three different treatment groups – one that was invited to join the social media community at the point of admission, one that was invited to join at the point of matriculation, and one that was never invited to join. The intention of dividing the sample in this way was to allow for an investigation into the impact of time on the distal outcomes. In other words, did participation in school-sponsored social media have the same impact on persistence and degree attainment if not initiated until students arrived on campus? Given the finding that participation has no statistically significant impact on those distal outcomes, the question became somewhat moot. However, it would have been impossible to answer regardless, because less than 1% of students offered the opportunity to join at the point of matriculation accepted the offer (as opposed to over 99% of those who ultimately matriculated and who received the offer at the point of admission). While the reason for this is unclear, it could be due to a number of factors. Students may have fewer questions at that point that they would be interested in raising via this medium, having had them answered through other channels prior to matriculation. They may already have formed or be in the process of forming social networks in other ways, such as through participation in orientation or welcome week activities. They may already have become involved in unofficial social media channels that fill the same niche. Or they may simply feel that participation in school-sponsored social

media is unnecessary or redundant once they are physically present on the campus.

Whatever the reason, it is interesting to note, and indicates that schools considering the use

of a tool of this type will be best served by offering access to students prior to their arrival

on campus.

Implications for Schools

The results of the first set of analyses suggest that, while most students make their

decision to attend a particular college based on criteria not accounted for in this study, social

media networking communities can have a significant impact on the matriculation decisions

of students who choose to participate. Overall yield was estimated to be more than 5%

greater for students who were offered access to and joined the university's social media

community than for those who likely would have joined but were not offered access.

In practical terms, this implies that offering prospective students opportunities to

network through social media could be used as an effective recruitment tool for colleges and

universities, particularly in increasing yield among students who are on the fence. However,

such services do not come without a cost. In addition to the direct cost of creating and

administering the community (something schools often pay a third party to do), there are

also myriad indirect costs associated with monitoring activity within the community,

answering questions that arise on chat boards, creating and maintaining interest-based

subcommunities, etc. At a time when colleges must increasingly be conscientious of how

limited recruitment dollars are spent, administrators thinking of using social media

communities for recruitment may need to consider whether this is a more cost effective tool

than others at their disposal, and whether it is likely to bring in students who could not have been brought in by other means.

That said, it is worth noting that nearly all transfer students who ultimately matriculated chose to join the social media community. This implies that students seriously considering the University had a strong interest in connecting via this medium, which may make it a worthwhile offering in terms of providing good student service and improving the overall student experience, regardless of the bottom-line impact to recruitment efforts. In addition, monitoring uptake could provide Admissions staff with a strong early yield indicator at a time when accurately predicting yield has become increasingly difficult.

It should also be mentioned that at the time this study was initiated, fewer institutions were making use of services of this type, but as the college recruitment landscape is rapidly evolving, more and more are likely to do so. As a result, the overall impact of such services may be mitigated as they become commonplace. However, there may also come to be a point at which institutions not offering such opportunities will be at a disadvantage when compared with peer institutions.

Because the second set of analyses showed no evidence that participation in school-sponsored social media communities provided any long-term academic benefits to students, schools considering such tools for retention and student success purposes should be cognizant of their limitations. More proactive and coordinated use of the community by the campus could improve its utility as an intervention, but schools should monitor the results over time to determine whether it is having the desired effect.

Since these analyses focused only on longer-term academic impacts, it is also possible that other types of positive impacts for matriculated students were overlooked. The literature indicated that the transition to a new college can be difficult, particularly for transfer students who lack many of the social supports that freshman matriculants enjoy. Institutions interested in easing this transition and improving earlier academic outcomes for students may find such tools useful in doing so. This is an area that may warrant further study.

Limitations

Generalizability of the Findings

Both the nature of the sample and the nature of the institution studied could limit the generalizability of the findings. Because the sample is made up entirely of prospective junior-level transfer students, it is impossible to say whether other populations of interest, such as freshman applicants or graduate school applicants, would behave similarly. Adjustment difficulties faced by transfer students have been well documented (Laanan, 2001), which in one sense seems to make them an ideal population to study, as they have so much to gain from the use of social media for networking prior to matriculation. However, given their differences in age, maturity level, and possibly college choice criteria from freshman applicants, there is no way to predict whether they are more or less likely to be influenced by this medium. In addition, it is reasonable to assume that students who choose to attend a community college before matriculating to a four-year institution are a fundamentally different population from students who choose to matriculate directly to a

four-year institution following high school, and would thus respond differently to the same stimuli.

The fact that the sample is limited to one major public research university in southern California may also limit the generalizability of the findings, as students or situations found at this university may differ substantively from those at other types of institutions, such as private institutions, smaller institutions, less selective institutions, or institutions in other states. Because both the features that attract students to a particular school and the nature of the students themselves can vary dramatically based on many criteria, it is likely that social media networking would have a greater impact at some institutions than at others.

Need for Additional Data Elements

There are a variety of data elements that would make for richer analyses if incorporated, such as socio-economic status or parent income, desired major, and pre-matriculation success indicators beyond transfer GPA. In addition, matriculation, persistence, and degree attainment may not be the only important outcomes for an intervention of this type. More qualitative outcomes, such as students' ease of adjustment, sense of belonging, and knowledge of campus resources might also warrant investigation.

Level of participation metric. A key missing element within the analyses is a measure of students' actual level of engagement or participation within the social media community, as simply joining the community may not be sufficient to constitute receipt of treatment. In order to truly benefit from an intervention of this nature, students would have to actually participate, thereby improving their social integration and overall sense of

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belonging. In order to simulate this, data was retrieved from the community regarding not only whether students chose to join, but also the number of conversations they initiated, and the number of people they "friended." Based on the patterns of behavior observed, norms were established, and these elements were combined into a single computed variable, "level of involvement." Level of involvement was continuous and ranged from 0.0 to 68.0. Students received one point for joining, one point for every conversation initiated within the first year of participation (up to 20), and one point for every five people within the community who they friended during the first year of participation. This variable was then used in place of the participation category variable in both sets of analyses.

Ultimately, however, this approach was discarded for several reasons. First, analyses run using this variable showed no substantively different results from those run with a single binary indicator of uptake. The overall story that emerged from the data was very similar, showing some indication that participation within the community had a modest impact on students' decision to matriculate, but no statistically significant impact on their distal outcomes. Second, there was concern over the validity of this measure and the way in which it was calculated. Though an attempt was made to observe norms and approximate the level of effort needed to complete each task used in the creation of the metric, a strong case could not be made for decisions such as assigning only a single point for joining, limiting the number of conversations to 20, or assigning only a single point for every five individuals friended. Finally, there was concern over the aspects of engagement not taken into account within this metric. For instance, data collected by the institution included only conversations initiated, but not responses or "likes" to posts initiated by others. There was

also no way to capture data on students whose level of participation consisted primarily of reading posts by others.

Given these concerns, and the fact that the actual results were similar, it made sense to use the simplest metric available. However, future research into this subject may benefit from the development of a metric to measure level of participation within a social media community.

Social integration or "sense of belonging" metric. The analyses could also have benefitted from more robust data on students' overall social integration or sense of belonging. Because this was not measured, it was not possible to determine whether the theorized mechanism by which social media participation could influence student outcomes (see Figure 3) was accurate, as there was no way to determine whether students participating in the community experienced stronger or earlier social integration.

In order to fill this need, a 12-question survey was sent to all students included in the study who matriculated in Fall 2012, intended to measure their level of integration during their first quarter of attendance. The survey included four questions in each of the following areas: ease of transition from their previous institution, overall sense of campus community, and knowledge of campus resources and how to access them. Unfortunately, the response rate for the survey was extremely low (around 10%), despite repeated reminders and a small incentive. This not only meant that the *n* was too small to be of practical value, but also that there was a strong possibility of self-selection bias, so the results were not used within the final analyses.

Competing influences to social integration. A common problem in social science research is that it cannot be conducted under strict lab conditions. Subjects are free agents, who may be influenced by a variety of factors beyond the control of the researcher. Incorporation of covariates is meant to control for this issue to an extent, but many influences may not be easily visible or measurable, and therefore cannot be controlled for. Within the current data set, two missing elements that could have a strong diluting effect on the observed results are the students' involvement in other school-sponsored activities, and the students' activity over other social media channels.

The literature pointed to a close tie between students' social integration or sense of belonging, and outcomes such as persistence and degree attainment. However, social integration can be achieved in a variety of ways, both formal and informal, as was modeled in Tinto's work (1993). The vast majority of the existing literature focuses on engagement in physical, rather than virtual, activities. Wang's research (2009) demonstrates a strong correlation between involvement in extracurricular activities and degree attainment among transfer students from community colleges to four-year universities. Hausmann, Schofield, and Woods (2007) found that students' sense of belonging could be directly influenced by school-sponsored interventions. Unfortunately, the data set used for this study, in addition to lacking a metric for sense of belonging, also lacks metrics for competing factors which might help to foster that sense, such as extra-curricular involvement or involvement in informal social activities, so the effect of such activities on student outcomes cannot be parsed out, and may therefore mask any additional impacts of social media participation.

Similarly, students have a variety of options for connecting virtually. Students who do not participate in official school-sponsored social media may still be actively involved in unofficial school-specific social media, such as Facebook or Instagram groups, or Twitter lists. Because data on student participation in these alternate networking opportunities was not available, the current study can only measure the impact of school-sponsored social media above and beyond that of other social media channels, and not the impact of social media in general. Given the number and variety of alternatives, it is likely that the overall impact of social media participation on social integration, and thus on matriculation, persistence, and degree attainment, is much stronger than indicated by the current study.

Personality and preference. Students' individual personality characteristics and preferences play a vital role in determining how they will respond to an offer of admission from a particular university, as well as how they will handle the challenges of attendance. Tinto's model incorporates these elements as "pre-entry attributes" and as "goals/commitments." As discussed in Chapter 3, it is logical to assume that within a pool of admitted students, some know that they will accept the offer, others know that they are unlikely to do so, while still others are unsure. This is analogous to Tinto's idea of institutional commitment, and, as demonstrated by his work, the same notion can be applied to persistence. A student who viewed a particular college as their safety school, and attended only because they did not get accepted to or could not afford their first-choice option, is likely to approach their experience there differently than a student who has had their sights set on that that college for a long time.

Inclusion of personality and preference measures could make for a much more complete analysis, but such measures are difficult to garner, particularly from students who do not anticipate attending, as they have little incentive to provide this information. They are also very difficult to measure, as there are so many aspects of personality that may influence these outcomes, and so many nuances to institutional preference and commitment.

Future Research

While this study provides some evidence that college transfer students' participation in a school-sponsored social media community can significantly influence their decisions to matriculate, its limitations suggest a variety of possibilities for further research.

In order to test the generalizability of these findings, similar research should be done on other populations of students, such as freshman applicants or graduate school applicants. Freshman applicants, for instance, may respond to an opportunity to network with other admitted students very differently from transfer applicants, having had no previous college experience to draw on. It is possible that they may make more robust use of such a tool to get information that would substantively impact their matriculation decision, or to get help in navigating the confusing transition to college life. Future research should also look at other types of institutions, such as small colleges, private institutions, or professional schools.

Because the results showed that uptake of the offer to participate was not uniform across all types of students, incorporation of additional covariates, such as SES, intended major, age, overall level of social media involvement, etc., might help to give a more nuanced picture of which students were most likely to be influenced by an intervention of

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this type. This, in turn, could better inform campus decision-makers looking to attract specific types of students, as they determined whether this tool would fit in well with their overall recruitment plan.

A more qualitative study looking into how prospective students used school-sponsored social media communities might provide valuable insight into how they could be used more effectively, as well as into what topics were of most interest to this population, and at what point in the recruitment process.

Though the study provided no evidence that students experienced longer-term academic benefits from participation in the community, the fact that participants did demonstrate slightly higher graduation rates and GPAs shows some promise, and may indicate that the academic impacts of social media participation also warrant further study. This is another area that could benefit from the incorporation of additional covariates, as controlling for the influence of other covariates on the distal outcomes could allow for the detection of a smaller influence by the variable of interest. However, it is also possible that this duration is simply too long to allow for the detection of any meaningful impacts. Because so many factors influence student success, and matriculated students have so many opportunities for positive interventions, it may be that even if social media communities do have a modest positive impact, it would be counterbalanced over the duration of their academic career by other interventions that other students are receiving. For instance, perhaps students participating in school-sponsored social media would have less difficulty with the initial transition to their new campus, and therefore perform better in their first term. The students who struggled in their first term would then, in turn, be more likely

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receive offers for appropriate assistance in the form of counseling services, tutoring services, or other interventions, thereby mitigating the impact of the social media participation. This suggests that future research into the academic impacts of school-sponsored social media participation may want to focus on more proximal outcomes, such as first-term GPA, or likelihood of ending the first term on academic probation.

A final area to consider for future research would be students' sense of belonging and ease of transition. Not only do these elements contribute to student success, as suggested by Tinto's model, but they also represent important aims in and of themselves, particularly given the rapid rise colleges nationwide are seeing in mental health issues among their students. The most recent annual report issued by the Center for Collegiate Mental Health at Penn State University found that between the 2009/2010 academic year and the 2014/2015 academic year, across 93 institutions studied, "on average, the growth in number of students seeking services at counseling centers (+29.6%) was more than 5x the rate of institutional enrollment (+5.6%). Further, the growth in counseling center appointments (+38.4%) is more than 7x the rate of institutional enrollment" (2016, p. 2). They also reported consistent growth in three types of self-reported distress: depression, anxiety, and social anxiety (p. 6). Social media may offer campuses an opportunity to mitigate some of the anxiety and social anxiety associated specifically with the initial transition to campus life by allowing students build social networks earlier, and by giving them an easy outlet to find answers to questions and access to resources.

While the current study gives some insight into the role social media networking communities can play in transfer student recruitment and success, it is clear that the picture

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is extremely complex. There is a great deal more to learn about this medium and its possibilities and pitfalls, and opportunities to do so should be abundant as the use of social media by colleges to reach their current and prospective students grows in the coming years.

References

Ackerman, R., DiRamio, D., Garza Mitchell, R. L. (2011). Transitions: Combat veterans as college students. In R. Ackerman & D. DiRamio (Eds.), *Creating a veteran-friendly campus: Strategies for transition and success* (pp. 5-14). San Francisco, CA: John Wiley & Sons.

Ackermann, S. P. (1991). The benefits of summer bridge programs for underrepresented and low-income transfer students. *Community Junior College Research Quarterly of Research and Practice, 15*(2), 211-224.

American Association of Community Colleges. (2016). *Students at community colleges.* Retrieved from http://www.aacc.nche.edu/AboutCC/Trends/Pages/studentsatcommunitycolleges.aspx

Angrist, J. D., & Imbens, G. W. (1995). Two-stage least squares estimation of average causal effects in models with variable treatment intensity. *Journal of the American Statistical Association, 90*(430), 431-442.

Baird, S., Bohren, J. A., McIntosh, C., & Ozler, B. (2014, March). Designing experiments to measure spillover effects (World Bank Policy Research Working Paper No. 6824). Retrieved from Social Science Research Network website: http://ssrn.com/abstract=2418726

Barefoot, B., Swing, R., Gardner, J. N. (2000). *National survey of first-year co-curricular practices responses.* Retrieved from the Policy Center on the First Year of College

(now Gardner Institute) website: http://www.jngi.org/wordpress/wp-content/uploads/2011/12/00co-curricularsurveyresponses_all.pdf

Bauer, P. F. & Bauer, K. W. (1994). The community college as an academic bridge: Academic and personal concerns of community college students before and after transferring to a four-year institution. *College and University, 69*, 116-122.

Becker, S. O., & Ichino, A. (2002). Estimation of average treatment effects based on propensity scores. *The Stata Journal, 2*(4), 358-377.

Bekker, P. A. (1994). Alternative approximations to the distributions of instrumental variable estimators. *Econometrica, 62*(3), 657-681.

Bhattacharya, J., & Vogt, W. B. (2007). Do instrumental variables belong in propensity scores? (Technical Working Paper 343). Retrieved from National Bureau of Economic Research website: http://www.nber.org/papers/t0343.pdf

Bowden, R. J., & Turkington, D. A. (1990). *Instrumental Variables*. Cambridge, UK: Cambridge University Press.

Brookhart, M. A., Rassen, J. A., & Schneeweiss, S. (2010, June). Instrumental variable methods in comparative safety and effectiveness research. *Pharmacoepidemiol Drug Saf, 19*(6): 537–554.

Cabrera, A. F., Castaneda, M. B., Nora, A., & Hengstler, D. (1992). The convergence between two theories of college persistence. *The Journal of Higher Education, 63*(2), 143-164.

Caliendo, M. & Kopeinig, S. (2008). Some practical guidance for the implementation of propensity score matching. *Journal of Economic Surveys*, *22*(1), 31-72.

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Cameron, A. C., & Trivedi, P. K. (2005). *Microeconometrics: Methods and applications.*
Cambridge, UK: Cambridge University Press.

Cameron, C. (2005). Experiences of transfer students in a collaborative baccalaureate
nursing program. *Community College Review, 33*(2), 22-44.

Center for Collegiate Mental Health. (2016, January). *2015 annual report* (Publication No.
STA 15-108). Penn State University, University Park, PA.

Clary, J. G., Gioia, C., Cartwright, C., & Cheong, C. (2010). *Evidence-based
communications: Global message gap research.* Retrieved from the Burson-
Marsteller website: http://www.burson-marsteller.com/what-we-do/our-
thinking/global-message-gap-research/

Common Application. (2015). *Current members.* Retrieved from
http://www.commonapp.org/member-institutions

Correa, T., Hinsley, A. W., & de Zuniga, H. G. (2010). Who interacts on the web?: The
intersection of users' personality and social media use. *Computers in Human
Behavior, 26*(2), 247-253.

Department of Veterans Affairs. (2014). *Education program beneficiaries.* Retrieved from
http://www.va.gov/vetdata/docs/quickfacts/education_beneficiaries.pdf

Desrochers, D. M. & Hurlburt, S. (2014, July). *Trends in college spending: 2001-2011*.
American Institutes for Research, Washington, DC.

Duggan, M. H. & Pickering, J. W. (2007). Barriers to transfer student academic success and
retention. *Journal of College Student Retention*, *9*(4), 437-459.

Dunning, T., & Hyde, S. (2008). Proceedings from the American Political Science

    Association Annual Meeting: *The analysis of experimental data: Comparing*

    techniques. Boston, MA.

Eggleston, L. E., & Laanan, F. S. (2001). Making the transition to the senior institution. *New*

    Directions for Community Colleges, (114), 87-97.

Flaga, C. T. (2006). The process of transition for community college transfer students.

    Community College Journal of Research and Practice, 30(1), 3-19.

Follmann, D. A. (2000). On the effect of treatment among would-be treatment compliers:

    An analysis of the multiple risk factor intervention trial. *Journal of the American*

    Statistical Association, 95(452), 1101-1109.

Goldfine, L. (2009, May). *Seamless transitions? Institutional, demographic, and course-*

    specific effects on transfer student success in next-in-sequence coursework. Paper

    presented at the Annual Forum of the Association for Institutional Research, Atlanta,

    GA.

Goldrick-Rab, S., & Pfeffer, F. T. (2009). Beyond access: Explaining socioeconomic

    differences in college transfer. *Sociology of Education, 82,* 101-125.

Griffin, W., Cohen, S. D., Berndtson, R., Burson, K. M., Camper, K. M., Chen, Y., & Smith,

    M. A. (2014). Starting the conversation: An exploratory study of factors that

    influence student office hour use. *College Teaching, 62*, 94-99.

Guo, S., & Frasier, M. W. (2009). *Propensity score analysis: Statistical methods and*

    applications. Thousand Oaks, CA: Sage Publications.

Hailpern, S. M., & Visintainer, P. F. (2003). Odds ratios and logistic regression: Further examples of their use and interpretation. *The Stata Journal, 3*(3), 213-225.

Hausmann, L. R. M., Schofield, J. W., & Woods, R. L. (2007). Sense of belonging as a predictor of intentions to persist among African American and white first-year college students. *Research in Higher Education*, *48*(7), 803-839.

Heinrich, C., Maffioli, A., & Vazquez, G. (2010). *A primer for applying propensity score matching* (Technical Notes IDB-TN-161). Retrieved from Inter-American Development Bank website: http://idbdocs.iadb.org/wsdocs/getdocument.aspx?docnum=35320229

Heinze, G. & Juni, P. (2011). An overview of the objectives of and the approaches to propensity score analysis. *European Heart Journal*, *32*, 1704-1708.

Hoffman, M., Richmond, J., Morrow, J., & Salomone, K. (2002). Investigating "sense of belonging" in first-year college students. *Journal of College Student Retention: Research, Theory and Practice, 4*(3), 227-256.

Hollis, S., & Campbell, F. (1999). What is meant by intention to treat analysis? Survey of published randomised controlled trials. *BMJ*, *319*(670).

Hooper, J., Pollanen, M., Teismann, H. (2006). Effective online office hours in the mathematical sciences. *MERLOT Journal of Online Learning and Teaching, 2*(3), 187-194.

Hoover, E. (2010, November 5). Application inflation. *The Chronicle of Higher Education.* Retrieved from http://chronicle.com/article/application-inflation/125277/

Hussar, W.J., & Bailey, T.M. (2016). *Projections of education statistics to 2023* (NCES 2015-073). U.S. Department of Education, National Center for Education Statistics. Washington, DC: U.S. Government Printing Office.

Jacobs, B. C. (1992). Assessing the orientation needs of transfer students. *College Student Affairs Journal, 12*(1), 91-98.

Jo, B., & Stuart, E. A. (2009). On the use of propensity scores in principle causal effect estimation. *Statistics in Medicine, 28*(23), 2857-2875.

Karp, M. M. (2013, May). *Entering a program: Helping students make academic and career decisions* (CCRC Working Paper No. 59). Retrieved from Community College Research Center website: http://ccrc.tc.columbia.edu/media/k2/attachments/entering-a-program.pdf

Koker, M., & Hendel, D. (2003). Predicting graduation rates for three groups of new advanced-standing cohorts. *Community College Journal of Research and Practice*, *27*(2), 131-146.

Laanan, F. S. (2001). Transfer student adjustment. *New Directions for Community Colleges, 2001*, 5–13.

Laanan, F. S. (2007). Studying transfer students - part II: Dimensions of transfer students' adjustment. *Community College Journal of Research and Practice, 31*(1), 37-59.

Lee, D., Olson, E. A., Locke, B., Michelson, S. T., & Odes, E. (2009). The effects of college counseling services on academic performance and retention. *Journal of College Student Development, 50*(3), 305-319.

Lee, V. E., & Frank, K. E. (1990). Students' characteristics that facilitate transfer from two-year to four-year colleges. *Sociology of Education*, *63*, 178–93.

Leventhal, T., & Brooks-Gunn, J. (2003). Moving to opportunity: An experimental study of neighborhood effects on mental health. *American Journal of Public Health*, *93*(9), 1576-1582.

London, H. B. (1992). Transformations: Cultural challenges faced by first generation students. *New Directions for Community Colleges, 1992*, 5-11.

Luo, M., Williams, J. E., & Vieweg, B. (2007). Transitioning transfer students: Interactive factors that influence first year retention. *College and University, 83*(2), 8-19.

Marandet, E., & Wainwright, E. (2010). Invisible experiences: Understanding the choices and needs of university students with dependent children. *British Educational Research Journal, 36*(5), 787-805.

McLachlan, G., & Peel, D. (2000). *Finite mixture models.* New York, NY: Wiley.

Mitchell, M., & Leachman, M. (2015, May). *Years of cuts threaten to put college out of reach for more students*. Retrieved from the Center on Budget and Policy Priorities website: http://www.cbpp.org/research/state-budget-and-tax/years-of-cuts-threaten-to-put-college-out-of-reach-for-more-students

Morgan, P.L., Frisco, M.L., Farkas, G., & Hibel, J. (2010). A propensity score matching analysis of the effects of special education services. *The Journal of Special Education*, *43*, 236-254.

Murnane, R. J., & Willett, J. B. (2011). *Methods matter: Improving causal inference in educational and social science research.* New York, NY: Oxford University Press.

National Association for College Admission Counseling. (2009). Social media:

    Considerations and implications in college admission. *Research to Practice Brief, 7*.

    Arlington, VA.

National Association for College Admission Counseling. (2015). *2014 state of college*

    admission. Arlington, VA: Clinedinst, M. E.

National Student Clearinghouse. (2013). *Current term enrollment estimates – Spring 2013*.

    Herndon, VA. Retrieved from http://nscresearchcenter.org/wp-

    content/uploads/CurrentTermEnrollment-Spring2013.pdf

National Survey of Student Engagement. (2008). *Promoting engagement for all students:*

    The imperative to look within. Bloomington, IN: Indiana University Center for

    Postsecondary Research.

PayScale. (2016, January). *Academic advisor salary (United States).* Retrieved from

    http://www.payscale.com/research/US/Job=Academic_Advisor/Salary

Pesaran, M. H., & Smith, R. J. (1994). A generalized R2 criterion for regression models

    estimated by the instrumental variables method. *Econometrica*, *62*, 705-710.

Rhine, T. J., Milligan, D. M., & Nelson, L. R. (2000). Alleviating transfer shock: Creating

    an environment for more successful transfer students. *Community College Journal of*

    Research and Practice, 24(6), 443-453.

Rickles, J. H. (2011). Constructing counterfactuals in a multisite observational study using

    propensity score matching and multilevel modeling: An empirical example looking

    at the effect of 8th grade algebra across students and schools. Society for Research

    on Educational Effectiveness. Evanston, IL.

Rojewski, J. W., Lee, I. H., & Gemici, S. (2010). Using propensity score matching to
    determine the efficacy of secondary career academies in raising educational
    aspirations. *Career and Technical Education Research*, *35*(1), 3-27.

Romano, C. R., Hanish, J., Phillips, C., & Waggoner, M. D. (2011). The new normal: Senior
    student affairs officers speak out about budget cutting. In L. E. Varlotta & B. C.
    Jones (Eds.), *Student affairs budgeting and financial management in the midst of
    fiscal crisis* (pp. 59-70). San Francisco, CA: John Wiley & Sons.

Rosenbaum, P. R., & Rubin, D.B. (1983). The central role of the propensity score in
    observational studies for causal effects. *Biometrika, 70*(1), 41–55.

Rosenbaum, P. R., & Rubin, D. B. (1984). Reducing bias in observational studies using
    subclassification on the propensity score. *Journal of American Statistical
    Association*, *79*(387), 516-524.

Rubin, D. B. (1976). Inference and missing data. *Biometrika, 63*(3), 581–592.

Rudner, L. M., & Peyton, J. (2006). Consider propensity scores to compare treatments.
    Practical Assessment, Research, and Evaluation, 11(9).

Sagarin, B. J., West, S. G., Ratnikov, A., Homan, W. K., & Ritchie, T. D. (2014). Treatment
    noncompliance in randomized experiments: Statistical approaches and design issues.
    Psychological Methods, 19(3), 317-333.

Schaffhauser, D. (2014, January). Five ways online advising can improve on face-to-face.
    Campus Technology, 27(5), 27-31.

Shapiro, D., Dundar, A., Wakhungu, P.K, Yuan, X., & Harrell, A. (2015, July). Transfer and
    mobility: A national view of student movement in postsecondary institutions – Fall

124

2008 cohort (signature report no. 9). Herndon, VA: National Student Clearinghouse Research Center.

Shulock, N., & Moore, C. (2005, May). Diminished access to the baccalaureate for low-income and minority students in California: The impact of budget and capacity constraints on the transfer function. *Educational Policy, 19*(2), 418-442.

Staiger, D., & Stock, J. H. (1997). Instrumental variables regression with weak instruments. *Econometrica, 65,* 557–86.

Steiner, P. M., Cook, T., D., Shadish, W. R., & Clark, M. H. (2010). The importance of covariate selection in controlling for selection bias in observational studies. *Journal of Psychological Methods*, *15*(3), 250-267.

Stuart, E., A., Cole, S. R., & Bradshaw, P. J. (2011). The use of propensity scores to assess the generalizability of results from randomized trials. *Journal of the Royal Statistical Society*, *174*(2), 369–386.

Stuart, E. A. & Green, K., M. (2008). Using full matching to estimate cause effects in nonexperimental studies: Examining the relationship between adolescent marijuana use and adult outcomes. *Journal of Developmental Psychology*, *44*(2), 395-406.

Szumilas, M. (2010). Explaining odds ratios. *Journal of the Canadian Academy of Child and Adolescent Psychiatry, 19*(3), 227-229.

Tabachnick, B. G., & Fidell, L. S. (2007). *Using multivariate statistics* (5th ed.). Boston, MA: Pearson Education.

Teixeira-Pinto, A., & Mauri, L. (2011). Primer on statistical interpretation or methods:

Statistical analysis of noncommensurate multiple outcomes. *Circulation:

Cardiovascular Quality and Outcomes*, *4*, 650-656.

Teixeira-Pinto, A., & Normand, S. T. (2009). Correlated bivariate continuous and binary

outcomes: Issues and applications. *Stat Med, 28*(13), 1753–1773.

Tinto, V. (1993). *Leaving college: Rethinking the causes and cures of student attrition* (2nd

ed.). Chicago, IL: University of Chicago Press.

Townsend, B. K., & Wilson, K. (2006). A hand hold for a little bit: Factors facilitating the

success of community college transfer students to a large research university.

Journal of College Student Development, *47*(4), 439-456.

Turner, C. S. V. (1994). Guests in someone else's house: Students of color. *The Review of

Higher Education, 17*(4), 355-371.

University of California. (2013). *Fall 2013 application tables.* Retrieved from

http://www.ucop.edu/news/factsheets/2013/13app.html

U.S. Department of Education, National Center for Education Statistics. (2014). *Digest of

education statistics, 2013.* Washington, DC. Retrieved from

http://nces.ed.gov/programs/digest/

U.S. Department of Education, National Center for Education Statistics. (2015*). The

condition of education, 2015.* Washington, DC. Retrieved from

http://nces.ed.gov/programs/coe/

U. S. Department of Education, National Center for Education Statistics. (2015, May).

    Characteristics of postsecondary students. Washington, DC. Retrieved from

    http://nces.ed.gov/programs/coe/indicator_csb.asp

Valenzuela, S., Park, N. & Kee, K. F. (2009). Is there social capital in a social network site?:

    Facebook use and college students' life satisfaction, trust, and participation. *Journal*

    of Computer-Mediated Communication, 14, 875–901.

Van Horn, M. L., Jaki, T., Masyn, K., Ramey, S. L., Smith, J. A., & Antaramian, S. (2009).

    Assessing differential effects: Applying regression mixture models to identify

    variations in the influence of family resources on academic achievement.

    Developmental Psychology, 45(5), 1298-1313.

VanderWeele, T. J., Hong, G., Jones, S., & Brown, J. L. (2013). Mediation and spillover

    effects in group-randomized trials: A case study of the 4Rs educational intervention.

    Journal of the American Statistical Association, *108*(502), 469-482.

Velasquez, P. (2002, November). A qualitative study of a summer bridge program's

    contribution to the persistence of underrepresented students of color at a selective,

    predominately white institution. Paper presented at the People of Color in

    Predominantly White Institutions (POCPWI) Seventh Annual National Conference,

    Lincoln, NE.

Warner, R. M. (2008). *Applied statistics.* Thousand Oaks, CA: Sage Publications.

Wang, X. (2009). Baccalaureate attainment and college persistence of community college

    transfer students at four-year institutions. *Research in Higher Education*, 50, 570-

    588.

Webber, D. A., & Ehrenberg, R. G. (2009). Do expenditures other than instructional

    expenditures affect graduation and persistence rates in American higher education?

    (Working Paper 15216). Retrieved from National Bureau of Economic Research

    website: http://www.nber.org/papers/w15216.pdf

White, I. R., Carpenter, J., & Horton, N. J. (2012). Including all individuals is not enough:

    Lessons for intention-to-treat analysis. *Clin Trials, 9*(4), 396-407.

Wikipedia. (2016). *Social media.* Retrieved from

    https://en.wikipedia.org/wiki/Social_media

Yen, J.-Y., Yen, C.-F., Chen, C.-S., Wang, P.-W., Chang, Y.-H., & Ko, C.-H. (2012). Social

    anxiety in online and real-life interaction and their associated factors.

    Cyberpsychology, Behavior and Social Networking, 15(1), 7–12.

Appendix A: Conceptual Comparison of the Methodologies Used in Chapter 3

Methodological Discussion

For the first set of analyses in this dissertation, which examined the impact of a school-sponsored social media networking community on college matriculation, four models were considered – three different instrumental variable models, and a propensity scoring model. A preferred model was chosen purely on the basis of resulting fit statistics. However, it is also useful to understand the conceptual differences between these models, and between the instrumental variable and propensity scoring methodologies.

It should be noted that for the purposes of this discussion, all references to propensity scoring refer specifically to the technique utilized for this study, originally suggested by Follmann in 2000 to control for treatment noncompliance within a randomized study, and not to other methods of propensity scoring.

Differences between the Models

The four models considered were similar in several ways. Each was a two-stage model, in which service uptake (participation category) was predicted in the first stage, and then predicted uptake scores were used to predict matriculation in the second stage. In all cases the same sets of covariates were used. As a result, the conceptual representations of each model (Figures A-1 through A-4) look similar.

The models differed in terms of when and how the inputs were introduced. In all three instrumental variable models, invitation category served as the primary instrument in predicting participation category, the variable of interest. However, within the propensity scoring model, invitation category was not incorporated until the second stage, as

incorporation of an instrumental variable into a propensity score estimation has been shown, both theoretically and in practice, to result in inaccurate scores (Bhattacharya & Vogt, 2007).
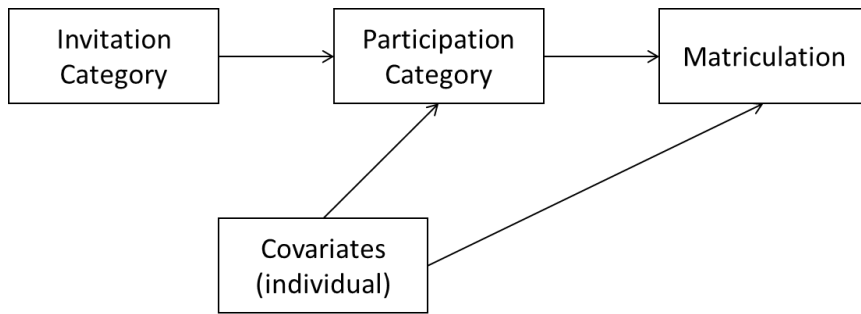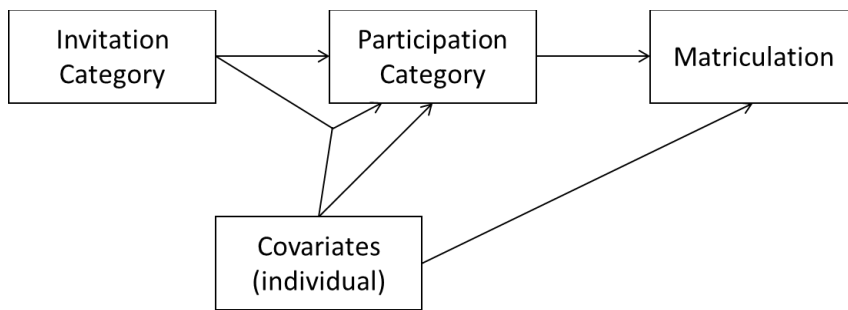

Figure A-1. Conceptual representation of IV Model 1.

Figure A-2. Conceptual representation of IV Model 2 (preferred model).
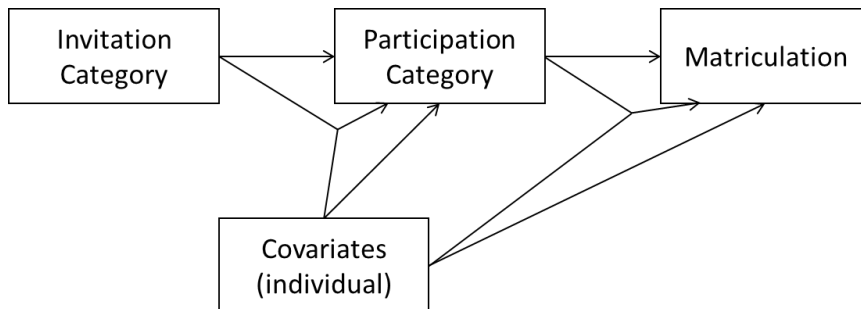

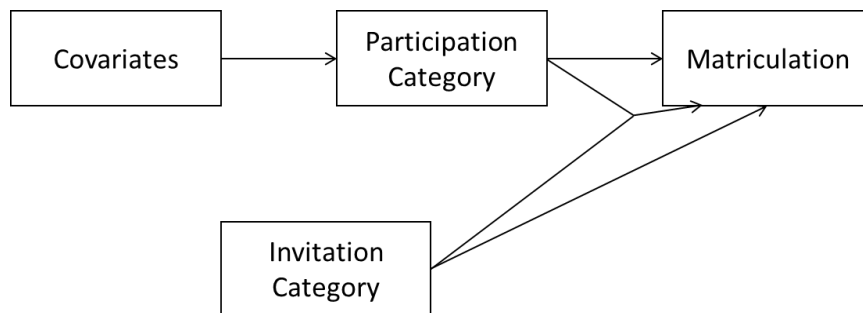*Figure A-3.* Conceptual representation of IV Model 3.

Figure A-4. Conceptual representation of PS Model.

The accuracy of the prediction of participation category, which in turn impacts the overall reliability of the model, relies heavily on the quality of the inputs, and their influence on the decision to uptake service. In the case of instrumental variable analyses, a strong instrument is key to producing accurate predictions, while in the case of propensity scoring, the prediction relies entirely on having the right mix of covariates.

Another major conceptual difference between the instrumental variable models and the propensity scoring model lies in the way covariates are treated. Within an IV analysis, covariates are considered individually, such that their individual impacts can be measured on second stage predictions. Within a PS analysis, all covariates are collapsed into the overall propensity score, making it impossible to tell exactly which covariates exert what impacts in the second stage results. This can be seen in Table 6, the side-by-side comparison of results, where detailed information about the covariates and their interactions are available for the IV analyses, but little data appears in the PS column.

Advantages and Disadvantages of the Methods

Ultimately the purpose of both of the quasi-experimental methods used in this study were to detect TOT effects, due to the fact that service uptake was low, making an ITT analysis unlikely to detect modest treatment effects. The methods differ dramatically in

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their statistical approach to detecting these effects, which gives them different strengths and weaknesses.

Incorporation of the covariates. IV analysis allows for a great deal of flexibility in the incorporation of covariates. Any covariates used in the analysis must be included in both the first and second stages of the regression, but in addition, IV allows for the optional inclusion of interaction effects in either the first stage only, or the first and second stages. When included in the first stage only, these interactions function as additional instruments to predict the independent variable of interest. (A condition of IV analysis, generally referred to as the "order" condition, is that the number of instruments must be greater than or equal to the number of independent variables being predicted.) This would be pertinent in situations where different groups would respond differently to the offer of treatment (more or less likely to accept), but consistently to the administration of treatment. When incorporated into both stages, the first stage interactions (between primary instrument and covariates) serve as instruments to predict the second stage interactions (between independent variable of interest and covariates). This would be pertinent in situations where different groups would respond differently to the treatment itself (more or less effective).

Like IV analysis, PS analysis requires that covariates be incorporated into both stages of the model. However, in the second stage this will always take the form of the combined propensity score. This effectively implies that the covariates drive the decision to uptake treatment, but do not otherwise directly affect the outcome, which is known to be a false assumption in many circumstances. In addition, this makes it impossible to know which covariates, specifically, contribute to the outcome, or by how much. PS is also more

restrictive in its incorporation of interaction effects. Interaction between the propensity

score and treatment group are introduced in the second stage only. Again, this means it is

impossible to know which covariates, specifically, may interact with the treatment, or to

what degree, and may result in the masking of significant effects. Thus, in situations where

the researcher has reason to believe treatment may interact with specific covariates, PS will

not be able to accommodate. This collapsing of covariate data is, more generally, one of the

weaknesses of all types of propensity scoring, as two individuals with similar propensity

scores may look very dissimilar in terms of their actual covariate makeup, begging the

question of the validity of the match.

Types of regression used. While a variety of IV techniques exist, the most common

is 2SLS, which is relatively easy to perform and interpret, and is included as a set command

in most statistical software packages. Unfortunately, 2SLS regression utilizes linear

regression in both stages, which may not be ideal in situations where the endogenous

variable or the outcome is binary, as binary outcomes violate the assumptions of linear

regression. In practice, however, 2SLS estimations have been shown to produce similar

results to non-linear analyses, even when the outcomes are binary in one or both stages, and

because the software will perform the necessary error corrections automatically, the

likelihood of making a mistake in the calculations is much lower than when other types of

multi-stage analyses are performed sequentially.

That said, propensity scoring does offer more flexibility in terms of the types of

analyses that can be run in the second stage, assuming that the error terms are properly

corrected. Follmann's 2000 study utilized a Cox regression in the second stage, due to its

time-dependent nature, whereas in the current study, a binary logistic regression was used in the second stage.

Ability to detect TOT effects. In the case of the current study, the IV analyses showed a stronger ability to detect modest treatment effects, as well as interactions between treatment and the covariates, than the PS analysis. While for some this may simply call into question the validity of the IV results, it is interesting to note, given that the intent of both methods is to correct for the lack of sensitivity of an ITT analysis, that the PS analysis actually showed the endogenous variable of interest to be substantially less significant than did the ITT analysis. At the very least one would expect these estimates to be similar. This may indicate weak propensity scores, leading to poor second-stage regression results. It should also be noted, as was mentioned in Chapter 3, that this version of Follman's method is known to be unable to produce a true LATE. In theory, a true LATE could be produced by excluding individuals in the treatment group who refused treatment, and excluding similarly scored individuals within the control group, but Follman recommends against this due to the difficulty in predicting who from the control group would likely refuse treatment.

Need for strong first-stage inputs. The accuracy of both methods relies on strong first-stage regression results. If the model poorly predicts likelihood of treatment uptake in stage one, it cannot then produce a useful prediction of matriculation in stage two.

For IV analysis, this requires a strong, valid instrument. Staiger and Stock (1997) suggest looking for an F statistic of 10 or greater in the first stage regression, but this is by no means definitive. Another tactic would be to establish a robust bivariate correlation between the instrumental variable and related endogenous variable. If a strong instrument is

not present, additional weak instruments will not resolve the issue, and have instead been shown to make the results less reliable.

PS is more poorly defined, as sources give limited guidance on how many and what types of covariates are sufficient for the generation of good propensity scores, or on how to assess the quality of propensity scores once generated. Examination of first stage fit statistics may give a clue. The limited number and scope of covariates available for the current study may account for its poor overall fit statistics, and inability to detect any effect.

Conclusion

Overall, the advantages of IV seem to outweigh the advantages of PS for the purpose of controlling for poor treatment uptake in a randomized study. The fact that it is easier to perform, better able to accommodate and detect specific covariate effects and interactions, and less reliant on a breadth of covariates to predict treatment uptake, make it preferable in most practical research situations, which may explain why Follmann's technique has never gained broad popularity for this purpose, and IV is widely used. PS could make sense in certain situations, such as when it is difficult to make the case for a valid instrument. However, this is generally not an issue in instances of poor treatment uptake within a randomized study, because unless insufficient controls within both the control and treatment groups have led to similar uptake among each of these populations, the initial randomization can always be used as a valid instrument. PS may also be useful in situations where small sample size means that degrees of freedom are a concern, as the collapsing of covariates leads to the burning of fewer degrees of freedom. When PS results are consistent with IV

results, researchers may want to present both in order to lend credence to their results,

particularly if the intended audience may have more familiarity with propensity scoring.