**3-Page, Oct 2018, Attitudinal Survey on Alternative Credentials**

This 3-pager summarily describes what was done, why it was done, and what I found. What was found takes the form of 5+ talking points. I also discuss future work.

**I. What Was Done**

A survey[[1]](#footnote-1) with TODO responses was taken over the course of 2018. TODO responses were obtained in February and an additional TODO responses were collected in October. TODO responses were purchased through SurveyMonkey, TODO responses were obtained using Mechanical Turk, and TODO responses were obtained through non-advertisement postings on social media and word of mouth[[2]](#footnote-2).

Mechanical Turk responses cost $.75 each and SurveyMonkey responses cost $1 each. Notably, Mechanical Turk responses were verified to be from US high school graduates, while SurveyMonkey responses were verified to be from US persons.

**II. Why it Was Done**

TODO

**III. What I Found**

Key results:

1. TODO
2. Appendix B is conceptual and question oriented; the variables themselves were slightly differently wrangled in the Feb study in comparison to earlier studies. For example, gender was obtained through survey monkey account data and then also explicitly asked, were in earlier studies it just came from the account info. When asking, a nonbinary option was available, which is unavailable within SurveyMonkey itself. As a result, Appendix C drills into variable level findings and the February data constitutes a conceptual-level reproduction of earlier study.
3. TODO: Appendix E is best model by variable and administration period.
4. TODO: Appendix F, key model results
5. TODO: specially discuss interesting topics: religion, conservatism (social vs fiscal), innovation bias, foreign bias, ideology and personality as relevant to support, manager support, nonbinary support, change over time, changes in traditional stuff over time (enrollment, graduation, costs…)
6. TODO: discuss hybridization as key
7. 2018, fewer samples, better long r2; almost makes you think 2018 had better variables right? Well kind of. It had more variables, but many were weak. In fact, 2019 maintained all strong 2018 variables. The 2019 goal was not so much to explore more variables as it was to really increase sample for the variables we care about. Oct 2018 explored many variables and found the best ones, and 2019 spent more survey budget on high sample for fewer questions than small sample for more variables. That’s why 2018 has fewer samples with more fit, but that doesn’t mean there was model degradation from 2018 to 2019. It’s true that some decision makers might prefer a model which squeaks out the slightly improved raw r2, but they will gain that benefit at the expense of super-standard model complexity and survey cost, where super-standard indicates the addition of variables which reduce adjusted r2. The adj r2 will be considerably similar for most use cases in the maxar models from 2018 to 2019\*, but the coefficients are determined with better precision using the latter, and even better in cases where the sample can draw from both pools.
   1. Elaborate on complexity cost with f and q complexity discussion. Complexity makes models less intuitive, harder to generate samples for, and harder to act on complex findings, but more they are more accurate which could improve profit.
   2. Weak variables matter too! In particular when the coefficient is large. Weak variables might simply be understudied, under sampled, poorly specified, or mismodeled strong variables. Long models contain superweak variables, or variables which don’t survive to the weak model. The value difference between superweak and weak variables may be immense. Superweak variables are relatively likely to have no true explanatory power, while weak variables are relatively likely to be understudied areas, rather than areas with no true explanatory power. Weak variables may be under sampled, poorly specified, in need of decomposition, or mismodeled. By mismodelling, I include all sorts of modelling issues like making a linear-linear model when the relationship is log-linear, linear-cubic, exponential, and so on, or perhaps highly discontinuous and better described by non-statistical model. Some problems, for example, are explained with relatively little error using an agent-based model instead of a standard statistical model.
   3. Remember; weak variable is .1 > p > .5. This indicates the probability of an effect existing is greater than the probability of an effect not existing.
   4. Another reason weak effects are important: we acknowledge time is important, but time is a superweak effect in 2018 188 obs study. It is much more reasonable to be sure time relates to our outcomes, but admit the relational details are weak or understudied, than it is to suppose or conclude that time has no bearing on our outcomes due to the weak p value.
8. Why does survey account deviate from reported? 1) real change over time (eg age), 2) account response limitation (eg gender), 3) erroneous entry, 4) the respondent is not from survey monkey paid audiences (not a response delta, but an observation which would otherwise be absent.)
9. Simple ismanager regression is positive, but complex regression shows a weak negative effect
10. Collector effects were omitted in 2019 long regression, meaning there wasn’t unique variation attributable…true in large sample reg?
11. Nvoifai was the only factor where linear, marginal, and cubic effects all survived to the strong model in the 2018 exploration, but it was the first variable eliminated in the 2019 exploration…at least the cubic effect was.
12. 6 individuals identified as nonbinary. It’s interesting to note that the direction of that effect was positive, although is was superweak with a maximum p value of .594. That p value is observed in special regression 12, with a nontrivial coefficient in the direction opposite male. If nonbinary individuals are high in openness, this could represent corroboration of the theory that openness underpins liberal over conservative support for alternative credentials.
13. In the 2019 exploration, crincome was better correlated to voi at every dimension (linear, marginal, and cubic effects) in comparison with csincome. This indicates survey response data is more reliable than survey monkey account data, and so income effects could be more important than one would think based on the 2018 exploration, or when generally referring to potentially outdated account information instead of survey-time information.
    1. Interestingly, when csincome1 was removed, cr variables weakened, so that cr variables were eliminated from the weak model, while cs marginal and cubic effects survived. All of this occurred without a sample size change. So maybe it’s not the case the survey-time data is more accurate or stable.
    2. Income effects didn’t make it to maxar model anyway. Doesn’t add much explanation when age effects are included.
14. Strongest nvoifregulation factor was the marginal / quadratic effect, positive, w p = .136
15. Reported age was most significant multidimensional effect in 2019 exploration. Two linear effects had p ~= 0.000: conventionalsoon and nvoifonline; both positive correlations
    1. Possible benefit from pegging \_cons to 1? Because min response is 1 and \_cons is negative; how would this shift values? Stata allows us to set const to 0, but it’s not obvious how to constrain constant to 1 or more; perhaps this? Idk: <https://www.stata.com/support/faqs/statistics/define-constraints-for-parameters/>
16. TODO: change income analysis to account for Prefer not to answer
17. Crage also supports under 18 age group, which surveymonkey accounts don’t support.
    1. Age group 1 is minors. I only have 6 responses in this group, but they are markedly pessimistic, another interesting finding! None of them responded over 7, and 2 of them responded with 1! See appendix G. indicates maybe parents of high school and college students are more favorable to alternative education options…a result which may be intuitive to some and counterintuitive to others. It’s not clear that the stereotype of technology and innovation-friendly youth is identified here.
18. TODO: mechanical turk 4-step microexperimental validation of awareness and favorability modification by information.
    1. Much better treatments exist, but this should validate the general idea that if familiarity is a key factor, just survey turks, send em to read about a couple, then survey them again.
    2. Ask them their opinion on the traditional degree, online learning, and hybrid learning.

**IV. Future Research**

1. Survey GitHub scraped addresses
2. In order to compare alternative credentials to a traditional degree, I asked “For many professions, alternative credentials can qualify a person for an entry-level position.” However, the assumption that a traditional degree can qualify a person for an entry-level position is questionable. Better analysis would survey individuals on that question as well for a better comparison.
   1. Alternative Credentials are on par with a college degree with respect to preparing a learner for their first job. About 60% of executives and hiring managers think that most college graduates are prepared to succeed in entry-level positions: <https://www.chronicle.com/article/Colleges-Say-They-Prepare/244376>
   2. 266/402 = 66% of my respondents indicate a score of 6-10 on Q2 which means they believe “For many professions, alternative credentials can qualify a person for an entry-level position.” is more true than false. Not only does this clearly indicate comparability, it may indicate an advantage for the average alternative learner.
3. Another interesting margin of comparison is learner-centric. A 2017 Strada-Gallup survey looked at student own-satisfaction with the level of career preparedness given by their traditional undergraduate degree: <https://www.insidehighered.com/blogs/just-visiting/different-look-gallup-survey-student-preparation>
   1. Many individual alternative credential programs report satisfaction for their own course, but I haven’t seen this done in an across-the-board way.
   2. A more apples-to-apples approach might be look at Google, Yelp, or other reviews for universities vs alternative programs to get a holistic view of satisfaction, including non-learning activities like dealing with administration.
   3. Perhaps a net promoter score is a way to compare these.
   4. Perhaps instead of an across-the-board survey, we simply speak narrowly about several popular providers, such as the ones listed in my survey: Udacity, Udemy, Coursera, etc, comparing their course satisfaction with the average university.
4. The scraper was effective at systematically obtaining many email addresses, but it was not possible to obtain all email addresses for tested locations, and neither were addresses obtained for users outside of the searched locations. For example, location-based search for “united states,” and it is case insensitive, returned 50,165 users. However, Github only allows us to browse 100 pages of results, and each result page contains 10 users. There are 7 sorting options, however, and we can browse the top 100 pages for each sorting option. This theoretically would allow up to 7000 email addresses per location string, however many users are repeated across sorting options and not all users publicize their email address to begin with. Some users also provide fake email addresses.
   1. The 7 sorting options can be used as a data point of their own, or perhaps for some instrumental variable analysis.
   2. Sorting options can be determined by looking at an output record’s sScrapedUrl, however, there are some reasons we expect the actual sort option effect to be greater than the observed sort option effect:
      1. A person might appear in multiple sort lists, but we are only capturing the initial observation then the program’s caching functionality will prevent aggregating multiple observations of the same person. There is a deterministic order for the sort options though, which may have an interactive effect.
      2. Most people won’t appear on any list due to the 100-page max.
      3. We can have some gauge of the person’s rank on a sorted list by looking at the page number in the scrapedurl, but this is an imprecise proxy. If, for example, we expect that developers who have been developing for a relatively long time will influence alternative credential disposition, an ideal measure would be to measure or ask the length of time they have been developing. The age of their Github account is a proxy, then their rank on the sorted list of least recently joined would be a proxy for github age, then the page number of the scraped url would be a proxy for the rank position. So the page number is a proxy several times removed from the variable of interest and therefore the lack of observed significant effect doesn’t rule out the possibility of an actual effect, although the presence of an effect would be a nice thing to find which might indicate the underlying true effect is quite strong and reliable.
      4. Github does have a so-called abuse prevention mechanism in place which occasionally prevented my scraper from obtaining results during a scraping run. It’s not obvious this matters, but worth mentioning.
      5. Scraped emails were double-cleaned using emaillistverify and mailgun.
      6. Undefined scrape date is before march 8

**Appendix A - Question Reference**

1. Do you contribute to hiring and firing decisions at your company?
   1. One selection among the following was allowed:
      1. Yes
      2. No
      3. Unemployed
2. For many professions, alternative credentials can qualify a person for an entry-level position.
   1. An integer selection inclusively between 1 and 10.
   2. Value of 1 labeled “Strongly Disagree”
   3. Value of 10 labeled “Strongly Agree”
   4. Other values unlabeled.
   5. This is the default answer pattern. If some question doesn’t specify the available answers, then the answers available are similar to question #2.
3. It will soon become fairly conventional for high school graduates to obtain alternative credentials instead of going to college.
4. When you add up the pros and cons for online education, it's probably a good thing for society overall
5. When you add up the pros and cons for artificial intelligence, it's probably a good thing for society overall.
6. When you add up the pros and cons for cryptocurrency, it's probably a good thing for society overall.
7. When evaluating an applicant's education, it is important is important to check whether the degree was awarded from a US institution.
8. Have you heard of any of the following online course providers?
   1. Zero to many selections among the following were allowed:
      1. Udacity
      2. Udemy
      3. Coursera
      4. Pluralsight
      5. Lynda.com
9. Do you work in a STEM profession?
   1. One selection among the following was allowed:
      1. Yes
      2. No
      3. Unsure
10. Which of these industries most closely matches your profession?
    1. Selections were not based on 2018 SOC codes, but in the future I would like to provide those options. https://www.bls.gov/soc/2018/major\_groups.htm
    2. One selection among the following was allowed:
       1. Agriculture
       2. Education
       3. Energy
       4. Finance, Investment, or Accounting
       5. Health
       6. Information Technology
       7. Law
       8. Manufacturing
       9. Military
       10. Other
       11. Retail
       12. Transportation
11. I consider myself religious
12. I consider myself Christian
13. Government regulation helps ensure businesses treat individuals more fairly.
14. Age
    1. Included by SurveyMonkey in 2018.
    2. In 2019 the question was explicitly asked.
    3. One selection among the following was allowed:
       1. < 18
       2. 18 -29
       3. 30-44
       4. 45-60
       5. > 60
15. Gender
    1. Included by SurveyMonkey in 2018.
    2. In 2019 the question was explicitly asked and the value of Other became a choice.
    3. One selection among the following was allowed:
       1. Male
       2. Female
       3. Other
16. Household Income
    1. Included by SurveyMonkey in 2018.
    2. In 2019 the question was explicitly asked.
    3. Measured annually, in nominal USD.
    4. One selection among the following was allowed:
       1. 0-9,999
       2. 10,000-24,999
       3. 25,000-49,999
       4. 50,000-74,999
       5. 75,000-99,999
       6. 100,000-124,999
       7. 125,000-149,999
       8. 150,000-174,999
       9. 175,000-199,999
       10. 200,000+
       11. Prefer not to answer
17. Region
    1. Included by SurveyMonkey
    2. One selection among the following was allowed:
       1. New England
       2. Middle Atlantic
       3. East North Central
       4. West North Central
       5. South Atlantic
       6. East South Central
       7. West South Central
       8. Mountain
       9. Pacific
18. Device Type
    1. Included by SurveyMonkey
    2. One selection among the following was allowed:
       1. iOS Phone / Tablet
       2. Android
       3. Other Phone / Tablet
       4. Windows Desktop
       5. MacOS Desktop
       6. Other

**Appendix B – Questions Per Survey**

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| **Question Definition ID** | **Factor Short Name** | **2018, Feb** | **2018, Oct** | **2019, Feb** |
| 1 | Employment | X | X | X |
| 2 | Entry-Level Suitability | VOI | VOI | VOI |
| 3 | Conventionalism | X | S | X |
| 4 | Online Education | X | S | X |
| 5 | Artificial Intelligence |  | S | X |
| 6 | Cryptocurrency | S | X |  |
| 7 | US Degree Centrism | S | X |  |
| 8 | Provider Recognition | S | S | X |
| 9 | STEM | X | X |  |
| 10 | Industry | S | X | X |
| 11 | Religiousness |  | X |  |
| 12 | Christianity |  | X |  |
| 13 | Regulatory Policy |  | S | X |
| 14 | Age | X | S | X |
| 15 | Gender | S | S | X |
| 16 | Household Income | S | S | X |
| 17 | Region | X | X | X |
| 18 | Device Type | X | X | X |
| 19 | Time |  | C | C |
| 20 | Collector |  |  | C |

C - Question is a calculated question, the answer of which was determined by the analyst instead of being explicitly asked of the respondent.  
S - Question was presented and associated with a strong effect.  
X - Question was present for survey. This does not guarantee every respondent answered the question. Particularly, Q14-Q18 were presented as SurveyMonkey included data for paid responses only during 2018. Beginning in 2019, Q14-Q16 were asked of all respondents, but Q17-Q18 remained observed for SurveyMonkey paid responses.  
VOI - Question was present and represents the variable of interest.

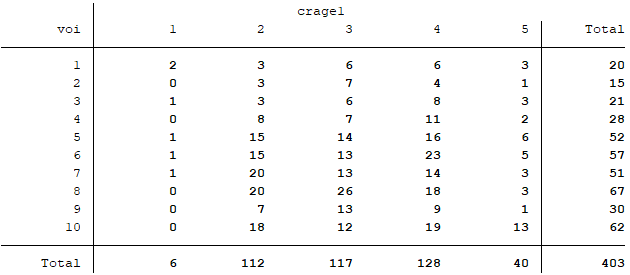
**Appendix C – Summary Statistics**

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**Appendix D – Survey Collector Reference**

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| **Collector Name** | **Responses** | **First Response Date** | **Last Response Date** |
| Oct 2018 - Work, Social Media, Misc | 20 |  |  |
| Oct 2018 - Targeted relaunch | 84 |  |  |
| Oct 2018 - MTurk | 30 |  |  |
| Oct 2018 - Targeted | 106 |  |  |
| Feb 2018 - Social Media, Work, Misc Web Link | 38 |  |  |
| Feb 2018 - Targeted Audience | 103 |  |  |

**Appendix G – Crosstab of Linear Age on the Variable of Interest, Entry Level Suitability of Alternative Credentials**



1. Aggregate results and questions asked are publicly viewable at TODO [↑](#footnote-ref-1)
2. See Appendix C for a Survey Collector Reference with additional information. [↑](#footnote-ref-2)