

1. Us employment rate ~60%. So, udacity’s is less without correction
2. Simple regression on nnano1 shows insignificant negative correlation
3. Reg \_employed nnano1 nnano2 neg linear, positive marginal! “noob effect” but not expected to persist as n -> infinite (permanent increasing returns is theoretically problematic)
4. Reg \_employed nnano1 nnano2 nnano3 has more important, positive nnano3 compared to nnano2
5. Age matters; and I’m interested in alt creds as a step to the first job; so what about including age?
   1. Age highly significant and nnano1, 2, 3 pattern is robust, even better p!
   2. Including linear interaction flips the negative marginal effect, but reduces factor significance; nnano1, 2, 3 is now strictly positive but interaction is negative. What does this mean for young folks? It means getting a nanodegree is a worse idea as you age. This confirms intuition. But wait, couldn’t this effect have some marginal caveat? So let’s introduce quadratic and cubic effects to the interaction.
   3. Yes, now all interactions are highly significant. Now we see a clear but complicated picture. Getting nanodegrees as you age is linearly beneficial, marginally problematic over an intermediate region, and somewhat beneficial at the extremes. The cubic benefit might seem negligible, but note that it is roughly twice the cubic negative effect of age. If being super old per se is cubically bad, being super old and super education is cubically good to the exact same degree.
   4. The important part here is that the noob effect remains; although it’s expressed in quadratic and cubic variables. A single nanodegree doesn’t seem to help much, but several do help. This noob effect seems like ‘knowing just enough to be dangerous’ and it may signal justification for the imposter syndrome experienced by many professionals who switch to a career in programming utilizing self-teaching means or alternative education. But it seems to also support the notion that some who push through can achieve high skill.
   5. The pattern is robust to language effects; interestingly, speaking English has a negative effect…?

jesse7 is a case where two people were in the image, so I didn’t process it via Kairos. With large samples this could introduce a bias because people with a profile picture of the opposite gender may tend to be married or affectionate relative to others, and we know that married couples have different employment outcomes as do those of high agreeableness. Shane is a guy, but his profile pic was him and his son. I can tell because his son is too young to be working age, but his profile info indicates current employment. In theory I could discriminate by selecting the Kairos response with the largest age, but this is not a generic procedure which I can run across the code. I should still do it anyway.

Try dropping experience = 0 and see what happens to r2; it mixes effects of those never previously employed with those just too lazy to fill out profile

I always skipped with 2 or more people in pic for consistency

This noob effect seems to be an anti-sheepskin effect and thereby indicates human capital, not signaling. Instead of passing a marker society expects and repeating reward, you get what society expects and see a negative effect (eg one nanodegree or unit of education) but then you proceed to some arbitrary, peculiar, no-way-employers-see-this-point-as-a-sheepskin-threshold, and you get gains.

Private sector lit review:

<http://businessblog.udacity.com/2016/02/26/your-next-great-tech-hire-may-not-have-a-computer-science-degree-and-thats-a-good-thing/>

<https://news.ycombinator.com/item?id=9313088>

<https://www.inc.com/jessica-stillman/why-elon-musk-doesnt-care-about-college-degrees.html>

-review blog (google study on degree decipation)

-review reddit

-talk about ‘degrees of alternativeness’ vocational, private k-12, and charter are some of the ‘least alt alts’ and they work well; rank them in altiness; more alt is like homeschooling and what else?

Some github scrapes were taken by tracking the github profile down by hand; for example, Audrey Klammer had her linkedIn url twice within Udacity data, so I took this to mean she probably had a Github account and misentered it. So, I searched her name in GitHub users and found the correct GitHub url, then scraped it.

Has linkedin url and has github url alone ought to be a couple data points\*

Effect has known attenuation which is people that deleted their accounts, so it’s in the udacity json but not real

Make several papers:

1. SurveyMonkey 1-off Survey
2. Udacity scrape
3. Github scrape
4. linkedIn scrape
5. Survey from above-scraped urls (udacity email survey)
6. Scrape github and survey (github survey)
7. Surveymonkey panel survey
8. Scrape stackoverflow
9. Company internal data extraction
10. ABM stuff
11. Stuff with Markus
12. Stuff with Ryan Turpyn
13. Stuff with Boettke, Cowen, Tabarrok, Storr, or whoever the last dude is (stratman???? But I think he didn’t get along w bryan)