Direct Ties to a Faculty Mentor Related to Positive Outcomes for Undergraduate Researchers

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Mentored research is critical for integrating undergraduates into the scientific community. Undergraduate researchers experience a variety of mentoring structures, including dyads (i.e., direct mentorship by faculty) and triads (i.e., mentorship by graduate or postdoctoral researchers [postgraduates] and faculty). Social capital theory suggests that these structures may offer different resources that differentially benefit undergraduates. To test this, we collected data from a national sample of more than 1,000 undergraduate life science researchers and used structural equation modeling to identify relationships between mentoring structures and indicators of integration into the scientific community. Undergraduates in dyads and triads with direct faculty interactions reported similar levels of science self-efficacy, scientific identity, and scholarly productivity, and higher levels of these outcomes than students in triads lacking faculty interactions. Undergraduates’ career intentions were unrelated to their mentoring structure, and their gains in thinking and working like scientists were higher if they interacted with both postgraduates and faculty.

Keywords: Undergraduate research, mentoring, social capital, science self-efficacy, scientific identity

Undergraduate research experiences (UREs), during which students conduct research as part of a faculty member’s research group, have long been championed as a “high impact” educational practice (Kuh 2008, Gentile et al. 2017). Students who complete UREs report a range of positive cognitive, affective, and behavioral outcomes related to their becoming a part of the scientific community, or their “scientific integration” (Laursen et al. 2010, Lopatto and Tobias 2010, Estrada et al. 2011, Wilson et al. 2018). For example, undergraduates report that research experiences improve their confidence in their ability to be successful in science (i.e., science self-efficacy) and their sense of identity as a scientist (Chemers et al. 2011, Estrada et al. 2011, Robnett et al. 2015). Research experiences are also considered important environments for undergraduates to clarify their educational and career pursuits and begin to contribute to the body of scientific knowledge through presentations and coauthorship of journal articles (Hunter et al. 2007).

Mentoring structures in undergraduate research. To maximize the availability of UREs, graduate students and postdoctoral associates (i.e., postgraduates) are often involved in mentoring undergraduate researchers (Dolan and Johnson 2009, Aikens et al. 2016). As a result, undergraduate researchers experience a variety of mentoring structures, including dyads, which involve direct, one-on-one mentoring by faculty mentors (i.e., dyad configuration in figure 1), and triads, in which undergraduates are mentored by postgraduates who are in turn mentored by faculty members (i.e., configurations 1–8 in figure 1). All three members of a triad may or may not interact directly with each other about the undergraduate’s research project, as indicated by a tie (or not) between the undergraduate, postgraduate, or faculty member. An undergraduate may not report a tie with a presumed mentor if there is little interaction with that person. An extreme example of this is configuration 1, which might arise if the undergraduate feels as if they have been left on their own in the lab. Although all of these configurations are theoretically possible, we have previously shown that configurations 7 and 8 are most common, representing more than 80% of the triads we have observed (Aikens et al. 2016). In triad 7, which is also known as an “open” triad, a faculty member advises a postgraduate regarding their work with an undergraduate researcher and the postgraduate in turn provides day-to-day guidance to the undergraduate. In triad 8, which is known as a “closed” triad, all three members interact directly with each other about the undergraduate’s research.
Social capital in undergraduate research. Social capital and social network theories provide ways of thinking about how these mentoring structures might affect undergraduate researchers. Social capital is defined as one’s access to and use of resources, information, and opportunities through social relations, or the people one knows (Lin 2002, p. 200). Bourdieu first proposed the notion of social capital as a parallel to economic capital, where the social relations one has (i.e., one’s social network) and the social behaviors one exhibits function as a form of capital by providing power or authority in social situations (Bourdieu 1997). Social networks are one’s relationships and social capital is the value of those relationships in terms of access to information, guidance, opportunities, support, and additional social connections.

In undergraduate research, a direct tie to a faculty mentor has the potential to be a unique and influential source of social capital that fosters undergraduates’ scientific integration, indicated by growth in their abilities to think and work like scientists as well as their science self-efficacy, scientific identity, scholarly productivity, and intentions to pursue a research-related career (Estrada et al. 2011, Weston and Laursen 2015, Aikens et al. 2016). For example, an undergraduate who directly interacts with a faculty mentor may receive more informative feedback and may experience greater role modeling of how scientists think and work. An undergraduate who interacts directly with a faculty member may perceive this experience as positive feedback from a respected authority, which boosts their science self-efficacy. Direct interaction with a faculty mentor may also make an undergraduate feel more like a scientist (i.e., scientific identity) because the faculty mentor is taking their work seriously enough to spend time discussing it. Direct interaction might also help keep an undergraduate’s research a priority for the faculty member, increasing the likelihood that the work will be presented or published (i.e., scholarly productivity). Finally, directly interacting with a faculty mentor may provide access to advice and role modeling for pursuing a research career.

To begin to determine whether mentoring structures influence undergraduates’ scientific integration, we previously compared reports of thinking and working like a scientist, science self-efficacy, science identity, scholarly productivity, and career intentions of undergraduates in open and closed mentoring triads (Aikens et al. 2016). We found that undergraduates in closed triads reported higher levels of all five outcomes than undergraduates in open triads. This result can be interpreted in two ways: Closed triads are uniquely beneficial, or direct interactions with faculty are uniquely beneficial. We attempted to distinguish between these interpretations by comparing the outcomes of undergraduates in triads that involved direct interactions with faculty (figure 1, triads 3 and 6 versus triad 8). We did not observe any differences, which supports the latter interpretation: Direct interactions with faculty are uniquely beneficial. However, triads 3 and 6 are relatively uncommon, and the small number of undergraduates in these triads limited the strength of this conclusion.

The present study. In the present study, we directly test the hypothesis that undergraduates in mentoring dyads will experience the same level of scientific integration as undergraduates in closed triads. If we observe no differences between the outcomes of undergraduates in dyads and closed triads, this supports the notion that direct interactions with faculty are sufficient for undergraduate researchers to maximize their scientific integration. If we observe that undergraduates in closed triads report more favorable outcomes, this suggests that closed triads offer a unique training environment beyond what is afforded by a faculty mentor alone. We also further test the hypothesis that direct mentorship by a faculty member is superior to mentorship by a postgraduate by comparing the outcomes of undergraduates in dyads with the outcomes of those in open triads. If undergraduates in dyads experience more favorable outcomes that undergraduates in open triads, this result would further demonstrate the importance of direct interaction with faculty mentors.

We collected data from a national sample of undergraduates who had participated in at least one semester or summer of life science research. We focus in the present article on comparing the outcomes of undergraduate researchers who reported being in a dyad with a faculty mentor (U–F) or one of the two common triads, open (triad 7 = U–F–P) or closed (triad 8 = U mentored by P and F; figure 1) and closed (triad 8 = U mentored by P and F; figure 1). We sought to identify what if any relationships there were between undergraduates’ research mentoring structures (dyad, closed triad) and their reported gains in thinking and working like a scientist, their levels of science

![Diagram of Undergraduate Research Mentoring Structures](https://academic.oup.com/bioscience)

**Figure 1. Undergraduate research mentoring structures.** In dyad mentoring structures (depicted on the left), the undergraduate researcher (U) is directly mentored by the faculty member (F). In triad mentoring structures, the undergraduate researcher is also mentored by a postgraduate (P). Lines between each member of the triad indicate a direct interaction (tie) between the triad members about the undergraduate’s research (Aikens et al. 2016). The mentoring structures in black (dyad and triads 7 and 8) were the focus of this study.
self-efficacy, scientific identity, and scholarly productivity, and their intentions to pursue a science research-related career. These outcomes are important indicators of integration into the scientific community, a major goal of undergraduate research programming (Estrada et al. 2011, 2018, Hernandez et al. 2017). Furthermore, these outcomes have been widely used to measure effectiveness of UREs (Laursen et al. 2010, Estrada et al. 2011), allowing for comparison between our results and published studies of UREs and enabling future meta-analyses.

Methods

Given the dearth of knowledge of how mentoring structures relate to the outcomes undergraduates realize from participating in research, we conducted an exploratory study to identify any preliminary differences between mentoring structures. We did not intend to make causal inferences about the effects of mentoring structures but, rather, to identify differences, if any, that should be explored further. We surveyed a national sample of undergraduate life science researchers about their mentoring structures and research outcomes. We then fit our data to structural equation models to test our hypotheses. We report details about the study participants and the methods we used to collect and analyze the data below.

Participants and data collection. Undergraduates were eligible to participate in the study if they had completed at least one semester or summer of research in the life sciences in the past 2 years, working with either a faculty member only or both faculty and postgraduate researcher. We recruited students by sending emails from February to August 2016 with description of the study and a link to our survey through listservs maintained by life science departments at colleges and universities (institutions) across the United States. We also recruited undergraduates in Maximizing Access to Research Careers, Research Internships in Science and Engineering, and McNair programs and from Historically Black Colleges and Universities and Hispanic Serving Institutions to increase the racial and ethnic diversity of our sample. Because we distributed emails to lists, we cannot accurately estimate response rates. All participants received $20 for completing the survey. Each institution that distributed our study invitation received a report of the institution-specific results (with identifiers removed to protect participant confidentiality) if at least eight undergraduates responded. A total of 1173 students responded to our survey. Of those, N = 1001 (approximately 85%), representing 148 institutions, indicated that they were in a dyad, an open triad, or a closed triad. Given our hypotheses, we analyzed data only from this subsample.

Measures. We collected data using a survey administered via Qualtrics. The survey contained measures of mentoring structure, five URE outcomes (thinking and working like a scientist, scientific self-efficacy, scientific identity, career intentions, and scholarly productivity), and several control variables. Descriptions of the scales and items used to measure these constructs are provided in supplemental table S1. Distributions of responses to the items are presented in supplemental figures S1–S5 (created using the ggplot2 package in R; Wickham 2016). Specific measures relevant to this study are described below. Cronbach’s alphas were calculated for three scales below using listwise deletion for missing data.

At the beginning of the survey, undergraduates were asked whether they worked only with a faculty member (dyad) or with a faculty member and a graduate student or a postdoctoral researcher (triad). Undergraduates who indicated they worked with both a faculty and postgraduate mentor were then presented the eight possible triads in figure 1 and asked to indicate which triad type best represented their working relationship with their mentors. For our analyses, we only used data from students who indicated being in a dyad, an open triad (i.e., triad 7), or a closed triad (i.e., triad 8). We created dummy coded variables for the open and closed triads, with the dyad group as the reference (dyad, n = 332; open triad, n = 277; closed triad, n = 392).

The Thinking and Working like a Scientist scale from the Undergraduate Research Student Self-Assessment instrument (URSSA; Hunter et al. 2007, Weston and Laursen 2015) measures the students’ perceptions of the intellectual gains that they made during research. The scale contains eight items asking the students to rate the extent of their gains (1, no gain; 5, great gain) on skills such as analyzing data for patterns and identifying limitations of research methods and designs. We added one item from the URSSA skills scale to our measure, defending an argument when asked questions, in order to capture this scientific practice. The scale with the additional item showed high internal consistency reliability in our sample (n = 925; Cronbach’s alpha = .90, 95% CI = 0.89–0.91).

We used a six-item science self-efficacy scale measures the students’ confidence in their ability to carry out research-related tasks (Estrada et al. 2011). We asked the students to rate their level of confidence (1, not confident; 5, very confident) in doing scientific tasks such as using technical science skills and figuring out what data or observations to collect and how to collect them. This scale also showed high internal consistency reliability in our sample (n = 995; Cronbach’s alpha = .90, 95% CI = 0.89–0.91).

We used a five-item scientific identity scale, which measures the extent to which the students agree (1, strongly disagree; 5, strongly agree) with statements such as “I have a strong sense of belonging to the community of scientists” and “I have come to think of myself as a ‘scientist’” (Estrada et al. 2011). This scale showed high internal consistency reliability in our sample (n = 991; Cronbach’s alpha = .85, 95% CI = 0.83–0.86).

We asked the students one question to measure their intent to pursue science related research career (Estrada
The responses were collected on a 10-item scale (1, definitely will not; 10, definitely will). We asked the students to rate how many times (from 0 to more than 5 times) they presented a poster or talk as part of a local program or event; presented a poster at a regional, national, or international conference; presented a talk at a regional, national, or international conference; participated in writing a manuscript for publication in a peer-reviewed journal; and published an article in a peer-reviewed journal. Following our prior methods, we created a score for each student according to level of potential scientific influence of each form of scholarship (Aikens et al. 2016). For example, presenting at a local event would be considered less influential and publishing a peer-reviewed article would be considered more influential from a scientific perspective, although all forms of scholarship might be influential from a student perspective. We then generated scores (0, no scholarly productivity; 1, presented at a local event; 2, presented at a regional, national, or international conference; 3, coauthored a manuscript). The score did not include the number of times the students completed the activities.

We included several student-related control variables that have been shown to correlate with triad type and our outcomes of interest (Aikens et al. 2016, 2017). We included gender, the number of prior research experiences, whether the student was in an honors program or not, the duration of current research experience, their current GPA, whether they conducted research in a research-intensive institution, and their race or ethnicity. Distributions of the control variables by mentoring structure are presented in table 1. For gender, very few students selected the “Other” category (n < 5). We indicated these students as having missing data. Students were asked whether they had any prior research experiences: no other experience, one other experience, two other experiences, and three or more other experiences. Students were asked whether they had participated in an honors program: yes, no, or did not know. Very few students answered that they did not know (n < 5); therefore, these responses were changed to missing.

| Table 1. Characteristics of participants by mentoring structure and overall. |
|-----------------------------|------------------------------------------|
| Sex                         | Dyad (n = 332)                           |
|                             | Closed triad (n = 392)                   |
|                             | Open triad (n = 277)                     |
|                             | Overall (N = 1001)                       |
| Female                      | 213 (64.2%)                              |
| Male                        | 116 (34.9%)                              |
| Missing                     | 3 (0.9%)                                 |
| Race/ethnicity              | Asian                                    |
|                             | 100 (30.1%)                               |
|                             | URM                                      |
|                             | 114 (34.3%)                               |
|                             | White                                    |
|                             | 112 (33.7%)                               |
|                             | Missing                                  |
|                             | 6 (1.8%)                                 |
| Prior experience            | No prior experience                      |
|                             | 199 (59.9%)                               |
|                             | 1 experience                             |
|                             | 83 (25.0%)                                |
|                             | 2 experiences                            |
|                             | 30 (9.0%)                                 |
|                             | 3 or more                                |
|                             | 20 (6.0%)                                 |
| Duration                    | 1 semester                               |
|                             | 94 (28.3%)                                |
|                             | 2 semesters                              |
|                             | 72 (21.7%)                                |
|                             | 3 semesters                              |
|                             | 51 (15.4%)                                |
|                             | More than 3                              |
|                             | 115 (34.6%)                               |
|                             | Missing                                  |
|                             | 0 (0%)                                   |
| Honors                      | No Honors                                |
|                             | 251 (75.6%)                               |
|                             | Honors                                   |
|                             | 71 (21.4%)                                |
|                             | Missing                                  |
|                             | 10 (3.0%)                                 |
| Current GPA                 | Mean (SD)                                 |
|                             | 3.46 (0.361)                              |
|                             | Median [Min, Max]                         |
|                             | 3.50 [2.00, 4.00]                         |
| Institution                | Research intensive                       |
|                             | 223 (67.2%)                               |
|                             | 351 (95.9%)                               |
The duration of research was measured as the number of terms (semesters or summers) that the student had been involved in the research experience of interest: one term, two terms, three terms, and four or more terms. Gender and honors were treated as categorical variables and were dummy coded. Duration and prior research experiences were treated as ordinal independent variables. The students’ GPA was included as a continuous covariate. We dummy coded whether the students conducted research at a research-intensive institution according to the Carnegie Classification of Institutions of Higher Education (Indiana University Center for Postsecondary Research). Specifically, institutions classified as R1, R2, or Doctoral/Professional Universities were coded as “research-intensive.” All other institution types were classified as nonresearch intensive.

We collected responses from the students who identified as American Indian/Alaskan Native (n = 12), African-American/Black (n = 90), Native Hawaiian/Pacific Islander (n = 14), or Hispanic/Latinx (n = 104). Students from these populations have been historically underserved by institutions of higher education (Ladson-Billings 2006). To create more balanced racial or ethnic categories for our analyses, we categorized the students who selected any of the four categories above as “underrepresented minority” (URM, n = 203). We then created categories for Asian (n = 392) and white (n = 385). We dummy coded the race or ethnicity variable with white as the reference group.

Data analysis. All of the analyses were conducted using R version 3.5.0 (R Core Team 2016, Wickham 2016, Wei and Simko 2017). We used structural equation modeling (SEM) to analyze the data using the lavaan package (Rosseel 2012). Unlike ordinary least squares regression, SEM allows for explicit modeling of measurement errors, as well as treatment of missing data. The full information maximum likelihood (FIML) method was used to treat missing data, and the maximum likelihood robust method was used to run the analyses.

We first ran measurement models for each of these three scale variables (thinking and working, efficacy, and identity) to check the unidimensionality of the scales. For these variables, we used the observed items from the respective scales as indicators of a latent factor (see the supplemental material for details). Then, we fit a structural model using the latent factor as the outcome variable. We measured career intentions with only one item (Estrada et al. 2011, Aikens et al. 2016), we calculated intraclass correlation coefficients (ICC) to explain the variance between institutions for the continuous outcomes studied in this article and found highest ICC of .022, which is weak. Therefore, we opted not to use multilevel modeling, but instead used cluster robust standard errors, using the institutions where the students conducted research as the clusters, when running the analyses.

Fit indices. For measures of fit, we present the results of the following: comparative fit index (CFI), Tucker–Lewis index (TLI), Steiger and Lind root mean square error of approximation (RMSEA), and standardized root mean square residual (SRMR). CFI and TLI values that are at least .95, RMSEA values less than .06, and SRMR values less than .05 were used as cutoff criteria for good fit (Byrne 1998, Hu and Bentler 1999). However, RMSEA values up to .07 and SRMR values as high as .08 can be acceptable (Steiger 1990, Hu and Bentler 1999). For values that did not strictly meet our cutoff criteria but were close, we judged them as indicating fair fit. We opted not to report the model chi-square test, because it is highly sensitive to sample size (Hooper et al. 2008).

Fit indices from the measurement models are presented in table S2. Factor loadings from the CFA models are provided in table S3. Fit indices from SEM analyses are presented in table 2. We do not present indices for models on career intentions and scholarly productivity, because these models did not include the measurement step. Structural equations models for these two variables showed perfect fit.

Results

Our results comparing the closed and open triads to dyads are shown in table 3. Full results, including the effects of all the covariates, are shown in table S5. A structural model with the thinking and working like a scientist factor as the outcome showed a good to fair fit (table 2). Holding all other variables constant, the students in a closed triad reported higher abilities to think and work like a scientist on average than the students in a dyad (table 3). The students in open triads and the students in

https://academic.oup.com/bioscience
dyads reported similar levels of thinking and working like a scientist.

A structural model with self-efficacy as the outcome showed a good fit (table 2). Holding all other variables constant, the students in closed triads and dyads reported similar levels of science self-efficacy. Holding all other variables constant, the students in open triads reported lower science self-efficacy on average than the students in dyads (table 3).

The structural model with scientific identity as the outcome showed a good to fair fit (table 2). The TLI value indicated inadequate fit, which can be attributed to the inadequate fit in the measurement model (see the supplemental material for details). Holding all other variables constant, the students in closed triads and dyads reported similar levels of scientific identity. In contrast, the students in open triads reported lower scientific identity on average than the students in dyads (table 3).

Holding all other variables constant, the students in closed triads and the students in dyads did not differ in their intentions to pursue a career in a science-related field. Students in open triads and in dyads also did not differ (table 3).

Holding all other variables constant, the students in closed triads and dyads reported similar levels of scholarly productivity, whereas the students in open triads reported lower scholarly productivity on average than did the students in dyads (table 3). The results did not change in a sensitivity analysis treating scholarly productivity as an ordinal variable using the DWLS method and the available listwise deletion method (n = 944). The students in open triads were more likely to report lower scholarly productivity than were the students in dyads (table S4).

Finally, we conducted a series of sensitivity analyses to identify influence of institutional context (i.e., being at a research intensive institution or a minority-serving institution) and found that our results did not differ substantially (supplemental tables S6–S9). We observe one difference: Students at research intensive universities in closed triads reported higher scientific identity than those at research universities in dyads. The students in dyads

| Table 2. Structural equation modeling fit indices. |
|-----------------------------------------------|
| Index | Thinking and working | Scientific self-efficacy | Scientific identity |
|-------|-----------------------|--------------------------|---------------------|
|       | 95% confidence interval | Fit | Value | 95% confidence interval | Fit | Value | 95% confidence interval | Fit |
| CFI   | .933                   | Fair | .954 | – | Good | .906 | – | Fair |
| TLI   | .922                   | Fair | .942 | – | Fair | .876 | – | Inadequate |
| RMSEA | .048                   | 0.043–0.054 | Good | .048 | 0.041–0.056 | Good | .063 | 0.056–0.070 | Fair |
| SRMR  | .025                   | – | Good | .016 | – | Good | .028 | – | Good |

Note: CFI and TLI values that are at least .95, RMSEA values less than .06, and SRMR values less than .05 were used as cutoff criteria for a good fit. Values close to the cutoff are categorized as indicating a fair fit.

| Table 3. Structural equation modeling results. |
|-----------------------------------------------|
| Outcome | Predictor | Estimate | Standard error | 2.5% | 97.5% | z | p-value | Standardized estimate |
| Thinking and Working | Closed | 0.173 | 0.060 | 0.055 | 0.292 | 2.865 | .004 | 0.137 |
| Open | –0.062 | 0.076 | –0.211 | 0.086 | –0.821 | .411 | –0.045 |
| Scientific Efficacy | Closed | 0.035 | 0.047 | –0.056 | 0.127 | 0.755 | .450 | 0.036 |
| Open | –0.127 | 0.041 | –0.208 | –0.047 | –3.111 | .002 | –0.119 |
| Scientific Identity | Closed | 0.161 | 0.069 | 0.026 | 0.297 | 2.331 | .020 | 0.107 |
| Open | –0.123 | 0.047 | –0.216 | –0.031 | –2.606 | .009 | –0.075 |
| Career Intentions | Closed | 0.090 | 0.206 | –0.314 | 0.494 | 0.435 | .663 | 0.018 |
| Open | –0.507 | 0.257 | –1.011 | –0.003 | –1.971 | .049 | –0.093 |
| Scholarly Productivity | Closed | –0.022 | 0.079 | –0.177 | 0.134 | –0.273 | .785 | –0.009 |
| Open | –0.320 | 0.082 | –0.481 | –0.159 | –3.899 | .000 | –0.119 |

Note: This table presents the outcomes of undergraduates in closed and open triads with undergraduates in dyads as the reference, holding control variables constant. Undergraduates in closed triads report significantly higher gains in thinking and working like a scientist than undergraduates in dyads, but otherwise report similar outcomes to students in dyads. Undergraduates in open triads report significantly lower levels of scientific self-efficacy, scientific identity, and scholarly productivity compared to students in dyads. Scholarly productivity is treated as continuous. Significant p-values based on the Bonferroni correction (p < .01) are in bold.
and open triads reported similar levels of scientific identity (table S8).

Conclusions

Considered collectively, our results show that a direct tie to a faculty mentor relates to positive scientific integration outcomes for undergraduate researchers. Students who experienced open triad mentoring structures and, therefore, lacked direct ties to faculty mentors reported lower levels of scientific self-efficacy, scientific identity, and scholarly productivity than the students with a direct faculty tie in the form of a dyadic mentoring structure. Students who had direct ties to faculty mentors, either through a dyadic or closed triadic mentoring structure, reported similar levels of these outcomes. Our prior research suggests that once weekly interactions with a faculty mentor may be sufficient for students to perceive a tie with a faculty mentor (Aikens et al. 2017).

The standardized estimates for all the significant comparisons we observed were small, indicating a change of around one-tenth of a standard deviation in the outcomes (Cohen 1992, Chen et al. 2010). Small differences in proximal outcomes have been associated with students’ long-term persistence in science. For instance, Estrada and colleagues found that one-third of a standard deviation in scientific identity positively predicts continuation in a science career and negatively predicts pursuit of a non-STEM career (Estrada et al. 2011, 2018). Longitudinal research is needed to determine the longer-term effects of different mentoring structures on the scientific integration of undergraduate researchers. Future research should also determine the comparative value for undergraduates of having no research experience and having research with mentorship by a postgraduate (open triad) and research with direct mentorship by a faculty member (closed triad, dyad).

Our results show that undergraduates’ career intentions do not differ between mentoring structures, suggesting that gaining research experience in general may be more important than the particular mentoring structure undergraduates experience. It may be that, in research-intensive institutions, closed triads are the best structure for balancing feasibility for the faculty mentor with maximizing outcomes for undergraduate researchers. However, the undergraduates in our sample reported either very high career intentions or a range of career intentions. Some undergraduates may enter research experiences with the intention to pursue a research-related career regardless of the mentoring they experience, whereas others have less firm intentions that are influenced by mentoring structure. Future research should address the extent to which undergraduates’ career intentions shift during research experiences and whether any changes are related to both their career intentions when they started research and their mentoring structures.

There are several plausible ways in which a direct connection to a faculty mentor could confer social capital to undergraduates in a way that affects their science self-efficacy, scientific identity, and scholarly productivity. It may be that faculty mentors provide higher quality mentoring because they are able to leverage their comparatively advanced knowledge, skills, and networks to provide greater access to information, resources, and networks to undergraduate researchers. Estrada and colleagues have shown that higher quality mentoring fosters scientific integration above and beyond the experience of doing research (Estrada et al. 2018). Alternatively, direct interactions with faculty mentors may provide access to support and encouragement that bolsters undergraduates’ development of science self-efficacy, which, in turn, influences their actions such as dedicating time to presenting their research (i.e., scholarly productivity) or intending to pursue a science research-related career (i.e., intentions; Pajares 1996, Bandura 1997). Individuals develop self-efficacy, or confidence in their ability to be successful in a task such as doing research, on the basis of mastery experiences (tackling and succeeding in a challenging task), vicarious experiences (observations of capable others), social persuasion (feedback and encouragement from peers and mentors), and emotional arousal due to positive or negative emotions (Usher and Pajares 2008, Chen and Usher 2013). Undergraduates who are mentored by faculty members may receive positive feedback and encouragement that is especially powerful because the undergraduate considers the faculty member to be more of an authority than a postgraduate. Future research should explore whether dyads, open triads, and closed triads differ in offering undergraduate researchers access to quality mentoring and sources of self-efficacy in order to yield insight into the mechanism by which mentoring structures with direct ties to faculty mentors confer advantages observed in our work.

These results also suggest that UREs should be designed and implemented in ways that help ensure that undergraduate researchers can interact directly with faculty mentors. Our prior work has shown that undergraduates only need to interact once weekly with their faculty mentor to report that their mentoring structure is a closed triad (Aikens et al. 2017). Additional research is needed to yield insight into whether these interactions are most effective if they are one-on-one meetings or if regular lab group or subgroup meetings are sufficient. Furthermore, research is also needed to understand the elements of these interactions that are most critical for undergraduate researcher development. For instance, to what extent should these meetings focus on connecting the undergraduate researcher’s project with ongoing research in the group and in the field? To what extent should these meetings include advising undergraduates about next steps if they have an interest in continuing to do research or an interest in pursuing graduate education?

Undergraduates in closed triads reported greater gains in thinking and working like a scientist than undergraduates in dyads. This is an intriguing result for two reasons. First, learning about the nature and practice of science is distinct from the other outcomes we studied. The idea of thinking
and working like a scientist relates to the undergraduate's epistemological development (Hunter et al. 2007), whereas scientific integration relates to their career development (Lent et al. 1994, Kelman 2006, Estrada et al. 2011). The environment of the closed triad may be unique for helping undergraduate researchers learn how science works (Burgin and Sadler 2013). Undergraduates in closed triads may be able to observe their postgraduate and faculty mentors discussing elements of their projects, debating how to interpret results, and making decisions about how to proceed. Ideally, undergraduates would actively engage in this discussion and have opportunities to get feedback from both mentors and may even observe their mentors critiquing one another's ideas. Alternatively, closed triads may be beneficial because of complementary social capital offered by the postgraduate and the faculty mentor (Dolan and Johnson 2010). For instance, undergraduates may discuss big picture elements of their research with their faculty mentors and get necessary help and guidance to carry out the work from their postgraduate mentors. In contrast, undergraduates in dyads may not have sufficient technical guidance or easily accessible support that can be offered by a postgraduate (Dolan and Johnson 2010), whereas undergraduates in open triads may not have sufficient insight into how their work connects with prior and ongoing research in the field or the lab group. Research that examines the nature of the interactions that occur in the different mentoring structures is needed to yield insight into the mechanisms by which the closed triad environment is promoting undergraduates' growth in their thinking and working like scientists.

Because our study involved a convenience sample, our results cannot be generalized to all life science undergraduate researchers. Future studies should use probability sampling techniques to improve external validity of results. Our cross-sectional study design also precludes making causal claims about the effects of undergraduates' research mentoring structures. It may be that undergraduates starting research with high levels of science self-efficacy, identity, and career intentions are most likely to garner attention from faculty mentors and develop working relationships with them, which are apparent as dyads or closed triads. We attempted to address this concern to some extent by controlling for confounds such as prior research experience, achievement in the form of honors program status, and other covariates that relate to the indicators of scientific integration we examined in this study. However, future research should make use of study designs and methods (e.g., propensity score matching, longitudinal studies) that allow for causal inferences between mentoring structures and undergraduate outcomes. To our knowledge, there is only one ongoing, longitudinal study of the effects of mentored research experiences, which is limited to URM undergraduates participating in highly selective URE programming and did not address the influence of mentoring structures per se (Estrada et al. 2011, 2018, Hernandez et al. 2018). Therefore, this work takes an important step toward addressing the black box of UREs, yielding insight into how the mentoring structures undergraduate researchers experience influence their outcomes (Linn et al. 2015, Gentile et al. 2017).

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Supplemental material
Supplemental data are available at BIOSCI online.

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